Fuzzy Logic Concepts in Computer Science and Mathematics

Rahul Kar | Aryan Chaudhary | Gunjan Mukherjee
Biswadip Basu Mallik | Rashmi Singh
Editors

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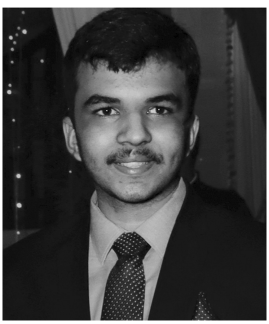

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Abbreviations

ACC	adaptive cruise control
ADAS	advanced driver assistance systems
AHP	analytic hierarchy process
AI	artificial intelligence
BPCL	Bharat Petroleum Corporation Limited
BSD	blind-spot detection
BSI	blind-spot intervention
CVT	continuously variable transmission
DCT	discrete cosine transform
DIFWA	dynamic intuitionistic fuzzy weighted averaging
DSS	decision support system
FCM	fuzzy C-means
FIS	fuzzy inference system
FLC	fuzzy logic controller
FS	fuzzy set
fsQCA	fuzzy-set qualitative comparative analysis
GTMA	graph theory and matrix approach
HAZOP	hazard and operability
HPCL	Hindustan Petroleum Corporation Limited
HR	Human Resource
HVAC	heating, ventilation, and air conditioning
ICU	intensive care unit
IFL	intuitionistic fuzzy logic
IFLBP	intuitionistic fuzzy local binary pattern
IFN	intuitionistic fuzzy number
IFS	intuitionistic fuzzy set
IFT	intuitionistic fuzzy transversal
IFTC	intuitionistic fuzzy transversal core
IFTHGs	intuitionistic fuzzy threshold hypergraphs
IIoT	Industrial Internet of Things
IOC	Indian Oil Corporation
IoT	Internet of Things
IT	indoor temperature
ITrFN	Intuitionistic Trapezoidal Fuzzy Number

KFCM	kernelized fuzzy c-mean
LDC	lane departure correction
LDW	lane departure warning
LMI	linear matrix inequality
MCDM	multicriteria decision-making
ML	machine learning
MQTT	Message Queuing Telemetry Transport
MRI	magnetic resonance imaging
NSE	National Stock Exchange
O.S.	overshoot
ONGC	Oil and Natural Gas Corporation
OPC UA	Open Platform Communications Unified Architecture
OT	outdoor temperature
PID	proportional, integral, and derivative
SCR	selective catalytic reduction
SVM	support vector machines
TFN	triangular fuzzy number
XAI	explainable AI

Preface

Fuzzy logic has become an important mathematical tool of the soft computing domain, which has vastly been applied to the field of computer science as well. The fuzzy-based decision structure has been used in many computer science domains with excellent results due to its tracking ability of vagueness. The fuzzy logic concept is versatile and can seek application in the allied engineering domains such as electrical, mechanical, electronics, civil, etc. The other social and economical fields are also being touched upon by the fuzzy concept with valuable outcomes.

This current edited book caters to the fuzzy application to many interconnected and versatile domains with fruitful outcomes. The electric machine performance can be measured and estimated with the help of a fuzzy system. The tracking of the current path can be determined with great certainty. The concept of fuzzy logic has been substantiated in the present book on tuning of machines. The electrical machine extends to the mechanical attachment through the gear-box system where the fuzzy concept can be applied to enhance the performance mechanism of the device.

The machine learning approach is also another category where the concept of fuzzy can be successfully applied. The bedrock of machine learning has been enhanced further with application of the soft computing aspect. The fuzzy system has become the altering tool for classification and categorization.

Health science is also another promising field where a number of research works are going on. The concept of fuzzy has been applied with great success to produce more accuracy in the classification of medical data. The diagnosis operation of any patient can be carried out with the help of precision approaches of task selection and proper categorization of it. Fuzzy logic plays a major role in performing such operations.

The current edited book also focuses on the variation of fuzzy logic schemes. The intuitionistic fuzzy logic concept has also played a major role in the field of mathematics. The main demerits of the fuzzy theory concept can better be understood by the concept of extension of fuzzy range and its utilization. The multicriteria decision-making aspect is also strongly connected to the fuzzy concept and has become the main focus area of this book.

Another important aspect of the fuzzy logic concept is its unique application of the concept to the industrial IoT for enhancing the smart manufacturing concept. The financial analysis is the main essence of share market or insurance data. The scientific and intelligent analysis of data can be easily done by the concept of fuzzy logic. Its financial impacts can also be seen in the giant companies. Control capability enhancement is a rudimentary part of any organization in its strategy making. The data is the basic component of the organization, can have a good impact on its overall transaction activities.

The security aspect can also be included to some extent to the model. The application of fuzzy logic can help in the strategy making for any organization involving the data as an essential part. The tourism portal and its implementation strategies have also been implicated by the fuzzy means.

Another crucial aspect of the fuzzy logic concerns the fuzzy controller-based greenhouse automation using sensor networks. The sensor is engaged in gathering data and information from the environment, which also provides responses to its variation.

The fuzzy logic concept in the automotive industry is also prominent to provide the application of intelligence to the industries.

Overall the present volume of the book, based on the fuzzy concept application, provides unique ideas about the rudimentary foundation of the subject and its versatile application to diversified fields of engineering. The presentation of the chapters with lucidity of the subject and smooth understanding is the key feature of this book. The in-depth research trends in the domain of fuzzy logic has become the main hotspot of such a book, which also renders much insights and knowledge to the readers comprising students, researchers, academicians, etc. This edited book also provides extra mileage in the fuzzy application in the near future for the engineering, medical, and even legal fields help to produce good and effective results.

—Editors

CHAPTER 1

Enhancing Electrical Machine Performance Through Fuzzy Logic Control

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ABSTRACT

This chapter explores the application of fuzzy logic in improving the performance and control of electrical machines, particularly direct current motors and single-phase asynchronous motors. Traditional crisp logic methods, often limited by their binary nature, struggle with the uncertainties inherent in real-world industrial applications. In contrast, fuzzy logic accommodates degrees of truth, offering a nuanced and flexible approach to motor control. This chapter details the design and implementation of fuzzy logic controllers using MATLAB SimPower Systems, highlighting their ability to manage complex motor behaviors and ensure precise speed regulation. Case studies demonstrate the superior adaptability and disturbance rejection capabilities of fuzzy logic compared to conventional methods. The integration of components like four-quadrant choppers and advanced control techniques emphasizes the robustness of this approach in addressing dynamic industrial requirements. The findings underscore fuzzy logic's potential to

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enhance efficiency, stability, and reliability in motor-driven systems across diverse applications.

1.1 INTRODUCTION

Logic is a fundamental concept in modern computer science and mathematics that facilitates decision-making, problem solving, and complex system modeling conventional logic, sometimes referred to as crisp or boolean logic, functions in a binary environment where variables can only be true or false, zero or one. While crisp logic has been indispensable in many applications, it often falls short when faced with the nuances of real-world scenarios, where absolutes are scarce, and uncertainty prevails [1, 2].

It was in this context that the pioneering work of Lotfi Zadeh in 1965 at the University of California, Berkeley, gave birth to a groundbreaking idea—fuzzy logic. Driven by the recognition that the real world seldom adheres to the rigid binary distinctions of crisp logic, Zadeh introduced a revolutionary concept that would change the landscape of reasoning and decision-making. He proposed a form of logic that allowed for degrees of truth, enabling a more human-like approach to addressing ambiguity and imprecision [1, 2].

Fuzzy logic acknowledges that not every question has a simple "yes" or "no" answer and instead embraces the complexity of partial truths and partial falsehoods. It operates in a world of shades of gray, where variables can take on values between 0 and 1, representing degrees of membership or truth. This paradigm shift laid the foundation for a new era in computing and mathematics—one where uncertainty is not tolerated but embraced as an inherent aspect of our interactions with the world.

In this chapter, the application of fuzzy logic to regulate the speed of electrical machines, including direct current motors (DCMs) and single-phase asynchronous motors, is explored. The complexities of industrial applications necessitate a suitable approach, which fuzzy logic provides. This study focuses on the complex fuzzy logic controller design and implementation procedures for these particular electrical machines. Detailed case studies, examining the application of fuzzy logic in speed regulation, are presented. The passive observer is guided through these applications, gaining insight into the precise control achieved through the integration of fuzzy logic within the MATLAB SimPower Systems framework. The role of MATLAB SimPower Systems as a robust simulation platform is emphasized, showcasing its ability to test and explore the efficacy of fuzzy logic controllers.

1.2 FUZZY LOGIC VERSUS CRISP LOGIC EXAMPLE: SPEED CONTROL OF A MOTOR

Consider the scenario of controlling the speed of a motor in an industrial setting. The goal is to modify the motor's speed in response to the received input signals.

1.2.1 CRISP LOGIC APPROACH

The approach of expressing motor speed using crisp values, as shown in Figure 1.1, has its limitations. Classifying speed into discrete ranges, such as less than 50 rad/s, between 50 and 100 rad/s, and so on, can lead to ambiguities and problems, especially when the speed falls in between these defined crisp values. This method proves weak when dealing with industrial applications where precision and fuzziness are crucial. Instances where motor speeds turn around critical points like 50 or 100 rad/s might pose challenges, potentially causing issues in industrial operations. Consequently, Because of this approach's lack of precision in representing speeds within these ranges, more complex and exact control strategies—like fuzzy logic—are required to address these complexities and guarantee optimal performance in industrial settings.

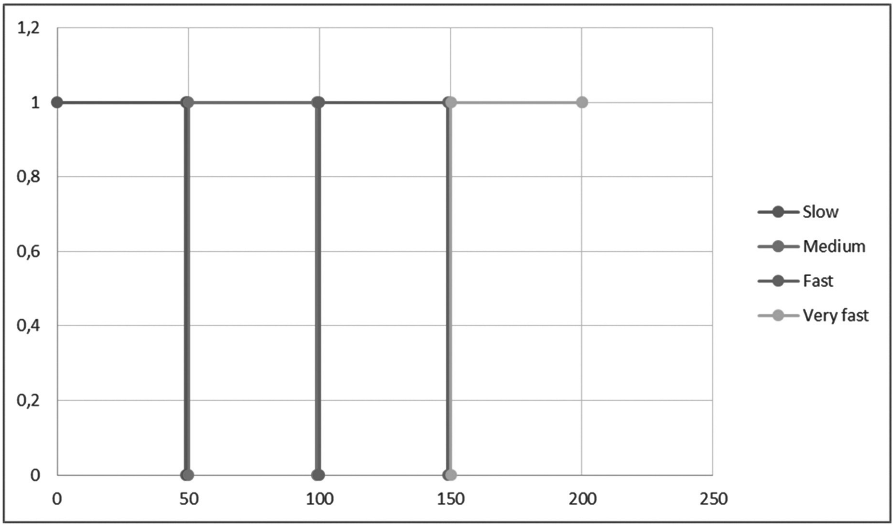

FIGURE 1.1 Crisp logic A motor speed control. ⏎

1.2.2 FUZZY LOGIC APPROACH

The fuzzy logic approach provides a more natural and realistic representation of motor speed. By defining linguistic fuzzy variables like “low speed,” “medium speed,” and “high speed” based on specific speed ranges, such as 0 to 50 rad/s, 50 to 100 rad/s, and 100 to 150 rad/s shown in Figure 1.2, the system gains a complex understanding of motor behavior. Each linguistic variable involves a percentage value calculated from the given speed range. For example, a speed of 75 rad/s can be interpreted as 50% medium speed and 50% slow. This approach enables more precise and nuanced control decisions by capturing the inherent imprecision and uncertainty in real-world scenarios. Using fuzzy logic to represent ranges of variables provides a flexible and adaptable configuration, ensuring a more natural and reliable control mechanism for industrial applications [3, 4].

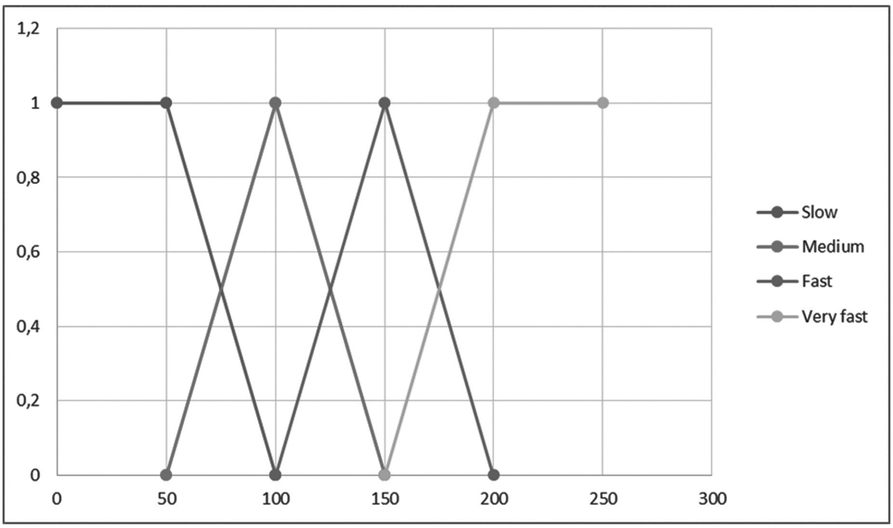

FIGURE 1.2 Fuzzy logic DC motor speed control. ⏎

More than this is the fuzzy logic approach, the system considers partial truths. Since the input signal is not just “low” or ``high,” but can have degrees of membership in multiple categories. So, the motor speed adjusts smoothly and continuously, representing a more realistic response to varying input conditions [2, 5, 6]. This example highlights the key difference: crisp logic operates in strict, discrete levels, while fuzzy logic allows for a smoother, more nuanced response, flexible the imprecise and uncertain nature of real-world input signals. This flexibility is vital in applications where precise boundaries are hard to define or where systems need to respond to a wide range of input conditions.

1.3 FUZZY LOGIC DCM CONTROL

1.3.1 DCM

In the vast landscape of industry, DCMs play a pivotal role, weaving their presence across diverse applications with exceptional precision and efficiency [7]. The intricate tasks of manufacturing are evidence of their silent but significant operation. where they master the synchronized favor of manufacturing processes in motion. In the textile sector, DCMs create complex patterns so that each pattern appears on the fabric precisely [5, 8]. These motors find their way into the heart of medical technology, empowering surgical tools with the finesse needed for intricate procedures and lending their reliability to life-saving medical devices [9–11].

Beyond these applications, DCMs are the driving force behind automation, coordinating the quick sorting in warehouses and the careful choreography of packing lines. Their adaptability shines in every industry, demonstrating their abilities to transform mechanical energy into purposeful movement, from the precise strokes of a robotic arm to the rhythmic motions of conveyor belts. Each rotation signifies the seamless fusion of technology and industry, a proof of the accuracy and dependability that DCMs provide to the foundation of industrial operations [12–15].

1.3.2 USING SIMPOWERSYSTEMS IN CONTROL SYSTEMS

Utilizing SimPowerSystems in the design and simulation of control systems for electrical motors offers a multitude of advantages, bringing simulations remarkably close to real-world scenarios, far beyond the reach of simplistic theoretical models. This powerful tool enables engineers and researchers to create complex virtual models of electrical power systems, for example, DC, asynchronous motors, and their corresponding control systems. These models function as dynamic replicas, emulating the behavior of the system in a range of scenarios with different loads and speeds [16–18].

What sets SimPowerSystems apart is its utilization of advanced mathematical models, capturing the intricacies of electrical, magnetic, and mechanical interactions within the system. These simulations take into account real-world elements like voltage drops in the stator and rotor circuits, rotor resistance, and magnetic saturation. As a result, SimPowerSystems offers a highly accurate visual representation of the behavior of the system, outperforming even the accuracy of more basic theoretical models.

Additionally, SimPowerSystems offers support for hardware-in-the-loop simulation and controller in the loop, allowing engineers to use physical components like motor drives and controllers to thoroughly test their control systems. Through the identification of possible problems or constraints in the control system prior to its implementation in a real-world application, this methodological approach further improves simulation accuracy.

1.3.3 DCMS IN MATLAB SIMSCAPE (SIMPOWERSYSTEMS)

The process of modeling a DCM in SI units using SimPowerSystems involves creating a new Simulink model. Engineers initiate this process by crafting a Simulink model tailored to their specific requirements. Within this model, the essential step involves selecting the suitable DCM block from the SimPowerSystems library. This pivotal block acts as the foundation of the model, enabling engineers to define crucial parameters, such as armature resistance (R_a) and inductance (L_a) in ohms and henries, respectively [16–18].

The choice to work in SI units is deliberate, aligning with international standards and ensuring consistency and accuracy in the modeling process. The DC machine, meticulously defined in SI units, is visually represented in Figure 1.3, providing engineers with a clear, graphical reference point.

In Figure 1.3, MATLAB Simscape presents a versatile platform for modeling DCMs. Engineers are offered a range of motor choices, exemplified by “choice 1,” featuring 5 HP, a 240 V armature voltage, a rated speed of 1750 RPM, and a 300 V field voltage. Notably, the parameters adjust automatically based on the selected motor, streamlining the configuration process. Engineers benefit from this automated precision while retaining the flexibility to make manual adjustments, granting full control over the modeling process. This dynamic interface embodies MATLAB’s user-friendly approach, empowering engineers to seamlessly transition from theory to practical application, enhancing modeling efficiency, and accommodating diverse motor configurations.

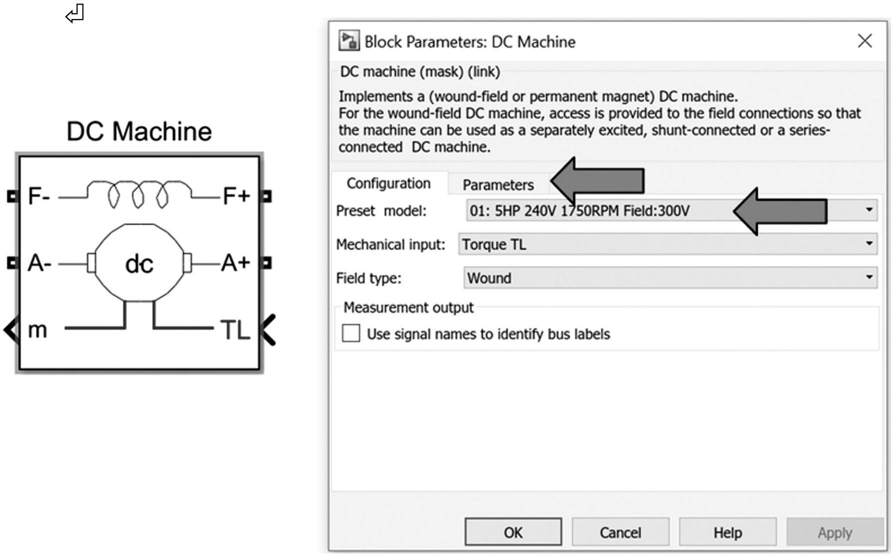

FIGURE 1.3 DC motor.

1.3.3 FOUR-QUADRANT CHOPPER DRIVE DCM

Within the intricate domain of power electronics, the four-quadrant chopper emerges as a linchpin, offering unparalleled bidirectional control over DCMs [19]. Operating seamlessly across all quadrants of the voltage–current plane, this electronic marvel facilitates dynamic reversals and meticulous speed adjustments in applications demanding rapid transitions. In this exploration, the theoretical underpinnings and practical applications of the four-quadrant chopper are dissected, shedding light on its pivotal role in modern power systems. Particularly noteworthy is its utilization as a driving force for DCMs, a strategic choice made to guarantee precise speed control in both forward and reverse directions. This deliberate selection not only underscores the chopper's versatility but also exemplifies its significance in ensuring efficient and controlled motor performance, making it a cornerstone in diverse industrial and commercial settings [15, 19–22].

In Figure 1.4, a comprehensive representation unveils a DCM controlled by a four-quadrant chopper in the power section. This intricate system is constructed using four insulated-gate bipolar transistor (IGBT)/diode components, where each pair of IGBTs (IGBT 1 and 2; IGBT 3 and 4) forms a distinct arm, strategically designed to avoid short circuits. The control mechanism ensures symmetrical operation, where IGBT 1 and 4, as well as IGBT 2 and 3, are synchronously controlled to maintain balance. The block denoted as "Bloc" is pivotal, providing the essential four-quadrant control. Here, DC voltage 1 regulates the field voltage, while DC voltage 2 governs the armature voltage. The bus selector, a critical component, facilitates the selection of the DCM's output, orchestrating the seamless operation of this complex system. Through this visual representation, engineers gain valuable insights into the intricate components and control mechanisms of a four-quadrant chopper, illuminating the path for precise and bidirectional control of DCMs. The series RLC branch is used to add an inductance that has a value of 1e-4 [Henry] to improve the quality of the current. A further step involves applying torque resistance through a defined procedure. This step spans a duration of six units, commencing with an initial value of 5 and gradually reaching the final value of 20.35. The objective is to achieve the rated torque, which equals the power divided by the speed (Figure 1.5).

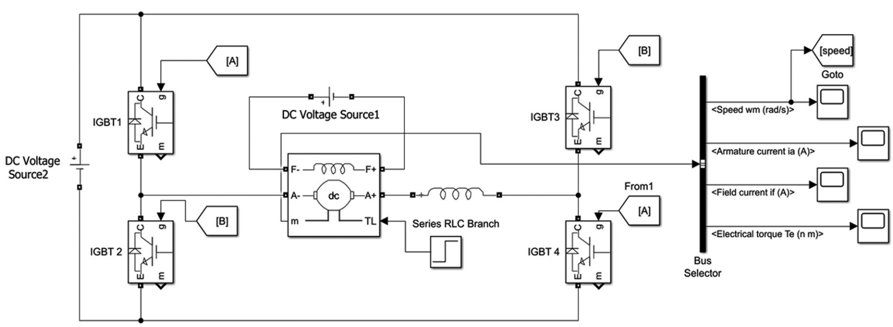

FIGURE 1.4 DC motor drived by a four-quadrant chopper and power part. ⏎

Select the bus selector to select the output of the machine

In Figure 1.6, the control segment of a DCM operated by a four-quadrant chopper is depicted. A pivotal component in this control system is as follows.

"Powergui" block: playing a vital role in regulating simulation time and type. This essential module not only facilitates precise control over the simulation duration but also offers an array of tools, enabling engineers to adjust various simulation parameters according to specific requirements set the: Simulation type to discrete, and Sample time (s) to 50e−5.

The speed reference is generated by the step function set: Step time: 3, Initial value: −150 *30/pi, Final value: 170* 30/pi.

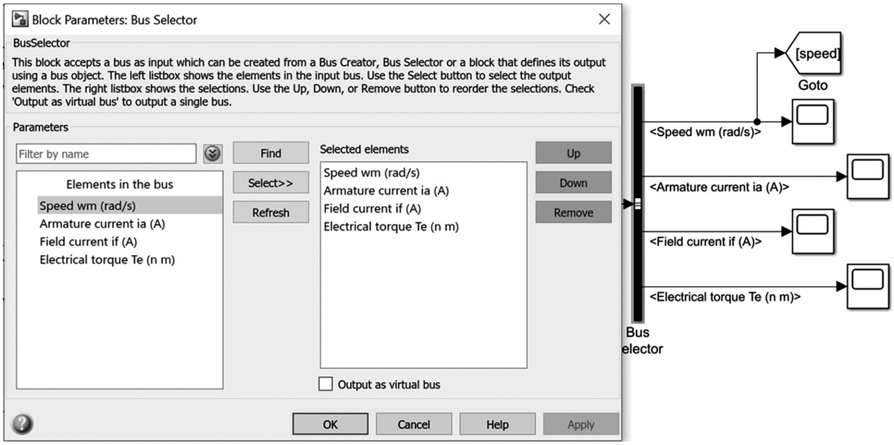

FIGURE 1.5 Bus selector output. ⏎

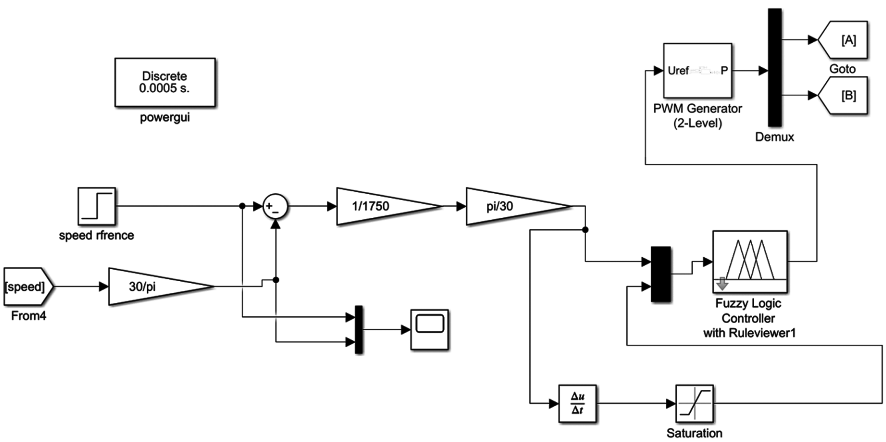

FIGURE 1.6 DC motor drived by a four-quadrant chopper, control part. ⏎

The speed produced by the “From” block must be assigned, similar to the “Goto” block, which records the output speed of the DCM. This ensures consistent data flow and synchronization between the generated speed data and the recorded motor speed output.

There are three gains in the system: the first is set to $^{1}/_{1750}$ to ensure error normalization, the second is set to $^{30}/_{pi}$ to convert speed from RPM to radians per second, and the third gain is adjusted to transform the speed from radians per second back to RPM.

The pulsewidth modulation (PWM) generator (two-level) block is configured with a frequency of 100*50, highlighting its crucial role in the control system. Its function is pivotal, emphasizing its significance in regulating the system's operations.

The fuzzy logic controller with Ruleviewer plays a key role in the fuzzy logic control of the DCM with two inputs: the error and its derivative.

1.3.4 FUZZY LOGIC CONTROLLER WITH RULEVIEWER

In this section, a comprehensive step-by-step guide on how to effectively utilize the fuzzy logic controller with Ruleviewer is provided. This powerful tool plays a pivotal role in the control system, enabling intelligent decision-making based on fuzzy logic principles.

Type "fuzzy" in the MATLAB command window.

Click on "file," then select "export," and save the file with the name "fuzzy controller." The file should be saved with the extension ".fis." Next, use the "edit" option to add variables. Use the cursor to modify the input and output names as demonstrated in Figure 1.7.

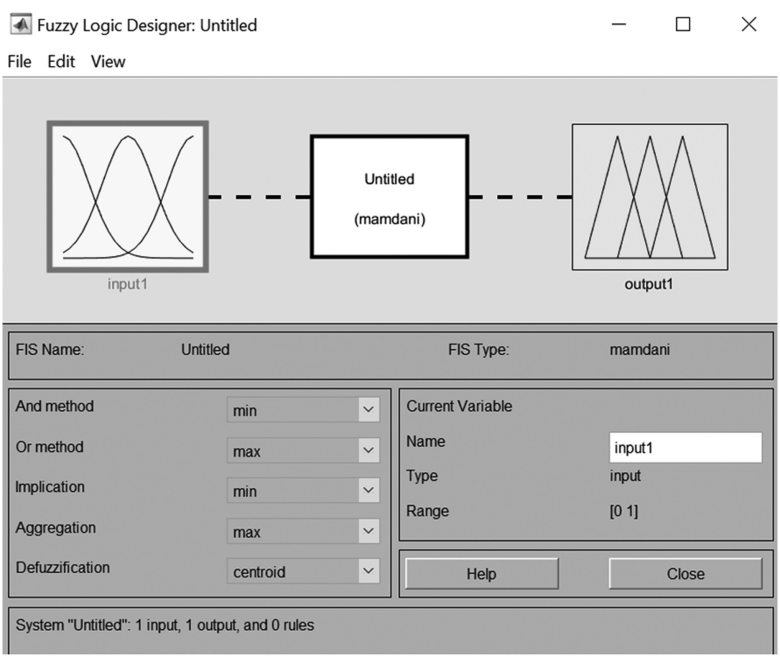

FIGURE 1.7 Fuzzy logic designer. ⏎

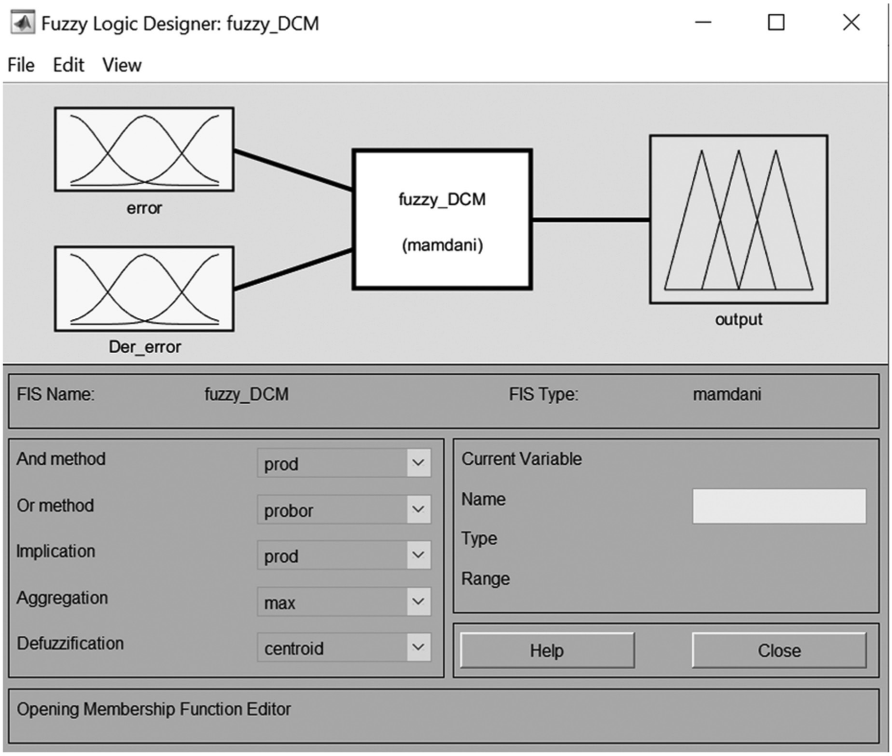

FIGURE 1.8 Fuzzy logic designer: Input and output naming. ⏎

Within the input section, modify all input parameters as demonstrated in Figure 1.8. Enter the names for each membership function plot and select the function type as "gaussmf." This choice is made because it aligns with natural data patterns. Adjust the range, display range, and parameters according to the details outlined in Figure 1.8.

Figure 1.9 illustrates the modifications made to the output. Select the function type as "trimf," as it is more suited to the nature of the output. Follow the other specified changes outlined in the figure for optimal configuration.

Figure 1.10 illustrates the speed response of the DCM using fuzzy control, where the motor accurately tracks the specified reference speed. The system exhibits a rapid response time of less than 1 second without overshooting or steady-state errors. The motor operates bidirectionally, effectively responding to speeds of −1432 and 1623 RPM. These responses are achieved under a resistive torque of 5 Nm. Upon applying a relative torque disturbance of 20.35 Nm at 6 s, the motor swiftly rejects the disturbance, experiencing minor oscillations. Figure 1.11 provides a detailed close-up view of the DCM Speed Response, highlighting slight oscillations introduced by the fuzzy control mode.

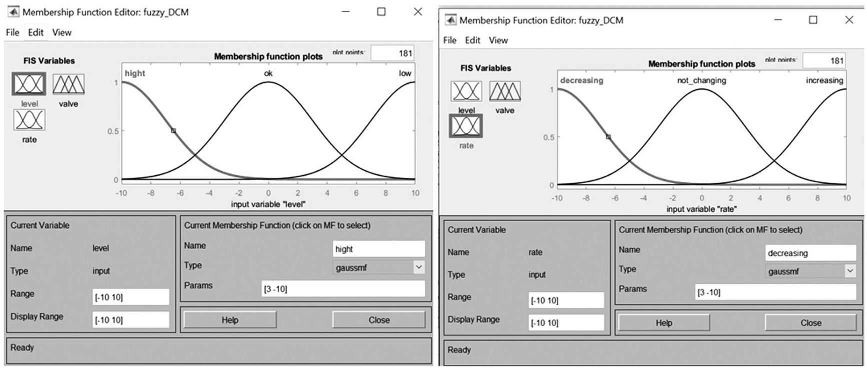

FIGURE 1.9 Fuzzy Logic Designer: Input parameters ⏎

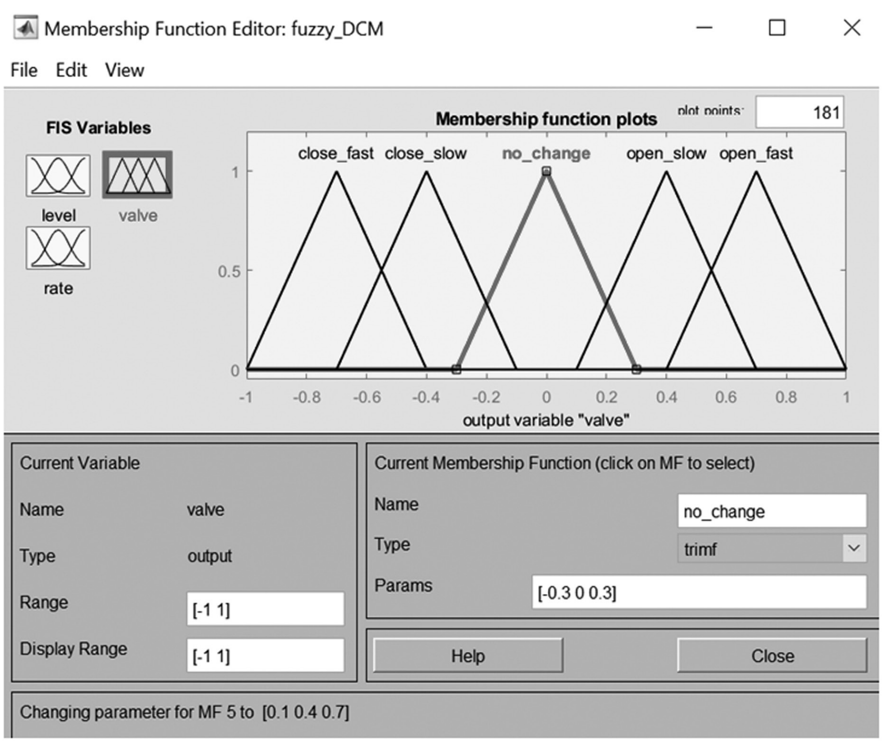

FIGURE 1.10 Fuzzy logic designer: Output parameters. ⏎

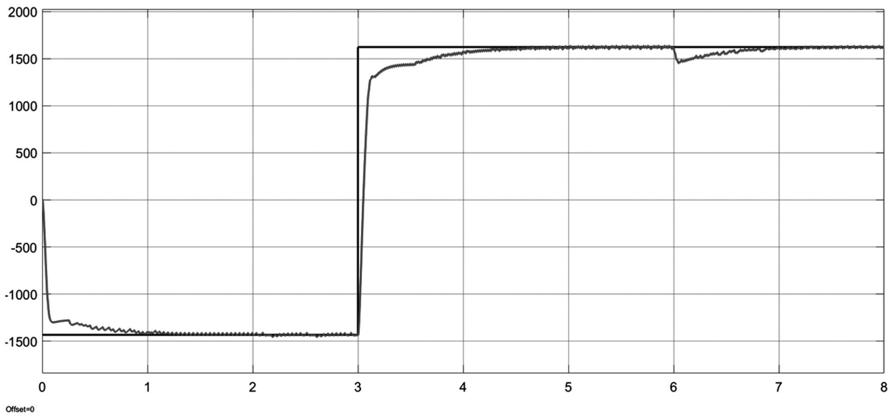

FIGURE 1.11 DC motor speed response. ⏎

Figure 1.11 depicts the responses of the DCM's armature current and torque. A notable similarity is observed between the profiles of armature current and electromagnetic torque, indicating the direct influence of current on torque changes. Even with an increase in resistive torque, resulting in a higher current, the starting current initiates an initial torque to commence motor operation. Changing the motor's direction requires another starting current to generate an additional starting torque. Figure 1.12 reveals oscillations in both torque and current responses, which directly influence the oscillations observed in the speed response.

1.4 FUZZY LOGIC SINGLE-PHASE ASYNCHRONOUS MOTORS CONTROL

1.4.1 SINGLE-PHASE ASYNCHRONOUS MOTORS

The single-phase asynchronous motor, also known as the single-phase induction motor, serves as a cornerstone in numerous applications owing to its simplicity, reliability, and adaptability. These motors power an array of essential devices, from household appliances like fans and air conditioners to industrial tools, water pumps, and heating, ventilation, and air conditioning systems [23, 24]. One of its primary advantages lies in its uncomplicated yet robust design, ensuring dependable performance and minimal maintenance requirements. Moreover, these motors are remarkably cost-effective to manufacture, making them economically viable for various applications [25]. Their ease of control, operating efficiently on a single-phase ac power supply, simplifies installation and reduces complexity in electrical systems. In addition to their versatility, single-phase asynchronous motors are characterized by their quiet operation and the ability to deliver substantial starting torque, enhancing their suitability for environments requiring both efficiency and minimal noise. Overall, these motors stand as a testament to practical engineering, offering reliable solutions for diverse industrial and domestic needs [26, 27].

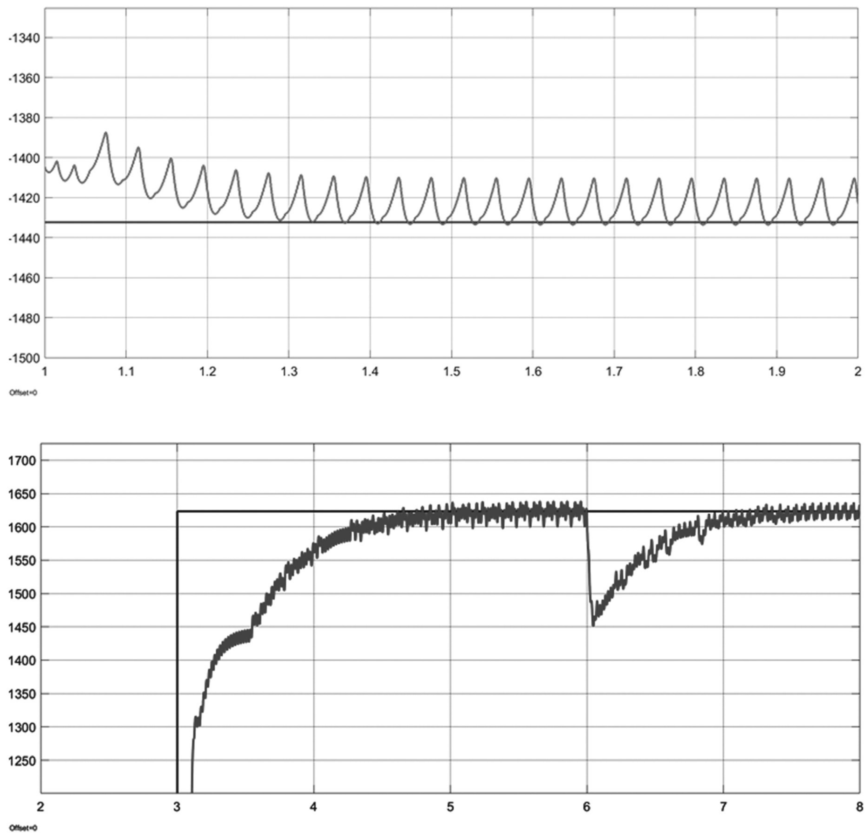

FIGURE 1.12 Close-up view of DC motor speed response. ⏎

1.4.2 *SINGLE-PHASE ASYNCHRONOUS MOTORS IN MATLAB SIMSCAPE (SIMPOWERSYSTEMS)*

Figures 1.13–1.15 illustrate single-phase asynchronous motors controlled by fuzzy logic within the MATLAB Simscape (SimPowerSystems) environment.

In Figure 1.13, the power section is depicted, where the single-phase asynchronous motors are linked to an inverter comprising two legs. Each leg consists of two IGBTs, resembling the structure of a four-quadrant chopper. The inverter is powered by a DC set at $\sqrt{2}V_{Rms}$ [26, 28].

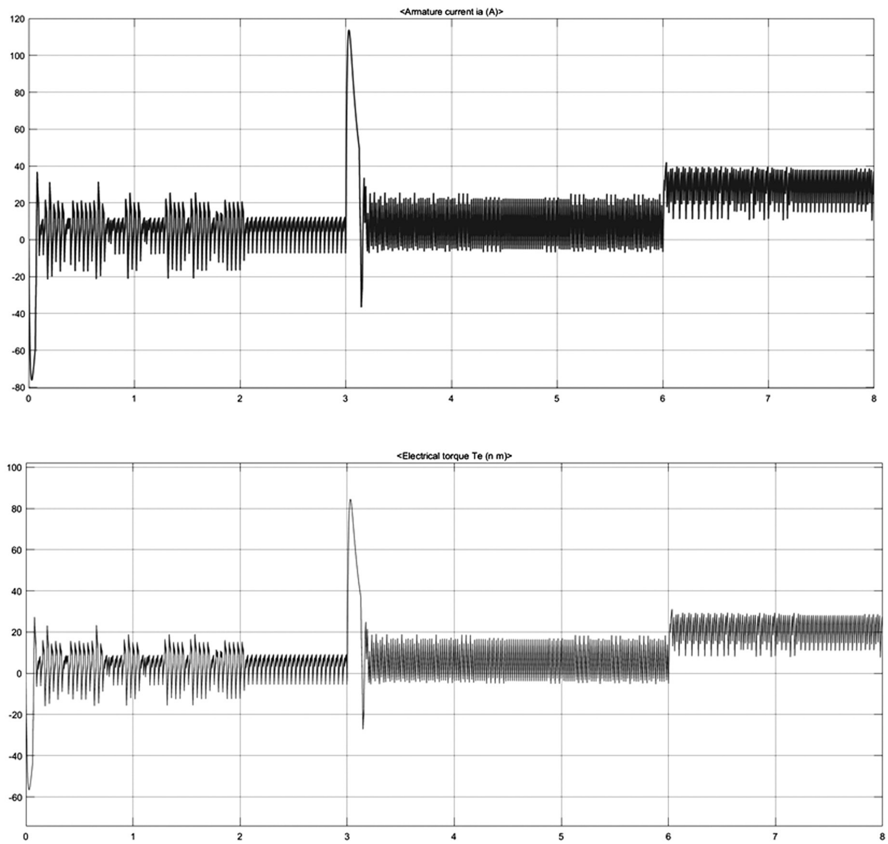

FIGURE 1.13 DC motor armature current and torque responses. ⏎

Figure 1.14 displays the essential parameters for configuring the single-phase asynchronous motor. Similar to the DCM [29, 30], the asynchronous motor allows for flexible adjustments, including the ability to change motor types. The parameters, including V_{Rms} (root-mean-square voltage), are clearly visible, offering a comprehensive overview of the motor's settings [17].

Figure 1.15 showcases a single-phase asynchronous motor driven by an inverter chopper in the control section. Within this segment, several blocks are utilized, including the following.

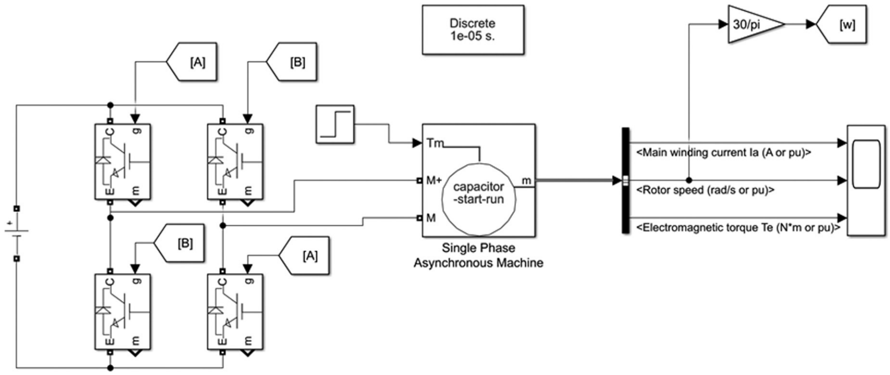

FIGURE 1.14 Single-phase asynchronous drived by an inerter chopper, power part. ⏎

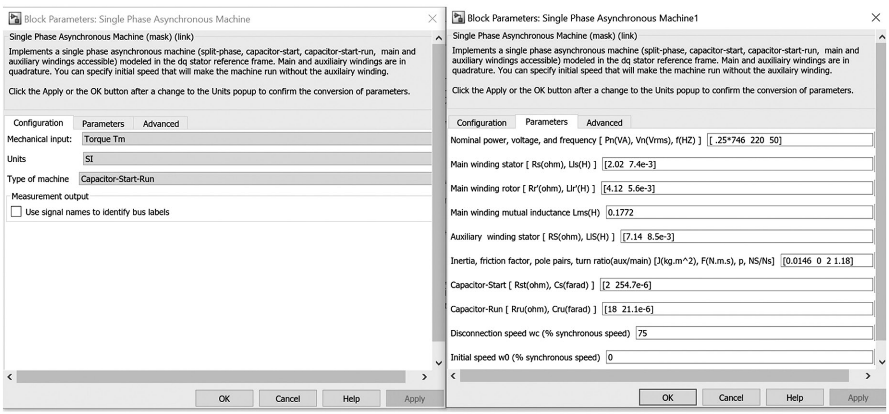

FIGURE 1.15 Single-phase asynchronous parameters. ⏎

Repeating Sequence Stair: This block represents the speed reference vector of output values: [400 800]. Sample time: 4.

Fcn: This block represents the function of the reference that composes the PWMcontrolling the inverter.

The inputs of the “Fcn” block consist of the amplitude and frequency, both sourced from the multiplexer (mux) component. These parameters are essential in controlling the reference PWM function, enabling precise modulation of the output signals that drive the single-phase asynchronous motor.

Repeating Sequence: This block represents the carrier signal that constitutes the other part of the PWM controlling the inverter. Time values: [0 .25 .5 .75 1]/5000 and output values: [0 −1 0 1 0].

The relational operator is utilized to generate the PWM signal, working in conjunction with logical operations. The inverter operates with two PWM signals. The "Not" operator is employed to negate and generate the complementary PWM signal.

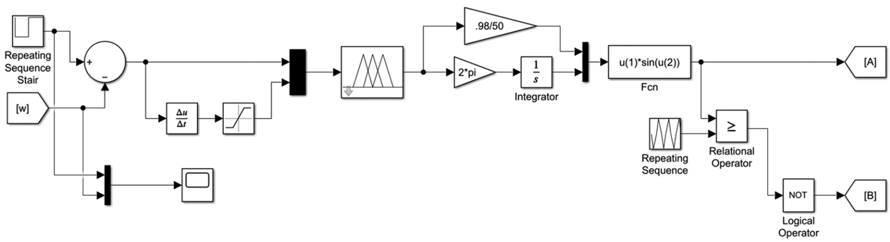

FIGURE 1.16 Single-phase asynchronous drived by an inverter chopper, control part.

After implementing the same fuzzy controller used for the DCM, the speed response of the single-phase asynchronous motor is depicted in Figure 1.17, demonstrating the motor's precise tracking of the specified reference speed. The system exhibits an impressive response time of just 0.5 s, displaying no overshooting or steady-state errors. The motor operates effectively, responding to speeds of 400 and 800 RPM. These responses are achieved under a resistive torque of 2 Nm. Upon the application of a torque disturbance of 5 Nm at 6 seconds, the motor promptly rejects the disturbance, with only minor oscillations observed.

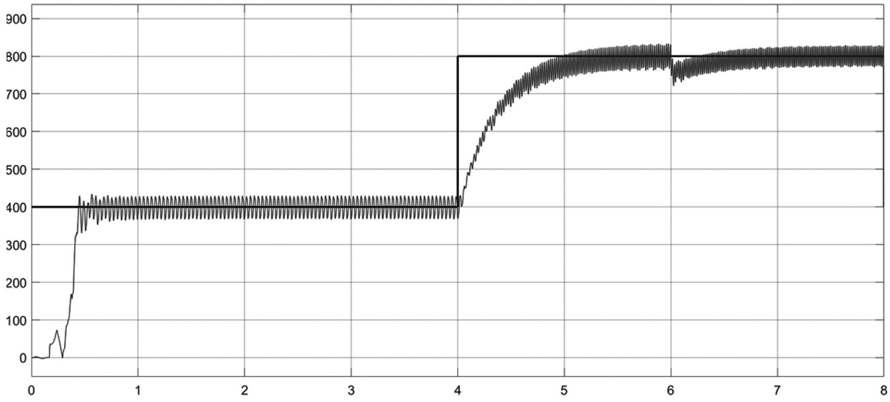

FIGURE 1.17 Single-phase asynchronous motor speed response.

Figure 1.18 illustrates the response of a single-phase asynchronous motor, showcasing current, speed, and torque. The current waveform exhibits a sinusoidal pattern. However, the relationship between current and torque is more intricate compared to the DCM.Similarly, the correlation between current and speed is notable, although not straightforward. In the case of the single-phase asynchronous motor, frequency plays a crucial role in determining the speed, adding complexity to the relationship between current and motor speed.

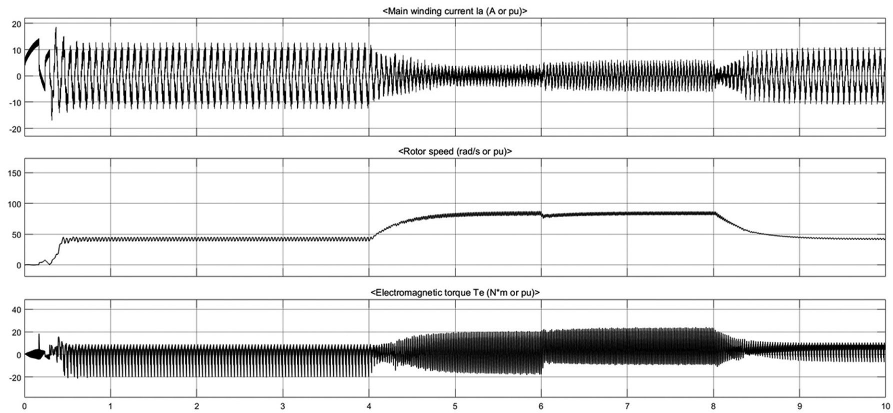

FIGURE 1.18 Single-phase asynchronous motor current, speed, and torque response.

1.5 CONCLUSION

Fuzzy logic control is a reliable and adaptable method for controlling the inherent uncertainties and complexities of real-world operations in motor systems. This study has emphasized several important points through thorough simulations and analyses.

1. *Fuzzy logic precision:* Fuzzy logic control allows precise motor speed regulation Taking into account the imprecision and uncertainties inherent in industrial applications. The use of linguistic variables and fuzzy sets allows for nuanced control decisions, enhancing the accuracy of motor responses.
2. *Flexibility and adaptability:* Fuzzy logic offers an adaptable system for motor control because of its capacity to deal with linguistic variables and define precise speed ranges. This flexibility is essential in industrial settings where fluctuating operating conditions and unpredictability are typical.

3. *Disturbance rejection:* Fuzzy logic control demonstrates excellent disturbance rejection capabilities. The motors swiftly recover from disturbances, ensuring stable performance even in challenging conditions.
4. *Realism in speed representation:* Fuzzy logic represents motor speeds as linguistic variables within defined ranges, which is more realistic and applicable to industrial scenarios than crisp value approaches. A more accurate representation of motor behavior is ensured by this complex approach, which captures the subtleties of speed variations.
5. *Industrial applicability:* For industrial motor applications, fuzzy logic control shows promise. Its capacity to manage imprecise inputs, adjust to changing situations, and offer steady and accurate control makes it a competitive option for use in actual manufacturing and automation processes.

Finally, this study demonstrates the significance of fuzzy logic control in enhancing the efficiency, stability, and adaptability of motor-driven systems in industrial settings. By bridging the gap between theoretical models and practical applications, fuzzy logic proves to be a valuable tool for engineers and researchers seeking reliable solutions for complex motor control challenges.

KEYWORDS

- **fuzzy logic**
- **direct current motors**
- **SimPowerSystems**
- **four-quadrant chopper**
- **insulated-gate bipolar transistor**

REFERENCES

1. Chen, G., & Pham, T. T. (2000). *Introduction to Fuzzy Sets, Fuzzy Logic, and Fuzzy Control Systems*. CRC Press. https://doi.org/10.1201/9781420039818
2. Ray, K. S. (2014). *Soft Computing and Its Applications, Volume Two: Fuzzy Reasoning and Fuzzy Control*, 1st edn. Apple Academic Press.

3. Barazane, L., Sicard, P., & Ouiguini, R. (2009). Cascade fuzzy variable structure control of induction motor based on the approach of fuzzy modelling of Ben-Ghalia. *International Journal of Systems Science*, *40*(3), 309–326. https://doi.org/10.1080/00207720802435986
4. Wang, H. G., & Rooda, J. E. (1996). Fuzzy control in a single-machine system. *Production Planning & Control*, *7*(6), 577–584. https://doi.org/10.1080/09537289608930391
5. Parhizkar, N., Shafiei, M., & Kouhshahi, M. B. (2011). Direct torque control of brushless DC motor drives with reduced starting current using fuzzy logic controller. In: *Proceedings of the International Conference on Uncertainty Reasoning and Knowledge Engineering, URKE 2011*, Vol. 1, pp, 129–132. https://doi.org/10.1109/URKE.2011.6007863
6. Xiu, Z., Guo, W., & Wang, W. (2006). Design of adaptive fuzzy controllers for warship weapon control systems. In: *2006 6th World Congress on Intelligent Control and Automation*, *1*.
7. Cheng, P.-J., Cheng, C.-H., & Tung, C.-C. (2009). Design of DC motor's torque control using DSP. *Journal of Information and Optimization Sciences*, *30*(6), 1197–1207. https://doi.org/10.1080/02522667.2009.10699935
8. Kim, I. H., Son, Y. I., Kang, S. H., & Lim, S. (2018). Robust position control of DC motor using a low-order disturbance observer against biased harmonic disturbances. In: *Proceedings—2018 IEEE International Conference on Industrial Electronics for Sustainable Energy Systems, IESES 2018*, January, 2018, pp. 484–489. https://doi.org/10.1109/IESES.2018.8349925
9. Omar, F., Ahmed, M., & Zouaoui, D. E. Y. (2015). Adaptive control with reference model of a doubly fed induction generator for wind turbine with sliding mode. *Electrical and Electronics Engineering: An International Journal (ELELIJ)*, *4*(2), 41–52.
10. Omar, F., Haddj, A., Mrabet, E., Belkraouane, I., & Djeriri, Y. (2021). Journal Europé en des Systèmes Automatisés. *Journal Européen Des Systèmes Automatisés*, *54*(6), 897–902.
11. Omar, F., Habib, H., Ahmed, N., & Sid, A. (2022). Adaptive control of DC motor without identification of parameters. *Facta Universitatis Series: Electronics and Energetics*, *35*(3), 301–312. https://doi.org/10.2298/FUEE2203301O
12. Abderrahmane, H. E. M., Belkraouane, I., & Fezazi, O. (2021). *Sliding Mode Control of a DC Machine*. Djillali Liabes.
13. Chaimaa, H., Chahinez, B., & Omar, F. (2020). *DC Motor Predictive Control*. Djillali Liabes.
14. Sabrine, B., Rihab, B., & Omar, F. (2021). *Adaptive Control for a DC Machine*. Djillali Liabes.
15. Salima, T., Siham, N., & Omar, F. (2022). *LQR Control of an Electric Vehicle based on a DC Motor*. Djillali Liabes.
16. Fezazi, O., El Islam, A. A. N., & Bechekir, S. E. (2023). Validation of a SimPower system simulation for a buck-boost chopper in the drive system of an electric vehicle using RT LAB. In: *Conference: 1. International Selçuk Scientific Research Congress*.
17. Omar, F., & El Islam, A. A. N. (2023). Association induction motors to converters. In: *Induction Motors—Recent Advances, New Perspectives and Applications*. IntechOpen. https://doi.org/10.5772/INTECHOPEN.1001574
18. Omar, F., & Djelloul, B. (2023). Validation of a PV-integrated drive system for electric vehicles using MATLAB SimPower systems and RT LAB. In: *1. International Selçuk Scientific Research Congress*.
19. Melkebeek, J. A. (2018). DC chopper. *Power Systems*, *9783319727295*, 263–275. https://doi.org/10.1007/978-3-319-72730-1_8/COVER

20. Abdou, M. M. A., & Omar, F. (2019). *Design and Control of a Chopper Powered by a Photovoltaic Source*. Djillali Liabes.
21. Fezazi., O., & Köten, H. (2023). Study of buck-boost chopper control modes for electric vehicle propulsion. In: *1st International Conference on Sustainable Energy and Advanced Materials*.
22. Omar F., El Islam, A. A. N., & Djehaf, M. A. (n.d.). Integration of photovoltaic panels in electric drive motors for sustainable electric vehicle operation. In: *Le 1er Séminaire National Sur Les Pollutions Environnementales et Le Développement Durable*.
23. Kirtley J. L. (1995). *Single-Phase Motors: Types, Construction, and Applications*. Wiley-IEEE Press.
24. Types of single phase induction motors. (n.d.). Java T Point. https://www.javatpoint.com/types-of-single-phase-induction-motors
25. Aissa, O., Moulahoum, S., Colak, I., Kabache, N., & Babes, B. (2016). Improved performance and power quality of direct torque control of asynchronous motor by using intelligent controllers. *Electric Power Components and Systems*, *44*(4), 343–358. https://doi.org/10.1080/15325008.2015.1117541
26. Abdelhadi, B., Abellali, A., & Omar, F. (2019). *Control of a Synchronous Motor Used for an Electric Car*. Djillali Liabes.
27. Fezazi, O. A. M. (2016). Predictive control of doubly fed induction generator used for wind energy. *Journal of Electrical Engineering*, *1*, 1–8.
28. Said, B., Kaouther, B., & Omar, F. (2021). *Inverter Control Techniques*. Djillali Labes.
29. Ershad, N. F., & Mehrjardi, R. T. (2018). A low cost single-phase to three-phase power converter for low-power motor drive applications. In: *2018 IEEE Texas Power and Energy Conference, TPEC 2018*, February 2018, pp. 1–6. https://doi.org/10.1109/TPEC.2018.8312061
30. Soomro, J., Memon, T. D., & Shah, M. A. (2017). Design and analysis of single phase voltage source inverter using Unipolar and Bipolar pulse width modulation techniques. In: *2016 International Conference on Advances in Electrical, Electronic and Systems Engineering, ICAEES 2016*, pp. 277–282. https://doi.org/10.1109/ICAEES.2016.7888052

CHAPTER 2

Fuzzy Logic Application for Enhancing Performance of Continuous Variable Gearboxes

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ABSTRACT

Fuzzy logic system is widely applied to many versatile engineering disciplines. The fuzzy inference system is the rule-based system, which can be applied to many types of control system where control capacity and mechanism are fully governed by the inference rule sets. The traditional system of power transmission is carried out either manually or automatically. The application of fuzzy logic systems helps in enhancement and smoothening of the transmission system. Continuously variable gearbox (CVT) is providing the number of gear ratios for the smooth and efficient delivery of power. Different application procedures toward the enhancement of transmission capability involve adaptive processes, shift control processes, load balancing processes, optimized energy recovery processes, etc. The concerned system is used to find the best and optimized parametric values represented by two variables K_p and T_i , needed to set up a special controller called the proportional-integral controller (or PI controller). This PI controller is used in mechanical systems to control the transmission of energy through CVT for

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smooth functioning. The fuzzy controller possesses several extra features, all of which are geared toward improving the machine's overall operational efficiency. This chapter provides a detailed overview of such optimization process based on the fuzzy logic concept.

2.1 INTRODUCTION

A continuously variable gearbox (CVT) is a type of gearbox that is specifically employed in conventional internal combustion engine vehicles. The power consumption of the engine can be the important factor on which the engine efficiency depends a lot. Optimization of the engine's power utilization can be minimized by means of the CVT. In contrast to conventional gearboxes that operate through discrete gear ratios (such as first gear and second gear), a continuously variable gearbox (CVT) possesses the ability to adjust the engine speed seamlessly and continuously in direct proportion to the rotational speed of the wheels. This facilitates the optimization of the engine's power utilization. When one desires to drive in an inexpensive manner, it is possible to conserve fuel and mitigate pollution. Conversely, if one seeks to engage in sporty driving, it is feasible to optimize power output. A continuously variable gearbox (CVT) operates by the use of a belt that connects two pulleys, each having a cone-shaped structure. The dimensions of these pulleys exhibit variability, expanding as the cones approach one other and contracting as they move apart. The figure presented in Figure 2.1 elucidates the operational mechanisms of the subject matter. The appropriate amount of pressure must be exerted on the pulleys (Pp and Ps) in order to ensure the optimal functioning of the belt. In the event that the tension exceeds the recommended threshold, the belt may experience failure as a result of excessive friction and stress. Insufficient tension in the engine might impede power transmission to the wheels, perhaps resulting in belt disengagement from the pulleys and subsequent complications. The normal range of revolutions per minute (r.p.m.) for the engine is 1000 to 4000. In order to regulate the pressures within the cylinders, a valve system is employed, which functions akin to a hydraulic amplifier. Additionally, a third pressure is employed in the context of a wet-plate clutch. The system is responsible for controlling three distinct components. This implies that the signals employed for the regulation of the continuously variable gearbox (CVT) exclusively rely on electrical means. The pressure levels for the 3nos. added valves are obtained from the central control system. The master control system adjusts the pressure levels by considering several factors, such as road conditions, target speeds, and the degree of throttle input, as depicted in Figure 2.2. The management of continuously variable transmissions (CVTs) presents a complex task due to the multitude of factors that must be taken into account. These factors include speed, temperature, oil viscosity, and the design of the valves. These various components all interact, resulting in a highly intricate system. Controlling a continuously variable gearbox (CVT) using conventional methods intended for less complex systems has inherent challenges. The main objective of this chapter is to throw light on the minimization of complexities of such gearbox and enhancement if speed of the engine concerned. The reduction of delay time of interaction among all the different parts of the system can bring down the load and help in gaining the good performance of the whole system. The design of the control system for obtaining pully pressure is demonstrated in Figure 2.1.

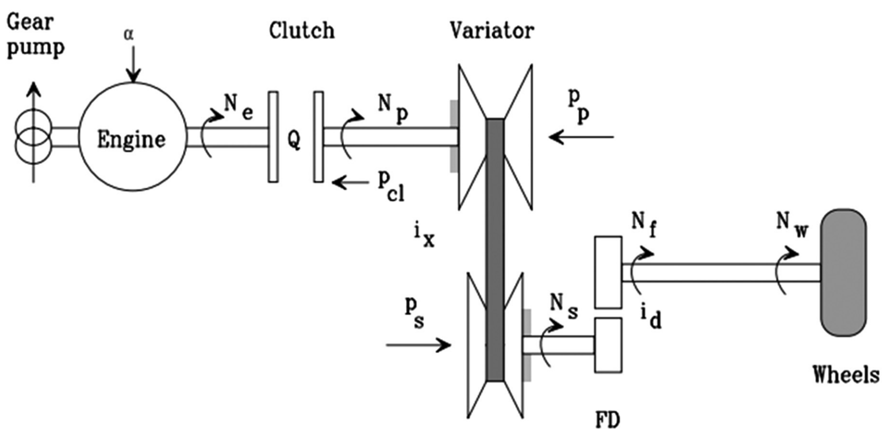

FIGURE 2.1 Vehicle's power train is equipped with a continuously variable gearbox (CVT) and a wet-plate clutch. FD is an acronym that stands for final reduction. ⏎

2.2 SPECIFICATIONS OF PERFORMANCE

The objective is to achieve the desired pressure at a reasonable timeframe, ideally between 60 to 70 ms, without exceeding the specified limits. The objective is to mitigate significant overshoots (O.S.) as they have the potential to induce excessive slackness in the belt, resulting in disengagement from the pulleys and potential damage to the system.

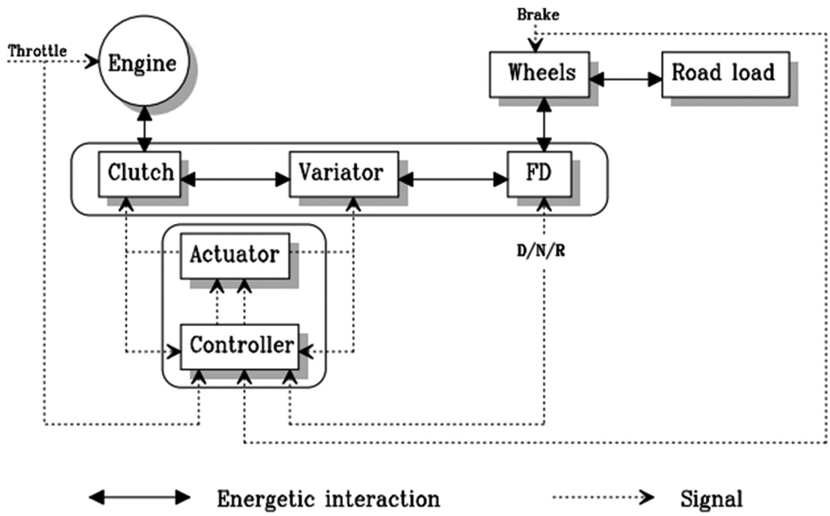

FIGURE 2.2 Schematic representation of the system, encompassing the high-level controller, is depicted in the diagram.

2.3 PHYSICAL MODEL OF THE CONTINUOUSLY VARIABLE TRANSMISSION (CVT)

Minten and Vanvuchelen developed an elaborate physical model of the system. The complexity of the topic arises from its comprehensive coverage of the activities of the continuously variable gearbox (CVT). The utilization of this method proves advantageous in replicating real-world phenomena; nonetheless, its protracted execution duration renders it impractical for the purpose of devising control mechanisms. Additionally, a more streamlined model was devised for the purpose of control. The system offers a single controllable parameter, namely the voltage supplied to the pulsewidth modulation servo valve, denoted as V_{in}. The measurement encompasses two variables, namely temperature (T) and engine speed (N_{engine}). This study focused on a single outcome variable, namely the magnitude of pressure exerted on the pulley. Figure 2.3 illustrates the relationship between the nonlinearity (f) and the engine speed (N_{engine}), indicating a significant dependence of the former on the latter.

The process is represented through the utilization of a static nonlinearity function, denoted as $f(V_{in}, N_{engine})$, as well as a dynamic linear system $G(s)$ that possesses changeable parameters. Figure 2.4 provides the correlation between the variable f and engine speed. The graphs are plotted for different engine speeds.

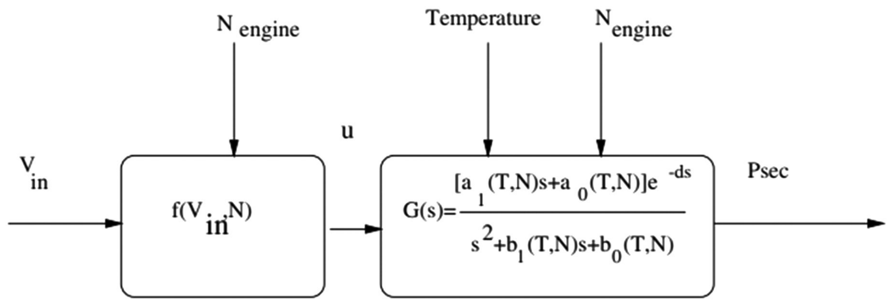

FIGURE 2.3 Relationship between the nonlinearity and engine speed. ⏎

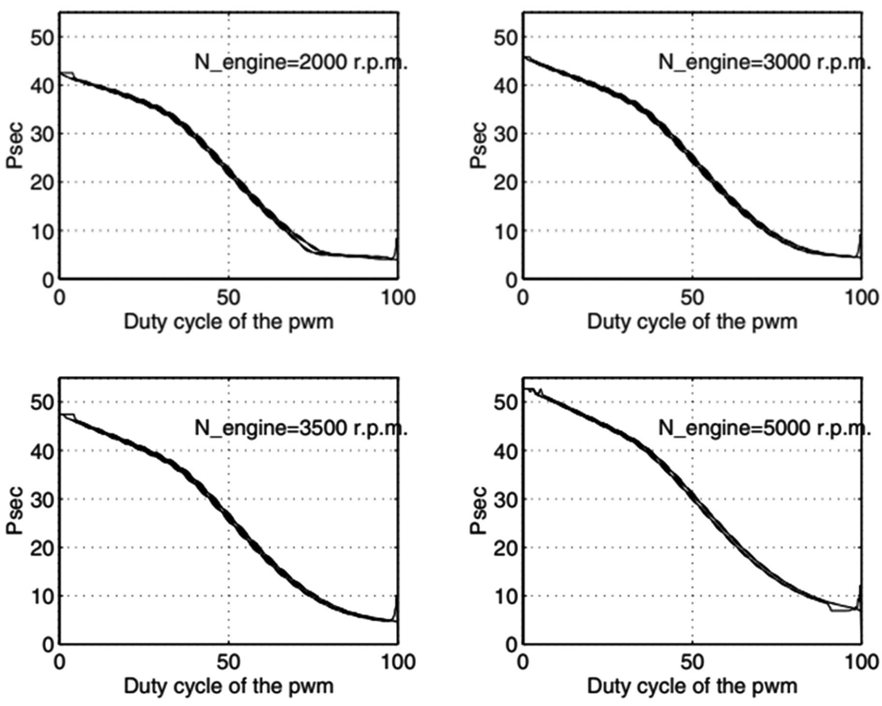

FIGURE 2.4 Distinct correlations between the variable *f* and the rotational speed of the engine. ⏎

The static nonlinearity, denoted as *f*, and is examined across various values of engine speed (N_{engine}) while maintaining a constant temperature. The fuzzy inference systems (FISs) [3–5] determine how the parameters *P* and *Ti* are generated.

2.4 DESIGN OF CONTROLLER

The initial stage in the construction of the controller is the compensation of the nonlinearity, $f(V_{in}, N_{engine})$, using its inverse function, $\hat{f}^{-1}(V_{in}, N_{engine})$. It can be observed that this technique is applicable as a result of the monotonic nature of the function $f(.,\ .)$. After obtaining the local linear models for various values of T and $N_{engine,}$ as well as the function $\hat{f}^{-1}(.,.)$, an optimization approach is employed to compute a suboptimal proportional-integral (PI) controller for the given operating point (Figure 2.5). The optimization's cost function is specified as

$$J(K_p,T_i) = \lambda M_p + (1-\lambda)\int_0^{\infty} t(e^2(t)dt)^{\frac{1}{2}} \tag{2.1}$$

where K_p and T_i represent the proportional gain and integral time of the PI controller, respectively. The value of λ is equal to 0.5 and is utilized to quantify the significance of the O.S. in the cost function.

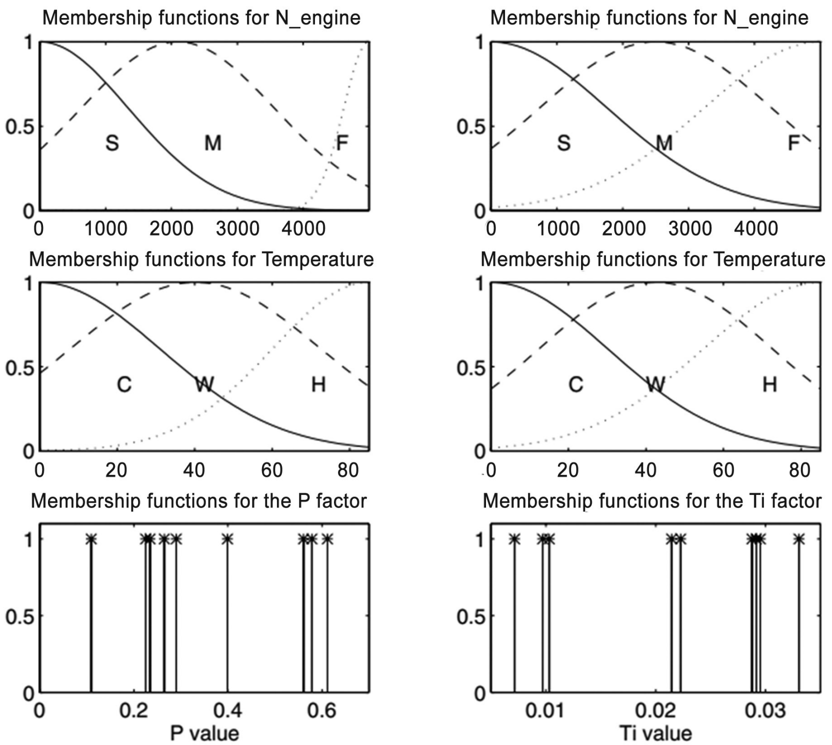

FIGURE 2.5 Generated parameters P and T_i.

The tracking error is denoted as

$$e(t) = P_{\mathrm{ref}}(t) - P_{\mathrm{sec}}(t) \tag{2.2}$$

represents the discrepancy between the preferred value and the secondary value at time t. The O.S., M_{p}, characterizes the maximum deviation of the output, $y(t)$. Mathematically, M_{p} is defined as

$$M_{\mathrm{p}} = \max\{\max(y(t) - 1), 0\}. \tag{2.3}$$

The use of the quasi-Newton approach to unconstrained multivariable optimization was demonstrated. The PI controller, which incorporates a collection of local PI controllers, can be mathematically expressed in continuous time as

$$C(s) = K_p(T, N_{\mathrm{engine}})\left(1 + \frac{1}{T_i(T, N_{\mathrm{engine}})^s}\right). \tag{2.4}$$

In the context of discrete time, the expression can be written as

$$C(z) = K_p(T, N_{\mathrm{engine}})\left(1 + \frac{1}{T_i(T, N_{\mathrm{engine}})(1 - z^{-1}}\right). \tag{2.5}$$

By employing this approach, all quantization effects are accounted for, resulting in enhanced precision of the controller. The values of $K_{\mathrm{p}}(T, N_{\mathrm{engine}})$, $T_i(T, \mathrm{N}_{\mathrm{engine}})$, and $\hat{f}^{-1}(V_{\mathrm{in}}, N_{\mathrm{engine}})$ are restricted to certain operating points. A method of interpolation is required in order to facilitate smooth transitions between various operational locations. The utilization of an interpolation approach is required. It has been determined that an effective approach would involve the utilization of an FIS [6–9] to approximate the lookup table. The primary attributes of this FIS [10–13] consist of Gaussian membership functions, employing the center of gravity method. The controller is depicted in Figure 2.6.

2.5 ANALYSIS FOR STABILITY

The stability of the gearbox has been achieved in terms of the stability of multiple interactive components of the gearbox. The shaft of the gearbox sometimes shows some problem toward the stabilization action, but the overall components and their interactions can be made stabilized by means of the fuzzy logic system [14–17]. Different fuzzy logic-based models [18–22] have been appointed in assessing the stability already in many reported works. We can portray the closed-loop system by employing a "Takagi–Sugeno fuzzy model," assuming that the nonlinearity labeled as f (., .) has been entirely removed. To illustrate this, consider one rule, Rulei, where we have αi representing the temperature and βi representing the engine. In this context, the equation for the rate of change of variable x can be expressed as

$$x = A_i\tilde{x} + B_i\tilde{u}. \tag{2.6}$$

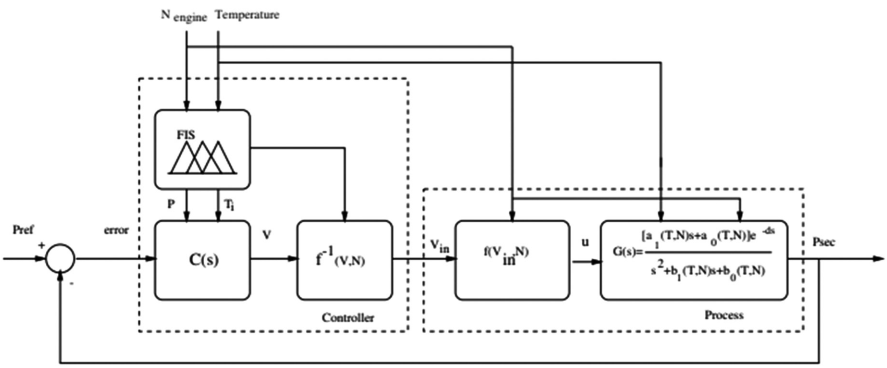

FIGURE 2.6 Fuzzy controllers in comparison to the linear planned controller. ⏎

The requirement for stability in this context is satisfied when there is a shared positive definite matrix P that fulfills the following inequalities:

$$P > 0 \tag{2.7}$$

$$A^{\mathrm{T}}_{\tilde{i}} P + PA_{\tilde{i}} < 0 \tag{2.8}$$

$$\forall ii \in \{1,\ldots,N_{\mathrm{rules}}\} \tag{2.9}$$

The determination of the P matrix can be achieved through the resolution of the feasibility linear matrix inequality (LMI) problem. A viable solution has been identified for this problem, ensuring stability. Figure 2.6 provides the model for fuzzy controller linear planned controller [23–27].

This study examines the enhancements achieved through the implementation of a fuzzy controller [28–30] in comparison to a linear planned controller. It is crucial to note that there exists not only an enhancement in performance, but also a facilitation in the implementation of design modifications, owing to the further information offered by the rule base explanation.

2.6 CONCLUSION

This section elucidates the process of designing a control system for a continuous variable transmission. The control system employs a fuzzy inference method to dynamically modify the parameters of the controller in response to measurements of disturbances. The following actions were undertaken.

1. Linear controllers were computed through the process of optimization for various scenarios.
2. Nonlinear compensators were developed to accommodate different engine speed values (N_{engine}).
3. In order to establish stability, a mathematical problem known as LMI was successfully resolved.
4. The controller that has been built also offers a comprehensive elucidation of the scheduling mechanism, hence facilitating the process of optimizing the system within an industrial context. The evaluation of the control system has been shown in Figure 2.7 in comparative fashion.

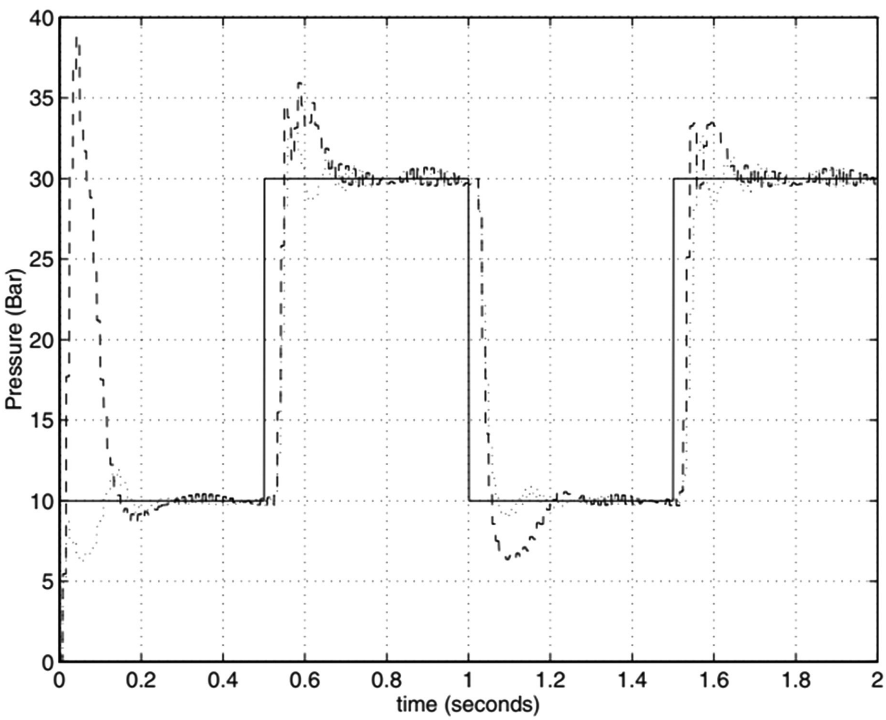

FIGURE 2.7 Comparative evaluation of control systems. ⏎

The diagram depicts a continuous line representing a reference, a dashed line representing a linear controller with feed-forward action, and a dotted line representing a fuzzy controller. It is evident that the fuzzy controller effectively reduces both the O.S. and settling time of the system.

KEYWORDS

- **fuzzy logic**
- **CVT**
- **fuzzy controller**
- **fuzzy inference system**
- **nonlinear compensators**

REFERENCES

1. Grace. (1992). *Optimization Toolbox—For use with MATLAB*. Mathworks, Inc.
2. Isidori. (1989). *Nonlinear Control Systems–An Introduction*, 2nd edn. Springer-Verlag.
3. Peña Reyes, C. A. (2002). Coevolutionary fuzzy modeling. PhD thesis, Ecole Polytéchnique Fédérale de Lausanne.
4. von Altrock. (1995). Fuzzy logic applications in Europe. *Industrial Applications of Fuzzy Logic and Intelligent System,* IEEE Press.
5. Broadbent. (1975). The magic number seven after fifteen years. *Studies in Long Term Memory*, Addison Wesley: USA.
6. Clarke, D., Mohtadi, C., & Tuffs, P. (1987). Generalized predictive control-parts i–ii. *Automatica*, *23*, 137–160.
7. Driankov, D., Hellendoorn, H., & Reinfrank, M. (1993). *An Introduction to Fuzzy Control*. Springer-Verlag.
8. Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison Wesley: USA.
9. Camacho, C. B. (1995). *Model Predictive Control in the Process Industry*. Springer-Verlag: London.
10. Gustafson, E., & Kessel, W. (1979). Fuzzy clustering with fuzzy covariance matrix. In: *Proc. IEEE Control Decision Conference*, pp. 761–766.
11. Ecole Nationale Supérieure de Techniques Avancées (ENSTA), Optimization and Control Group: (1998), LMITOOL-2.0 package.
12. Allgöwer, T. B., Qin, J., Rawlings, J., & Wright, S. (1999). Nonlinear predictive control and moving horizon estimation–an introductory overview. *Advances in Control–Highlights of ECC'99*. Springer-Verlag.
13. Box, G. J. (1970). *Time Series Analysis, Forecasting and Control*. Holden Day: San Francisco, CA.
14. Goodwin, G., & Sin, K. (1984). *Adaptive Filtering Prediction and Control*. Prentice Hall: Englewood Cliffs, NJ.

15. Lightbody, G., & Irwin, G. (1997). Nonlinear control structures based on embedded neural system models. *IEEE Transactions on Neural Networks and Learning Systems*, *8*, 553–567.
16. Akaike. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*, 716–723.
17. Ying, H. (1998). The Takagi–sugeno fuzzy controllers using the simplified linear control rules are the nonlinear variable gain controller. *Automatica*, *34*(2), 157–167.
18. Abonyi, H. A., Nagy, L., & Szeifert, F. Inverse fuzzy-process-model based direct adaptive control. URL citeseer.nj.nec.com/abonyi99inverse.html.
19. Bezdek. (1976). A physical interpretation of fuzzy data. *IEEE Transactions on Systems, Man, and Cybernetics 6*(5), 387–389.
20. Espinosa, J., & Vandewalle, J. (1998). Fuzzy modeling and identification, using afreli and fuzion algorithms. In: *Proceedings of the 5th. International Conference on Soft Computing IIZUKA-98 Iizuka, Japan*, pp. 535–540.
21. Espinosa, J., & Vandewalle, J. (1998). Fuzzy modeling with linguistic integrity. In: *Proceedings of the International Workshop on Advanced Black Box Techniques for Nonlinear ModelingLeuven, Belgium*, pp. 197–202.
22. Espinosa, J., & Vandewalle, J. (1998). Predictive control using fuzzy models applied to a steam generating unit. In: Ruan, D., Abderrahim, H. A., D'hondt, P., & Kerre, E. (Eds.), *Fuzzy Logic and Intelligent Technologies for Nuclear Science and Industry*. World Scientific: Singapore.
23. Espinosa, J., & Vandewalle, J. (1999). Constrained predictive control using fuzzy models. In: *Proceedings of the Eight International Fuzzy Systems Association World Congress (IFSA-99) Taiwan*, pp. 649–654.
24. Espinosa, J., & Vandewalle, J. (1999). Predictive control using fuzzy models. In: Roy, R., Furuhashi, T., & Chawdhry, P. (Eds.), *Advances in Soft Computing Engineering Design and Manufacturing*. Springer-Verlag: London.
25. Espinosa, J., & Vandewalle, J. (2000). Constructing fuzzy models with linguistic integrity-afield algorithm. *IEEE Transactions on Fuzzy Systems*, 8(5), 591–600.
26. Espinosa, J., & Vandewalle, J. (2003). Extracting linguistic fuzzy models from numerical data-afreli algorithm. In: Casillas, J., Cordon, O., Herrera, F., & Magdalena, L. (Eds.), *Interpretability Issues in Fuzzy Modeling*. Springer-Verlag: London.
27. Espinosa, J., Hadjili, M., Wertz, V., & Vandewalle, J. (1999). Predictive control using fuzzy models-comparative study. *Proceedings of the European Control Conference-99*.
28. Rawlings, J. (1999). Tutorial: Model predictive control technology. In: *Proceedings of the ACC San Diego,* CA.
29. Richalet, J. (1993). Industrial applications of model-based predictive control. *Automatica*, *29*, 1251–1274.
30. SJöberg, J., Zhang, Q., Ljung, L., Benveniste, A., Delyon, B., Glorennec, P., Hjalmarsson, J., & Juditsky, A. (1995). Nonlinear black-box modeling in system identification: A unified overview. *Automatica*, *31*, 1691–1724.

CHAPTER 3

Fuzzy Logics in Machine Learning and AI: A Comprehensive Review

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ABSTRACT

Fuzzy logic, a mathematical framework introduced by Lotfi Zadeh in the 1960s, has found profound applications in various domains of artificial intelligence (AI) and machine learning (ML). This abstract explores the role of fuzzy logic in enhancing the capabilities and addressing the challenges of AI and ML applications. Fuzzy logic, which deals with uncertainty and imprecision, offers a valuable approach to model complex real-world phenomena, human reasoning, and decision-making processes [1]. In this context, we discuss key applications, methodologies, and advantages of incorporating fuzzy logic into AI and ML systems. One of the primary areas where fuzzy logic shines is in handling uncertainty and vagueness in data. In AI and ML, data is often incomplete or imprecise, making traditional binary logic inadequate. Fuzzy logic provides a framework to represent and reason with vague information, allowing AI systems to make more nuanced decisions [4]. This is particularly useful in applications such as natural language processing, sentiment analysis, and expert systems. Furthermore, fuzzy logic is integral in the development of fuzzy inference systems (FIS), which are widely employed in AI and ML applications. FIS can model complex relationships between inputs and outputs, making them suitable for tasks, such as control systems, prediction, and pattern recognition. They are especially useful in applications like autonomous vehicles, where real-time decision-making relies on interpreting diverse and dynamic

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sensor data [10]. In the context of machine learning, fuzzy clustering, and fuzzy classification algorithms have been developed to handle datasets with overlapping or uncertain boundaries. These algorithms, such as fuzzy c-means and fuzzy decision trees, have been applied in areas such as image segmentation, medical diagnosis, and recommendation systems. They allow for a more granular classification of data points, improving the accuracy and interpretability of ML models. Fuzzy logic also plays a pivotal role in rule-based systems, which are crucial for expert systems and knowledge representation in AI. Fuzzy rules capture human expertise and can be used to build systems that emulate human decision-making. These systems are valuable in applications like medical diagnosis, financial risk assessment, and industrial process control. In conclusion, fuzzy logic continues to be a valuable tool in AI and ML applications, providing a means to handle uncertainty, imprecision, and complex relationships in data and decision-making. By embracing fuzzy logic, AI and ML systems can achieve greater robustness, adaptability, and human-like reasoning capabilities, opening doors to a wide range of real-world applications across various industries. This abstract provides a glimpse into the multifaceted landscape of fuzzy logic's contributions to the advancement of AI and ML.

3.1 INTRODUCTION TO FUZZY LOGIC

Fuzzy logic is a mathematical framework and a form of multivalued logic that deals with uncertainty, imprecision, and vagueness in data and decision-making [1]. Unlike classical binary logic, which is based on "true" or "false" values (0 or 1), fuzzy logic allows for the representation of partial truths and degrees of membership in a set, making it a valuable tool in various fields, including artificial intelligence (AI), control systems, and decision-making. It was developed by Lotfi Zadeh in the 1960s as a way to model and represent human-like reasoning under uncertainty.

3.2 COMPONENTS OF FUZZY LOGIC

3.2.1 FUZZY SETS

Fuzzy sets are a fundamental concept in fuzzy logic that allows us to represent and work with uncertainty and imprecision. Unlike classical sets, where an element is either a member (with a membership degree of 1) or not a member (with a membership degree of 0), fuzzy sets allow elements to have partial membership degrees between 0 and 1. Some of the real-time examples are as follows.

3.2.1.1 TEMPERATURE CLASSIFICATION

Imagine you want to categorize temperatures as "cold," "warm," and "hot." In classical set theory, you might set a crisp boundary, such as temperatures below 50°F are "cold," temperatures between 50°F and 70°F are "Warm," and temperatures above 70°F are "hot." However, in fuzzy sets, you can assign degrees of membership to each category. For instance, a temperature of 60°F might belong 0.6 to "warm" and 0.4 to "cold," indicating that it is partially warm and partially cold.

3.2.1.2 IMAGE SEGMENTATION

In image processing, fuzzy sets can be applied to image segmentation, where you classify each pixel's membership to different regions. This is useful when an object's boundary is not well-defined, and pixels can belong to multiple regions simultaneously, with varying degrees of membership.

3.2.1.3 CONTROL SYSTEMS

Fuzzy sets are widely used in control systems. For instance, in an air conditioning system, you can define fuzzy sets for "cool," "comfortable," and "warm" to determine how the system adjusts the temperature based on the user's preferences. These sets allow the system to make gradual and smooth adjustments.

3.2.2 MEMBERSHIP FUNCTIONS

Membership functions are a crucial component of fuzzy logic, used to determine the degree to which an element belongs to a fuzzy set. These functions map the input values to membership degrees on a continuous scale between 0 and 1. These functions can take various shapes, such as triangular, trapezoidal, or sigmoidal, depending on the nature of the problem and the desired representation of uncertainty.

3.2.2.1 TRIANGULAR MEMBERSHIP FUNCTION

The triangular membership function is defined by three parameters: the left boundary, the peak, and the right boundary.

Example: Let us define a triangular membership function for the fuzzy set "tall" based on a person's height in centimeters.

Left boundary = 150 cm, peak = 165 cm, and right boundary = 175 cm.

In this case, if a person's height is 165 cm, their membership degree in the "tall" set would be 1. If their height is 150 cm, then the membership degree would be 0. If their height is 175 cm, then the membership degree would be 0.5.

3.2.2.2 TRAPEZOIDAL MEMBERSHIP FUNCTION

A trapezoidal membership function has four parameters: the minimum, left shoulder, right shoulder, and maximum values. It represents a more gradual transition with a flat region in the middle.

Example: Air conditioning control.

In an air conditioning system, you might have a "comfortable temperature" fuzzy set. The trapezoidal membership function could have a minimum value of 20°C, a left shoulder at 22°C, a right shoulder at 26°C, and a maximum value of 28°C. A room temperature of 24°C would have a moderate membership degree.

3.2.2.3 GAUSSIAN MEMBERSHIP FUNCTION

The Gaussian membership function has a bell-shaped curve and is characterized by parameters for the mean (μ) and the standard deviation (σ). It is often used when there is uncertainty around a central value.

Example: Height classification.

"Tall" fuzzy set with a Gaussian membership function:

μ = 180 cm (mean height).

σ = 10 cm (standard deviation).

This membership function represents the degree of "tallness" for individuals, with a peak at 180 cm and decreasing membership as heights deviate from the mean.

3.2.2.4 SIGMOIDAL (S-SHAPED) MEMBERSHIP FUNCTION

The sigmoidal membership function resembles an "S" shape and is often used for variables with gradual transitions between membership degrees.

Example: In the context of "customer satisfaction," you might use a sigmoidal membership function to capture the transition from "dissatisfied" to "satisfied." As satisfaction ratings increase, the membership degree gradually increases.

3.2.3 FUZZY LOGIC OPERATORS

Fuzzy logic operators are fundamental components of fuzzy logic that allow for the manipulation of fuzzy sets and reasoning with uncertain or imprecise information. Fuzzy logic operators are analogous to the logical operators (AND, OR, NOT) in classical (Boolean) logic but are adapted to handle degrees of membership rather than binary true/false values.

3.2.3.1 FUZZY AND (MIN OPERATOR)

The fuzzy AND operator computes the minimum of the membership degrees of two or more fuzzy sets. It represents the degree to which all conditions are simultaneously true.

Example: If you have two fuzzy sets, "tall" with a membership degree of 0.6 and "slim" with a membership degree of 0.7, then the fuzzy AND operation yields a membership degree of 0.6 [min(0.6, 0.7)] for the intersection of "tall" and "slim."

3.2.3.2 FUZZY OR (MAX OPERATOR)

The fuzzy OR operator computes the maximum of the membership degrees of two or more fuzzy sets. It represents the degree to which any one of the conditions is true.

Example: If you have two fuzzy sets, "high" with a membership degree of 0.8 and "Medium" with a membership degree of 0.6, the fuzzy OR operation yields a membership degree of 0.8 [max(0.8, 0.6)] for the union of "high" and "medium."

3.2.3.3 FUZZY NOT (COMPLEMENT OPERATOR)

The fuzzy NOT operator computes the complement of the membership degree of a fuzzy set. It represents the degree to which a condition is not true.

Example: If you have a fuzzy set "not very hot" with a membership degree of 0.3, the fuzzy NOT operation yields a membership degree of 0.7 (1–0.3) for the condition "not very hot."

3.2.3.4 FUZZY IMPLICATION OPERATORS

Fuzzy implication operators are used in fuzzy rule-based systems to determine the strength of an implication (consequent) based on the truth value of an antecedent condition.

Examples of fuzzy implication operators include the Mamdani implication and the Larsen implication.

3.2.3.5 FUZZY AGGREGATION OPERATORS

Fuzzy aggregation operators are used to combine the outputs of multiple fuzzy rules in a FIS. Common aggregation operators include the max (maximum), sum, and weighted average operators.

3.2.3.6 FUZZY T-NORM AND T-CONORM OPERATORS

T-norm (t-normative) and t-conorm (t-conormative) operators are used to compute the intersection and union of fuzzy sets, respectively. Popular t-norm operators include the min and product operators, while common t-conorm operators include the max and probabilistic sum operators.

3.2.3.7 FUZZY COMPARISON OPERATORS

Fuzzy comparison operators are used to compare two fuzzy numbers or sets and determine their relationship, such as equality, dominance, or intersection.

These fuzzy logic operators allow for a more flexible and nuanced representation of uncertainty and imprecision in decision-making and modeling.

They are essential components in FISs, which are used in various fields, including control systems, pattern recognition, and AI, where traditional binary logic may not adequately capture the complexity of real-world data.

3.2.4 FUZZY INFERENCE SYSTEMS

FISs are computational models based on fuzzy logic that mimic human decision-making processes by incorporating uncertainty and imprecision. These systems use fuzzy sets, rules, and membership functions to make decisions or perform tasks in a way that is more flexible and human-like than traditional binary logic. FISs are widely used in control systems, decision support, pattern recognition, and AI.

3.2.4.1 COMPONENTS OF A FUZZY INFERENCE SYSTEM

3.2.4.1.1 Fuzzification

In the fuzzification stage, crisp inputs are converted into fuzzy sets using membership functions. This step transforms quantitative input values into linguistic terms, such as “low,” “medium,” or “high.”

3.2.4.1.2 Knowledge base (rule base)

The knowledge base consists of a set of linguistic rules that relate the fuzzy input variables to the fuzzy output variables. These rules are often expressed in the form of “IF–THEN” statements and capture expert knowledge or domain-specific information. Each rule defines a relationship between input and output fuzzy sets.

3.2.4.1.3 Inference engine

The inference engine is the core of the FIS. It uses the fuzzy input values and the knowledge base to make inferences and determine the fuzzy output values. It employs fuzzy logic operators (AND, OR, NOT) to evaluate the rule antecedents and combine them to produce intermediate fuzzy values.

3.2.4.1.4 Fuzzy rule evaluation

Each rule's antecedent (IF part) is evaluated to determine its degree of truth based on the degree of membership of input variables. The degree of truth of a rule represents how strongly the rule applies to the current input values.

3.2.4.1.5 Aggregation

The results of multiple rules are aggregated to produce a combined output fuzzy set. Common aggregation methods include the max (maximum) operator, sum, and weighted average.

3.2.4.1.6 Defuzzification

In the defuzzification stage, the aggregated fuzzy output set is converted into a crisp output value. Various defuzzification methods can be used, such as the centroid method, which finds the center of mass of the aggregated output set.

3.2.5 OPERATION OF A FUZZY INFERENCE SYSTEM

3.2.5.1 INPUT FUZZIFICATION

Crisp input values are mapped to fuzzy sets using membership functions. This step involves assigning membership degrees to each linguistic term based on the input values.

3.2.5.2 RULE EVALUATION

The fuzzy input values are matched to the antecedents of the fuzzy rules. Each rule's degree of truth is calculated based on how well the input values match the rule's conditions.

3.2.5.3 INFERENCE

The inference engine combines the rule outputs to form a fuzzy output set. This is done by applying fuzzy logic operators (AND, OR) to the rule consequences (THEN part) based on the degrees of truth of the rules.

3.2.5.4 AGGREGATION

Aggregation methods (e.g., max operator) combine the fuzzy outputs from different rules to create a single aggregated output fuzzy set.

3.2.5.5 DEFUZZIFICATION

The aggregated output fuzzy set is transformed into a crisp output value using defuzzification methods. This value represents the system's final decision or action.

FISs are particularly useful in applications where decision-making involves uncertain or imprecise information, making them applicable in fields such as control systems, expert systems, and pattern recognition. They allow for the incorporation of human-like reasoning and are capable of handling complex and ambiguous data effectively.

3.3 APPLICATIONS

Fuzzy logic has found applications in various fields, including control systems, AI, pattern recognition, decision-making, robotics, and more. It excels in situations where ambiguity and imprecision are inherent, such as in natural language processing, temperature control, and financial forecasting.

3.4 CONTROL SYSTEMS

Fuzzy logic control systems are widely used in various industries, including automotive, industrial automation, and heating, ventilation, and air conditioning. They can adapt to changing conditions and provide precise control even when system dynamics are not well-defined.

3.4.1 AUTOMOTIVE INDUSTRY

Fuzzy logic is used in vehicle systems, such as antilock braking systems, automatic transmissions, and engine control units, to optimize performance and improve safety.

3.4.2 CONSUMER ELECTRONICS

Fuzzy logic is applied in appliances like washing machines to adjust washing cycles based on load size and dirt level, making them more energy-efficient and user-friendly.

3.4.3 ROBOTICS

Fuzzy controllers are used in robotic systems for tasks, such as path planning, obstacle avoidance, and grasping objects. Fuzzy logic helps robots make real-time decisions in uncertain environments.

3.4.4 MEDICAL DIAGNOSIS

FISs can assist medical professionals in diagnosing diseases and conditions by combining imprecise medical data and expert knowledge to determine the likelihood of different diagnoses.

3.4.5 TRAFFIC MANAGEMENT

Fuzzy logic is employed in intelligent traffic management systems to control traffic lights, optimize traffic flow, and reduce congestion during peak hours.

3.4.6 FINANCIAL MODELING

Fuzzy logic can be used in financial forecasting and portfolio optimization, taking into account imprecise market data and economic indicators to make investment decisions.

3.4.7 NATURAL LANGUAGE PROCESSING

Fuzzy logic aids in natural language processing tasks like sentiment analysis, fuzzy search, and language translation, where words and meanings are often imprecise.

3.4.8 QUALITY CONTROL

Fuzzy logic can be used to improve quality control processes in manufacturing by making real-time adjustments to production parameters to maintain product quality.

3.4.9 ECONOMICS AND PRICING

Fuzzy logic is applied in pricing strategies, particularly in e-commerce, to adjust prices dynamically.

3.4.10 AGRICULTURE

Fuzzy logic is employed in precision agriculture for tasks like irrigation scheduling, crop yield prediction, and pest control, taking into account variations in soil and weather conditions.

3.5 ADVANTAGES

Fuzzy logic offers advantages over classical logic in scenarios where precise, binary decisions are not suitable. It can handle real-world problems with inherent uncertainty and variability, making it a valuable tool for modeling complex systems.

3.6 CHALLENGES

Fuzzy logic is not without its challenges. It can be computationally intensive, and interpreting fuzzy rules and membership functions can be complex. Additionally, determining the appropriate fuzzy sets and rules requires domain expertise.

3.7 CONCLUSION

In summary, fuzzy logic provides a way to capture and work with uncertainty in a systematic manner, allowing machines to make decisions and control systems in a manner that resembles human reasoning. It has found wide-ranging applications in various fields and continues to be an important tool in the realm of AI and control systems.

KEYWORDS

- **artificial intelligence and machine learning**
- **fuzzy logic**
- **fuzzy inference systems**
- **fuzzy sets**

REFERENCES

1. Zadeh, L. A. (1965). Fuzzy sets. *Information and Controls*, *8*(3), 338–353.
2. Jang, J. S. (1993). ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, and Cybernetics*, *23*(3), 665–685.
3. Mamdani, E. H., & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*, *7*(1), 1–13.
4. Klir, G. J., & Yuan, B. (1995). *Fuzzy Sets and Fuzzy Logic: Theory and Applications*. Prentice Hall.
5. Pedrycz, W., & Gomide, F. (2007). *An Introduction to Fuzzy Sets: Analysis and Design*. MIT Press.
6. Lee, C. C. (1990). Fuzzy logic in control systems: Fuzzy logic controller—Part I. *IEEE Transactions on Systems, Man, and Cybernetics*, *20*(2), 404–418.
7. Bezdek, J. C., Ehrlich, R., & Full, W. (1984). FCM: The fuzzy c-means clustering algorithm. *Computers & Geosciences*, *10*(2–3), 191–203.
8. Pal, N. R., & Pal, K. (1993). A review on image segmentation techniques. *Pattern Recognition*, *26*(9), 1277–1294.
9. Mamdani, E. H., & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*, *7*(1), 1–13.
10. Jang, J. S. R., Sun, C. T., & Mizutani, E. (1997). *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*. Prentice-Hall.
11. Sugeno, M., & Kang, G. T. (1988). Structure identification of fuzzy model. *Fuzzy Sets and Systems*, *28*(1), 15–33.
12. Gupta, M. M., & Tanaka, K. (1988). A survey of fuzzy applications in control. *Fuzzy Sets and Systems*, *27*(2), 113–131.
13. Wu, D., & Mendel, J. M. (1998). Uncertainty bounds of continuous-time fuzzy systems. *Fuzzy Sets and Systems*, *94*(1), 67–76.
14. Castaneda, V., & Melin, P. (2001). Fuzzy logic applications in image processing. *Artificial Intelligence Review*, *15*(3), 311–333.
15. Ross, T, J. *Fuzzy Logic with Engineering Applications*. John Wiley & Sons, Ltd.

CHAPTER 4

Applications of Fuzzy Logic in Allied Health Sciences

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ABSTRACT

Fuzzy logic, a mathematical framework designed to address the challenges posed by uncertainty and imprecision, has garnered considerable attention across several disciplines owing to its capacity to effectively represent intricate systems characterized by ambiguous or partial data. Fuzzy logic has become a helpful tool in the domain of allied health sciences, where decision-making frequently entails ambiguity and reliance on qualitative input. The present work examines the various applications of fuzzy logic in the field of allied health sciences, emphasizing its capacity to augment diagnostic precision, optimize treatment approaches, and boost the quality of patient care. The main subjects addressed encompass the underlying principles of fuzzy logic, its significance in related fields of healthcare, and concrete instances of its use in medical diagnostics, disease prognosis, healthcare administration, and individualized treatment strategies.

4.1 INTRODUCTION TO FUZZY LOGIC

Fuzzy logic is a mathematical and computational framework for addressing uncertainty and imprecision in problem-solving and decision-making. It extends traditional binary (true/false) logic to manage ambiguous, incomplete,

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or unclear information. Instead of absolute distinctions (e.g., something is either completely true or completely false), fuzzy logic [1] allows for the representation of partial truths and partial falsehoods. This adaptability makes fuzzy logic especially useful in scenarios involving human judgment and natural language [2].

Fuzzy logic has applications in numerous disciplines, such as engineering (particularly control systems), artificial intelligence, robotics, healthcare, and decision support systems (DSSs), where handling uncertainty and imprecision is crucial [3]. The fuzzy logic extends the principles of classical logic to manage uncertain and ambiguous situations by introducing fuzzy sets and linguistic variables. It is a useful instrument for modeling and solving problems in situations where precise binary logic may not be suitable [4]. Following are the fundamental key concepts of fuzzy logic [5].

4.1.1 FUZZY SETS

Fuzzy logic is based on fuzzy sets, which are an extension of classical sets. In classical sets, an element is either included (true) or excluded (false). In contrast, in fuzzy sets, an element can be a member of the set to a degree between 0 and 1, which reflects the degree of membership. Membership functions characterize the level of membership for each element.

4.1.2 LINGUISTIC VARIABLES

Fuzzy logic frequently deals with ambiguous linguistic variables, such as “hot,” “cold,” “tall,” or “short.” Linguistic variables are represented as fuzzy sets whose membership functions map linguistic terms to varying degrees of membership.

4.1.3 RULES

Fuzzy logic employs a set of IF–THEN principles, typically expressed as “if condition A is true, then action B is taken.” These principles connect linguistic variables and their respective membership functions based on fuzzy logic operators (AND, OR, NOT).

4.1.4 FUZZY INFERENCE

Fuzzy inference is the process of using fuzzy principles to make decisions or draw conclusions. It consists of three essential steps: fuzzification (converting input values to fuzzy sets), rule evaluation (applying fuzzy rules to determine the level of satisfaction), and defuzzification (converting the hazy output to a crisp value).

4.1.5 FUZZY OPERATORS

Fuzzy logic operators include "AND," "OR," and "NOT," which are modified to function with fuzzy sets. These operators are employed to combine fuzzy sets and determine the degree of membership in the resultant sets.

4.1.6 FUZZY CONTROL SYSTEMS

Fuzzy logic is widely employed in control systems, where it can model and regulate nonlinear, complex systems. Fuzzy control systems use linguistic principles and fuzzy sets to make decisions in real-time and to adapt to fluctuating conditions.

4.2 RELEVANCE OF FUZZY LOGIC IN ALLIED HEALTH SCIENCES

The significance of fuzzy logic in the field of allied health sciences stems from its distinctive capacity to tackle the inherent uncertainty, imprecision, and ambiguity frequently encountered in decision-making processes within healthcare. In the field under consideration, wherein clinical data may exhibit characteristics of vagueness, subjectivity, or incompleteness, the utilization of fuzzy logic offers a valuable framework for the purpose of modeling and processing said information [6]. Fuzzy logic provides a solution for addressing the complexity of real-world healthcare scenarios and the requirement for precise, data-driven decisions. This is achieved through the utilization of fuzzy sets that represent varying degrees of symptom severity for diagnosing medical conditions, considering multifactorial influences for predicting disease outcomes, and incorporating patient-specific parameters for personalizing treatment plans. Fuzzy logic plays a vital role in enhancing diagnosis accuracy, treatment efficacy, and overall patient care within the domain of allied health sciences by effectively accommodating the intricate nature of medical data and human expertise [7].

Fuzzy logic exhibits a high degree of suitability for healthcare decision-making owing to a number of significant factors.

4.2.1 MANAGEMENT OF UNCERTAINTY AND AMBIGUITY

The field of healthcare data is intrinsically characterized by uncertainty and frequently encompasses diverse levels of ambiguity. Patients may express their symptoms using vague or imprecise language, while diagnostic tests may produce results that fall within ambiguous or uncertain ranges. Fuzzy logic enables healthcare practitioners to effectively handle and analyze uncertainty by employing membership functions to quantify the extent of truth or falsehood, hence facilitating more sophisticated decision-making processes.

4.2.2 HANDLING LINGUISTIC VARIATIONS

Fuzzy logic demonstrates proficiency in managing linguistic variations, a common occurrence within the healthcare domain. In the medical field, it is common for healthcare practitioners to employ terminology such as "mild," "moderate," or "severe" when characterizing various medical illnesses or symptoms. The utilization of fuzzy sets and linguistic variables enables the integration of subjective descriptions into decision models, hence enhancing their alignment with real-world clinical assessments.

4.2.3 INTEGRATING AND PRIORITIZING CRITERIA

Healthcare decisions often encompass a multitude of variables, including but not limited to patient history, test results, and clinical competence, hence necessitating the application of multicriteria decision-making techniques. Fuzzy logic offers a theoretical framework for the integration and prioritization of criteria, taking into account their interrelationships. This holds particular significance in tasks such as treatment planning, whereby the achievement of a harmonious equilibrium between opposing objectives is imperative.

4.2.4 FACILITATING EXPERT KNOWLEDGE INCORPORATION AND PATIENT-CENTERED CARE

The incorporation of expert knowledge into decision models in healthcare systems is facilitated by the adaptability of fuzzy logic [8]. Clinicians have the ability to articulate their expertise through the utilization of fuzzy rules, which effectively encapsulate their cognitive processes and clinical discernment. This guarantees that the system is in accordance with the knowledge and expertise of healthcare professionals. The concept of patient-centered care is enhanced by the application of fuzzy logic, which facilitates the customization of healthcare decisions based on individual needs and preferences. The consideration of unique patient features, preferences, and tolerances facilitates the customization of treatment plans and procedures. The implementation of a patient-centered strategy has been shown to improve the overall quality of care and increase patient satisfaction.

4.2.5 COMPLEXITY MANAGEMENT

Complexity management is a common challenge encountered within healthcare systems, as they frequently encounter intricate and nonlinear interdependencies among many factors. The utilization of fuzzy logic in the modeling and control of intricate systems proves to be advantageous in several circumstances, such as optimizing drug dosages, predicting illness progression, and monitoring patients. This is particularly significant as conventional linear models may exhibit limitations in these contexts.

4.2.6 CONTINUOUS MONITORING AND FEEDBACK

Fuzzy logic demonstrates a high level of suitability for the purposes of ongoing monitoring and adaptation. In the field of healthcare, it is common for patients' situations to undergo fast changes, necessitating the corresponding adjustment of treatment regimens. Fuzzy logic possesses the capability to effectively handle incoming data and promptly adjust judgments in real-time, so guaranteeing the maintenance of up-to-date and efficient treatment. The interpretability of fuzzy logic-based systems is frequently superior to that of black-box machine learning algorithms. Healthcare professionals possess the ability to comprehend and place confidence in the outcomes rendered by fuzzy logic systems due to their capacity to trace the underlying logic and rules employed in order to reach a specific outcome.

In summary, the utilization of fuzzy logic in healthcare decision-making is advantageous due to its capacity to effectively handle uncertainty, integrate linguistic variables, address multicriteria decision-making scenarios, accommodate expert knowledge, personalize care, manage complexity, provide ongoing feedback, and facilitate interpretability [9]. The utilization of this approach not only improves the overall effectiveness of decision-making processes, but also facilitates the provision of healthcare services that are more patient-centered and adaptive in nature.

4.3 THE IMPORTANCE OF ACCOMMODATING UNCERTAINTY AND IMPRECISION IN MEDICAL DATA

The accommodation of uncertainty and imprecision in medical data is crucial due to its alignment with the intrinsically unpredictable nature of the healthcare field [10]. The accuracy and certainty of medical data are sometimes limited, leading healthcare professionals to frequently encounter challenges related to diagnostic uncertainty, unpredictability in patient reactions, and insufficient information. Failure to recognize and manage this ambiguity can result in decision-making that is less than ideal, misdiagnoses, and treatment choices that are ineffective. Healthcare workers can enhance their decision-making process by embracing uncertainty, enabling them to make more informed and nuanced judgments. This approach helps them avoid premature conclusions and consider the inherent variety in patient circumstances. This methodology promotes a perspective that is both realistic and centered on the patient, resulting in enhanced safety, increased diagnostic accuracy, customized treatment strategies, and eventually, improved healthcare results. Furthermore, in light of the growing integration of medical data with new technologies and artificial intelligence, it is imperative to place greater emphasis on comprehending and quantifying uncertainty. This is essential to guarantee the dependability and ethical use of automated DSSs within the healthcare domain.

4.3.1 FUZZY LOGIC IN MEDICAL DIAGNOSIS

Using fuzzy logic to diagnose patients more accurately is a useful application of fuzzy logic. It can help with differential diagnosis and be utilized to create systems that are more sensitive and accurate than conventional diagnostic techniques [11]. Fuzzy logic technology is expected to become even more important in the future for medical diagnostics as it advances. When it comes to medical diagnosis, fuzzy logic works especially well because symptoms and results are frequently ambiguous and subjective.

Generally, fuzzy logic systems consist of three primary parts.

1. *Fuzzifier:* This part transforms numerical inputs into fuzzy membership values, such as test results or patient symptoms.
2. *Inference engine:* Fuzzy rules are applied to the fuzzy membership values by the inference engine, which produces a fuzzy output.
3. *Defuzzifier:* This part turns the fuzzy result into a numerical result (such as diagnosis or recommended course of therapy).

Statements describing the relationship between inputs and outputs in a fuzzy system are known as fuzzy rules. IF–THEN clauses, in which the IF clause specifies the inputs and the THEN clause specifies the outcome, are commonly used to express them. An imprecise guideline for identifying diabetes, for instance, could be:

Diabetes is probably present if there is elevated blood sugar, increased thirst, and frequent urination [12]. Numerous illnesses and medical issues can be diagnosed using fuzzy logic systems, including cardiovascular conditions (heart attacks, strokes, etc.), respiratory conditions (such as pneumonia and asthma), neurological conditions (such as Parkinson's and Alzheimer's illnesses), and infectious disorders (such as tuberculosis and malaria).

4.3.1.1 EXAMPLES AND CASE STUDIES

Here are a few instances of current medical diagnosis using fuzzy logic:

In order to identify cardiac disease, a fuzzy logic system has been developed that takes into account the patient's age, gender, blood pressure, cholesterol, and smoking status. It has been demonstrated that the technology is more accurate than conventional diagnostic techniques.

Based on mammography pictures, a new fuzzy logic system has been developed to diagnose breast cancer. It has been demonstrated that the system is more sensitive than conventional diagnostic techniques, which lowers the possibility that a cancer diagnosis may be missed.

In addition, systems for diagnosing and tracking chronic illnesses like diabetes and asthma are being developed using fuzzy logic. Patients can lower their chances of problems and better control their diseases with the use of these technologies.

4.3.1.2 HOW DIFFERENTIAL DIAGNOSIS CAN BENEFIT FROM FUZZY LOGIC

The practice of differentiating between two or more illnesses or medical problems that have similar symptoms is known as differential diagnosis. This can be a difficult undertaking, particularly if there is ambiguity or subjectivity in the symptoms [13].

Using fuzzy logic, one may simulate the imprecision and ambiguity related to symptoms and findings, which can help in differential diagnosis. To differentiate between various kinds of headaches, for instance, a fuzzy logic system might be created based on the patient's description of the pain, its location, and any additional symptoms that may be present.

Combining data from several sources, including the patient's medical history, physical examination, and test results, is another use for fuzzy logic systems. In complex instances, in particular, this can help to increase the accuracy of differential diagnosis.

In general, fuzzy logic shows great promise as a diagnostic tool for medicine. It can be applied to create systems that surpass conventional diagnostic techniques in terms of sensitivity and accuracy. Additionally, differential diagnosis—which can be difficult, particularly in cases when symptoms are ill-defined or subjective—might be aided by fuzzy logic.

4.3.2 HEALTHCARE MANAGEMENT WITH FUZZY LOGIC

The planning, organizing, directing, and controlling of an organization's resources is known as healthcare management. A wide range of stakeholders, including patients, professionals, administrators, and policymakers, are involved in this complex undertaking [14]. There are several ways that fuzzy logic might be applied to enhance healthcare administration. Fuzzy logic, for instance, can be applied to the following.

1. *Boost decision-making:* Models for decisions that take into consideration the imprecision and uncertainty included in healthcare data can be created using fuzzy logic. Making better and more informed decisions may result from this.
2. *Optimize resource allocation:* Allocation of resources can be made more efficient by using fuzzy logic, including personnel and equipment. This may contribute to cost savings and increased efficiency.

3. *Boost care quality:* Systems for quality control that monitor and enhance the caliber of medical services can be created using fuzzy logic.
4. *Boost patient satisfaction:* Systems that personalize healthcare services and raise patient satisfaction can be created using fuzzy logic.

The following are some particular instances of fuzzy logic's current application in healthcare management.

Appointment and surgical scheduling systems are being developed with fuzzy logic. Numerous variables, including patient preferences, physician availability, and resource limitations, might be considered by these systems. Patients' wait times may be shortened and the healthcare system's efficiency increased as a result.

Technologies for *forecasting patient demand for services* are being developed using fuzzy logic. By using this data, healthcare institutions may guarantee that patients receive the care they require at the appropriate time and with the right team.

Systems for *tracking patient risk* are being developed using fuzzy logic. Patients who are most likely to experience difficulties or require readmission can be identified by these systems. By using this knowledge, early intervention can be done to stop these issues from happening.

Healthcare service quality assessment systems are being developed with fuzzy logic. Numerous variables, including patient outcomes, patient satisfaction, and adherence to clinical recommendations, can be considered by these systems. You can use this data to pinpoint areas that require quality improvement.

Fuzzy logic is an effective tool for healthcare management overall. It can be applied to raise patient satisfaction, optimize resource allocation, make better decisions, and improve the quality of care. Future developments in fuzzy logic technology should see it become increasingly important in the administration of healthcare.

4.4 EXPLORING EMERGING TRENDS AND RESEARCH AREAS IN FUZZY LOGIC APPLICATIONS IN ALLIED HEALTH SCIENCES

A mathematical framework known as fuzzy logic makes it possible to represent and process imprecise and uncertain data. It works especially well in the allied health sciences, where it is common for symptoms, conclusions, and available treatments to be ambiguous and subjective [15].

The following are some new directions and topics of study for applications of fuzzy logic in the allied health sciences:

4.4.1 DECISION ASSISTANCE SYSTEMS FOR DIAGNOSIS AND THERAPY BASED ON FUZZY LOGIC

DSSs with fuzzy logic as a foundation are being created to help allied health practitioners diagnose illnesses and create treatment regimens. To provide more precise and individualized diagnoses and treatment regimens, these DSS might use a range of variables, including as the patient's symptoms, medical history, and test findings. One possible use of fuzzy logic DSS is in the diagnosis and treatment of musculoskeletal problems by physical therapists. The DSS might create a customized therapy plan based on the patient's pain threshold, range of motion, and other variables.

4.4.2 SYSTEMS FOR TRACKING AND CONTROLLING CHRONIC ILLNESSES BASED ON FUZZY LOGIC

Systems based on fuzzy logic are also being developed to track and treat long-term conditions, such as diabetes, asthma, and heart disease. In addition to tracking patient data, such as blood pressure, blood sugar levels, and respiratory function, these devices can send alerts and suggestions to patients to help them manage their diseases. For instance, a system based on fuzzy logic might be created to track diabetic patients' blood sugar levels. The patient's blood sugar levels might be analyzed by the system to see trends and get advice on how to change their diet or insulin dosage.

4.4.3 SYSTEMS BASED ON FUZZY LOGIC FOR INDIVIDUALIZED HABILITATION AND REHABILITATION

Patients with impairments or injuries can benefit from customized rehabilitation and habilitation programs thanks to fuzzy logic-based solutions. These systems are able to create a program that is customized to each patient's unique demands by taking into consideration their goals and needs. For instance, a system based on fuzzy logic could be created to tailor a stroke patient's rehabilitation regimen. To create a program that will assist the patient with regaining as much function as possible, the system may consider the patient's strength, coordination, and range of motion.

4.4.4 SYSTEMS BASED ON FUZZY LOGIC TO ENHANCE PATIENT SAFETY AND CARE QUALITY

There are several ways in which fuzzy logic-based systems might raise the standard of care and ensure patient safety. Fuzzy logic, for instance, can be used to create healthcare guidelines, monitor patient infection risk, and detect and avoid bad medication events.

One possible use of fuzzy logic is the detection and prevention of adverse medication effects. In order to help doctors avoid prescribing drugs that potentially have unfavorable side effects, the system might consider the patient's medical history, present medications, and allergies.

4.5 CONCLUSION

This chapter aims to provide a comprehensive overview of the applications of fuzzy logic in allied health sciences, from diagnosis to treatment planning and healthcare management, highlighting its potential to enhance DSSs and ultimately improve patient outcomes. One extremely useful technique that could completely change the way allied health services are provided is fuzzy logic. Systems based on fuzzy logic can be used to make better decisions, create individualized treatment program, track and manage chronic illnesses, and enhance patient safety and care quality. As fuzzy logic technology advances, many more ground-breaking and significant applications in the allied health sciences should be anticipated.

KEYWORDS

- **Fuzzy logic**
- **decision support systems**
- **fuzzy inference**
- **fuzzy control systems**
- **healthcare decision-making**

REFERENCES

1. Zadeh, L. A. (2008). Is there a need for fuzzy logic. *Information Sciences*, *178*(13), 2751–2779.
2. Laengle, S., Lobos, V., Merigó, J. M., Herrera-Viedma, E., Cobo, M. J., & De Baets, B. (2021). Forty years of fuzzy sets and systems: A bibliometric analysis. *Fuzzy Sets and Systems*, *402*, 155–183.
3. Maddiboyina, H. V., & Ponnapalli, V. S. (2019). Fuzzy logic based VANETS: A review on smart transportation system. In: *2019 International Conference on Computer Communication and Informatics (ICCCI)*. IEEE, pp. 1–4.
4. Makkar, R. (2018). Application of fuzzy logic: A literature review. *International Journal of Statistics and Applied Mathematics*, *3*(1), 357–359.
5. Peckol, J. K. (2021). *Introduction to Fuzzy Logic*. John Wiley & Sons.
6. Yalçinkaya, F., Sevinç, A., Aydilek, H., & Erbaş, A. (2023). Ultrasonic therapy device using fuzzy-logic for clinical use. *International Journal of Engineering Research and Development*, *15*(2), 776–785.
7. Fakharian, E., Nabovati, E., Farzandipour, M., Akbari, H., & Saeedi, S. (2021). Diagnosis of mechanical low back painusing a fuzzy logic-based approach. *International Journal of Intelligent Systems and Applications in Engineering*, *9*(3), 116–120.
8. Ahmed, T. I., Bhola, J., Shabaz, M., Singla, J., Rakhra, M., More, S., & Samori, I. A. (2022). Fuzzy logic-based systems for the diagnosis of chronic kidney disease. *BioMed Research International*, *2022*, 2653665.
9. Ghosh, G., Roy, S., & Merdji, A. (2020). A proposed health monitoring system using fuzzy inference system. *Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine*, *234*(6), 562–569.
10. John, R. I., & Innocent, P. R. (2005). Modeling uncertainty in clinical diagnosis using fuzzy logic. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, *35*(6), 1340–1350.
11. Awotunde, J. B., Matiluko, O. E., & Fatai, O. W. (2014). Medical diagnosis system using fuzzy logic. *African Journal of Computing & ICT*, *7*(2), 99–106.
12. Phuong, N. H., & Kreinovich, V. (2001). Fuzzy logic and its applications in medicine. *International Journal of Medical Informatics*, *62*(2–3), 165–173.
13. Gürsel, G. (2016). Healthcare, uncertainty, and fuzzy logic. *Digital Medicine*, *2*(3), 101–112.
14. Quasim, M. T., Shaikh, A., Shuaib, M., Sulaiman, A., Alam, S., & Asiri, Y. (2021). Smart healthcare management evaluation using fuzzy decision making method. doi:10.21203/rs.3.rs-424702/v1
15. Patriarca, R., Ramos, M., Paltrinieri, N., Massaiu, S., Costantino, F., Di Gravio, G., & Boring, R. L. (2020). Human reliability analysis: Exploring the intellectual structure of a research field. *Reliability Engineering & System Safety*, *203*, 107102.

CHAPTER 5

Transversals and Its Properties of Intuitionistic Fuzzy Threshold Hypergraphs

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ABSTRACT

In intuitionistic fuzzy threshold hypergraphs (IFTHGs), a transversal is a hyperedge that cuts more than two hyperedges instead of a line that intersects two lines in geometry. The intuitionistic fuzzy transversal (IFT), minimum IFT, locally minimal IFT, and intuitionistic fuzzy transversal core of IFTHG are defined and it has been established that every IFTHG has a nonempty IFT. Some of the characteristics of transversals of IFTHGs were additionally examined. Also, this chapter explores the application of transversals in the context of IFTHGs for optimizing drip irrigation practices in agriculture.

5.1 INTRODUCTION

Leonhard Euler's [11] seminal paper on graph theory is titled as solution of a problem in the geometry of position was published in 1736 in the Journal Commentaries of the St. Petersburg Academy of Sciences. Graph theory with applications by Bondy and Murty [2] covers fundamental concepts such as graph representation, graph algorithms, network flows, and matchings. A first course in graph theory by Choudum [3] covers some basic and various topics in graph theory.

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The paper "Aggregation of Inequalities in Integer Programming," was authored by Chvatal and Hammer [4] and published in 1977. The book titled as *Threshold Graphs and Related Topics* by N.V.R. Mahadev, Peled [13] has numerous open questions and research proposals appealing.

Hypergraphs by Berge [6] is a seminal book in the field of combinatorial mathematics and graph theory. Graphs and hypergraphs by Berge [5] is a classic textbook that provides a comprehensive introduction to the theory and applications of both graphs and hypergraphs. *Hypergraph Theory: An Introduction* book by Bretto [1] provides an introduction to hypergraphs and aims to overcome the lack of recent manuscripts on this theory. Connection and separation in hypergraphs by Bahmanian and Sajna [14] investigates different fundamental connectivity features of hypergraphs from a graph-theoretical perspective, with a focus on cut edges, cut vertices, and blocks.

Fuzzy sets by Zadeh [20] discussed the concepts of inclusion, union, intersection, complement, relation, convexity, etc. and various features of these concepts are established in the context of fuzzy sets in 1965. *Fuzzy Graph Theory* by Mathew et al. [19] is a book that provides a thorough exploration of fuzzy graph theory, offering a balanced mix of theoretical foundations, methodologies, and practical applications. *Fuzzy Graphs and Fuzzy Hypergraphs* book by Mordeson and Nair [7] provides a comprehensive introduction to fuzzy graphs, covering basic concepts, properties, and algorithms. *Modern Trends in Fuzzy Graph Theory* book by Pal et al. [12] offers a comprehensive set of methods for applying graph theory and fuzzy mathematics to practical issues.

One of the key strengths of the book named as on intuitionistic fuzzy sets: *Theory and Application* by Atanassov [9] lies in its clear and rigorous mathematical formalism. The book *On Intuitionistic Fuzzy Set Theory* by Atanassov [8], consists of the concept of IFS, operations and relation over IFS, and geometrical interpretations of IFS. The paper "Intuitionistic Fuzzy Threshold Graphs" by Yang and Mao [10] provides three concepts of intuitionistic fuzzy threshold graphs, intuitionistic fuzzy alternating four-cycle, and threshold dimension of intuitionistic fuzzy graphs and provides an extension of threshold graphs.

Parvathi et al. [18] were the first to introduce the intuitionistic fuzzy hypergraph. Then Akram and Dudek [15] explained about intuitionistic fuzzy hypergraphs with applications. Some types of intuitionistic fuzzy-directed hypergraphs are discussed in [16]. In [17], properties of transversals of intuitionistic fuzzy-directed hypergraphs were discussed.

5.2 PRELIMINARIES

Definition 5.2.1. The intuitionistic fuzzy threshold hypergraph (IFTHG) is denoted by $\mathbb{H}_{\mathbb{G}} = (U, \varepsilon; s_1, s_2)$ where,

1. $U = \{u_1, u_2, \ldots, u_n,\}$ is finite set of intuitionistic fuzzy vertices,
2. $\varepsilon = \{\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_m,\}$ is a family of crisp subsets of U,
3. $\varepsilon_j = \{u_i, u_j(u_i), v_j(u_i) \mid 0 \le u_j(u_i) + v_j(u_i) \le 1\}, j = 1,2,\ldots, m$
4. $\varepsilon_j \ne \emptyset, j = 1,2,\ldots, m$
5. $\bigcup_j \text{supp}(\varepsilon_j) = U, j = 1,2,\ldots,m$
6. An independent set $V \subseteq U$ be set of all different combinations of a nonadjacent vertices in $\mathbb{H}_{\mathbb{G}} \Leftrightarrow \exists\, s_1 \;\&\; s_2 > 0$ such that $\sum_{u_i \in V} \mu_{ij}(u_i) \le s_1$ & $\sum_{u_i \in V} (1 - v_{ij}(u_i)) \le s_2$

Where the hyperedges of ε_j are crisp sets of intuitionistic fuzzy vertices, $\mu_j(u_i)$ and $v_j(u_i)$ represent the membership and nonmembership degrees of a vertex u_i to an hyperedge ε_j.

Definition 5.2.2. Let $\mathbb{H}_{\mathbb{G}} = (U, \varepsilon; s_1, s_2)$ be an IFTHG. If an independent set $V \subseteq U$, then the height of $\mathbb{H}_{\mathrm{G}}$ is named as $\hbar_t(\mathbb{H}_{\mathbb{G}}) = \{\max(\min(u_{ij})), \max(\max(v_{ij}))\}$ for which $\sum_{u_i \in V} \mu_{ij}(u_i) \le s_1$ and $\sum_{u_i \in V} (1 - v_{ij}(u_i)) \le s_2$ for all $i = 1,2,\ldots, m$ and $j = 1,2,\ldots, n$, where u_{ij} & v_{ij} is the membership and nonmembership value of jth hyperedge in ith vertex, respectively.

Definition 5.2.3. Let $\mathbb{H}_{\mathbb{G}} = (U, \varepsilon; s_1, s_2)$ be an IFTHG and an independent set $V \subseteq U$ exist, if $\varepsilon_j, \varepsilon_k, \in \varepsilon$ and $0 < \alpha, \beta \le 1$. Then, the (α, β) -level is defined by $(\varepsilon_j, \varepsilon_k)^{(\alpha,\beta)} = \{u_i \in U \mid \min(\mu_{ij}^{\alpha}(u_i)) \ge \alpha,\ \max(v_{ij}^{\beta}(u_i)) \le \beta\}$ for which $\sum_{u_i \in V} \mu_{ij}(u_i) \le s_1$ and $\sum_{u_i \in V} (1 - v_{ij})(u_i) \le s_2$.

Definition 5.2.4. Let $\mathbb{H}_{\mathbb{G}} = (U, \varepsilon, s_1, s_2)$ be an IFTHG, there exists an independent set $V \subseteq U$ such that $\mathbb{H}_{\mathbb{G}}^{(y_i,z_i)} = \langle U^{(y_i,z_i)}, \mathcal{E}^{(y_i,z_i)} \rangle$ be the (y_i, z_i)-level of $\mathbb{H}_{\mathbb{G}}$. The sequence of real numbers $\{y_1, y_2, \ldots, y_n; z_1, z_2, \ldots, z_n\} \in 0 \le y_i \le \hbar_{t_\mu}(\mathbb{H}_{\mathbb{G}})$ and $0 \le z_i \le \hbar_{t_v}(\mathbb{H}_{\mathbb{G}})$, satisfying the following conditions:

1. If $y_1 < \alpha \le 1$ and $0 \le \beta < z_1 \Rightarrow \varepsilon^{(\alpha,\beta)} = \varphi$;
2. If $y_{i+1} \le \alpha \le y_i; z_i \le \beta \le z_{i+1} \Rightarrow \varepsilon^{(\alpha,\beta)} = \varepsilon^{(y_i,z_i)}$; and
3. $\varepsilon^{(y_i,z_i)} \subset \varepsilon^{(y_{i+1},z_{i+1})}$

for which $\sum_{u_i \in V} \mu_{ij}(u_i) \le s_1$ and $\sum_{u_i \in V} (1 - v_{ij}(u_i)) \le s_2$ is known as *fundamental sequence* of $\mathbb{H}_{\mathbb{G}}$ and is represented by $\mathcal{F}(\mathbb{H}_{\mathbb{G}})$

Definition 5.2.5. Let $\mathbb{H}_{\mathbb{G}} = (U, \varepsilon; s_1, s_2)$ be an IFTHG, also an independent set $V \subseteq U$ exist. Then, the *core set* of $\mathbb{H}_{\mathbb{G}}$ is noted as $C(\mathbb{H}_{\mathbb{G}})$ for $0 < (y_i, z_i) \le \hbar_t(\mathbb{H}_{\mathbb{G}})$, and is defined by $C(\mathbb{H}_{\mathbb{G}}) = \left\{\mathbb{H}_{\mathbb{G}}^{(y_1,z_1)}, \mathbb{H}_{\mathbb{G}}^{(y_2,z_2)}, ..., \mathbb{H}_{\mathbb{G}}^{(y_n,z_n)}\right\}$. The corresponding set of (y_n,z_n)-level hypergraphs is $\mathbb{H}_{\mathbb{G}}^{(y_1,z_1)} \subset \mathbb{H}_{\mathbb{G}}^{(y_2,z_2)} \subset ... \subset \mathbb{H}_{\mathbb{G}}^{(y_n,z_n)}$ for which $\sum_{u_i \in V} \mu_{ij}(u_i) \le s_1$ and $\sum_{u_i \in V} (1-\nu_{ij}(u_i)) \le s_2$ called the $\mathbb{H}_{\mathbb{G}}$-induced fundamental sequence and is noted as $I(\mathbb{H}_{\mathbb{G}})$. The (y_n, z_n)-level is said to be a support level of $\mathbb{H}_{\mathbb{G}}$ and the $\mathbb{H}_{\mathbb{G}}^{(y_n, z_n)}$ is known as the support of $\mathbb{H}_{\mathbb{G}}$.

Definition 5.2.6. Suppose $\mathbb{H}_{\mathbb{G}} = (U, \varepsilon; s_1, s_2)$ and $\mathbb{H}_{\mathbb{G}}' = (U', \varepsilon'; s_1', s_2')$ are IFTHGs, $\mathbb{H}_{\mathbb{G}}$ is called a *partial IFTHG* of $\mathbb{H}_{\mathbb{G}}'$ and an independent set $V \subseteq U$ such that

$$u' = \begin{cases} \min\left(\operatorname{supp}\left(\mu_{ij}\right)\right) \text{ and } \sum\limits_{u_i \in V} \mu_{ij}(u_i) \le s_1 \mid \mu_{ij} \in \varepsilon' \\ \max\left(\operatorname{supp}\left(\nu_{ij}\right)\right) \text{ and } \sum\limits_{u_i \in V} (1-\nu_{ij})(u_i) \le s_2 \mid \nu_{ij} \in \varepsilon' \end{cases}$$

the partial IFTHG generated by ε' and is represented by $\mathbb{H}_{\mathbb{G}} \subseteq \mathbb{H}_{\mathbb{G}}'$. Then we write $\mathbb{H}_{\mathbb{G}} \subset \mathbb{H}_{\mathbb{G}}'$ if $\mathbb{H}_{\mathbb{G}} \subseteq \mathbb{H}_{\mathbb{G}}'$ and $\mathbb{H}_{\mathbb{G}} \neq \mathbb{H}_{\mathbb{G}}'$.

Definition 5.2.7. Let $\mathbb{H}_{\mathbb{G}} = (U, \varepsilon; s_1, s_2)$ be an IFTHG, there exists an independent set $V \subseteq U$ such that $C(\mathbb{H}_{\mathbb{G}}) = \left\{\mathbb{H}_{\mathbb{G}}^{(y_1,z_1)}, \mathbb{H}_{\mathbb{G}}^{(y_2,z_2)}, \ldots, \mathbb{H}_{\mathbb{G}}^{(y_n,z_n)}\right\}$ for which $\sum_{u_i \in V} \mu_{ij}(u_i) \le s_1$ and $\sum_{u_i \in V} (1-\nu_{ij}(u_i)) \le s_2$. $\mathbb{H}_{\mathbb{G}}$ is said to be *ordered* if $C(\mathbb{H}_{\mathbb{G}})$ is ordered. That is $\mathbb{H}_{\mathbb{G}}^{(y_1,z_1)} \subset \mathbb{H}_{\mathbb{G}}^{(y_2,z_2)} \subset ... \subset \mathbb{H}_{\mathbb{G}}^{(y_n,z_n)}$ for which $\sum_{u_i \in V} \mu_{ij}(u_i) \le s_1$ and $\sum_{u_i \in V} (1-\nu_{ij}(u_i)) \le s_2$. The IFTHG is known as *simply ordered* if $\{\mathbb{H}_{\mathbb{G}}^{(y_i,z_i)} \mid \text{i}=1,2,\ldots,n\}$ is simply ordered, (i.e,) if it is ordered and if $\varepsilon \in \mathbb{H}_{\mathbb{G}}^{(y_{i+1},z_{i+1})} \setminus \mathbb{H}_{\mathbb{G}}^{(y_i,z_i)}$ then $\varepsilon \nsubseteq \mathbb{H}_{\mathbb{G}}^{(y_i,z_i)}$

5.3 NOTATIONS

$\mathbb{H}_{\mathbb{G}} = (U, \varepsilon; s_1, s_2)$: IFTHG with hyperedge set ε, vertex set U and s_1, s_2 are threshold values.

$\hbar_t(\mathbb{H}_{\mathbb{G}})$: Height of IFTHG

$\mathcal{F}_t(\mathbb{H}_{\mathbb{G}})$: Fundamental sequence of IFTHG.

$C(\mathbb{H}_{\mathbb{G}})$: Core set of IFTHG.

$I(\mathbb{H}_{\mathbb{G}})$: Induced fundamental sequence of IFTHG.

$\mathbb{H}_{\mathbb{G}}^{(y_i,z_i)}$: (y_i, z_i)-level of $\mathbb{H}_{\mathbb{G}}$.

(y_i, z_i): Hyperedge membership and nonmembership values.

$\mathrm{T}\Upsilon(\mathbb{H}_{\mathbb{G}})$: Minimal intuitionistic fuzzy transversal (IFT) of IFTHG.

5.4 MAIN RESULTS

Definition 5.4.1. Assume an IFTHG $\mathbb{H}_{\mathbb{G}} = (U, \varepsilon; s_1, s_2)$. An IFT T of IFTHG is an IF subset of U with $\mathrm{T}^{(\varepsilon_j, \varepsilon_k)} \cap \mathcal{A}^{(\varepsilon_j, \varepsilon_k)} \neq \varphi$ $\forall$ $\mathcal{A} \in \varepsilon$ where $\varepsilon_j = \wedge(\mu_{ij})$ and $\varepsilon_k = \vee(v_{ij})$ for which $\sum_{u_i \in V} \mu_{ij}(u_i) \leq s_1$ and $\sum_{u_i \in V} (1 - v_{ij}(u_i)) \leq s_2$, $\forall 1 \leq i \leq m, 1 \leq j \leq n.$ Also μ_{ij} and v_{ij} is the membership and nonmembership value of i^{th} vertex of j^{th} hyperedge.

Definition 5.4.2. A minimal IFT T for IFTHG is a transversal of $\mathbb{H}_{\mathbb{G}}$, which satisfies the condition that if $\mathrm{T}_1 \subset \mathrm{T}$, then T_1 is not an IFT of $\mathbb{H}_{\mathbb{G}}$.

Note: The set of all minimal IFT of IFTHG is represented by $\mathrm{T}\boldsymbol{\gamma}(\mathbb{H}_{\mathbb{G}})$. Always $\mathrm{T}\boldsymbol{\gamma}(\mathbb{H}_{\mathbb{G}}) \neq \varphi$.

Example 5.4.3. An IFTHG $\mathbb{H}_{\mathbb{G}}$ with $U = \{u_1, u_2, u_3, u_4, u_5, u_6\}$, $\varepsilon = \{\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4\}$ has been considered.

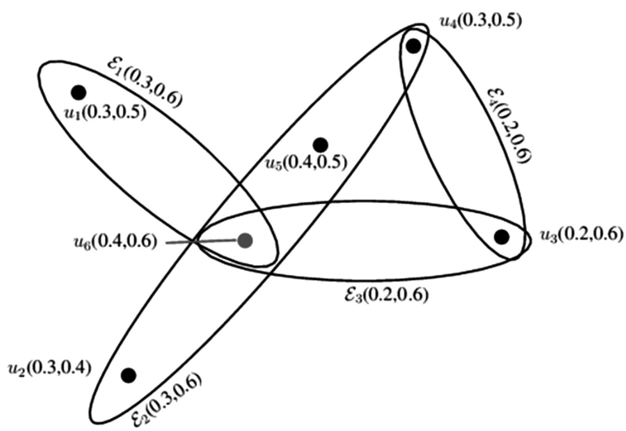

FIGURE 5.1 Intuitionistic fuzzy threshold hypergraph $\mathbb{H}_{\mathbb{G}}$. ⏎

Using Figure 5.1, we can construct an IFTHG $\mathbb{H}_{\mathbb{G}}$, with $\varepsilon = \{\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4\}$ is denoted by the following incidence matrix as

$$\begin{array}{c} \\ u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \\ u_6 \end{array} \begin{pmatrix} \varepsilon_1 & \varepsilon_2 & \varepsilon_3 & \varepsilon_4 \\ \langle 0.3, 0.5 \rangle & \langle 0,1 \rangle & \langle 0,1 \rangle & \langle 0,1 \rangle \\ \langle 0,1 \rangle & \langle 0.3, 0.4 \rangle & \langle 0,1 \rangle & \langle 0,1 \rangle \\ \langle 0,1 \rangle & \langle 0,1 \rangle & \langle 0.2, 0.6 \rangle & \langle 0.2, 0.6 \rangle \\ \langle 0,1 \rangle & \langle 0.3, 0.5 \rangle & \langle 0,1 \rangle & \langle 0.3, 0.6 \rangle \\ \langle 0,1 \rangle & \langle 0.4, 0.5 \rangle & \langle 0,1 \rangle & \langle 0,1 \rangle \\ \langle 0.4, 0.6 \rangle & \langle 0.4, 0.6 \rangle & \langle 0.4, 0.6 \rangle & \langle 0.4, 0.6 \rangle \end{pmatrix}.$$

The minimal IFT of IFTHG is represented as follows:

$$\begin{array}{c} \\ u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \\ u_6 \end{array}\left(\begin{array}{cc} T_1 & T_2 \\ \langle 0,1\rangle & \langle 0,1\rangle \\ \langle 0,1\rangle & \langle 0,1\rangle \\ \langle 0.2,0.6\rangle & \langle 0,1\rangle \\ \langle 0,1\rangle & \langle 0.3,0.5\rangle \\ \langle 0,1\rangle & \langle 0,1\rangle \\ \langle 0.4,0.6\rangle & \langle 0.4,0.6\rangle \end{array}\right)$$

The correspondent IFTHG is shown in Figure 5.2.

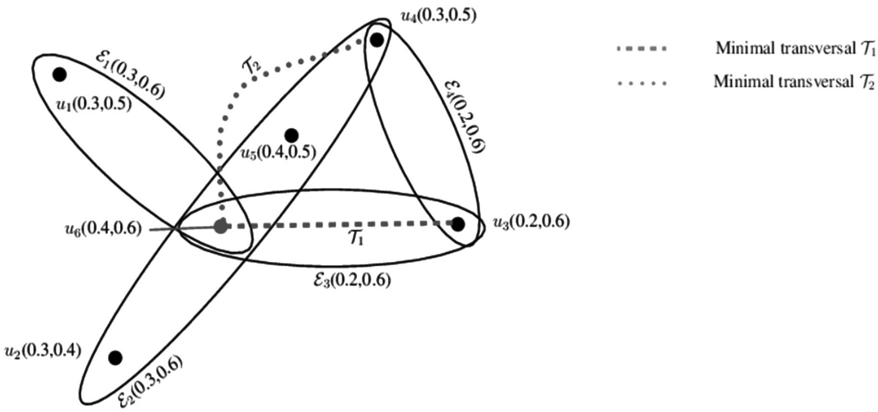

FIGURE 5.2 $\mathbb{H}_{\mathbb{G}}$ and minimal IFT of $\mathbb{H}_{\mathbb{G}}$. ⏎

Definition 5.4.4. If T is an IFS with $T^{(y_i,z_i)}$ as a minimal IFT of $\mathbb{H}_{\mathbb{G}}{}^{(y_i,z_i)}$ $\forall$ $(y_i, z_i) \in (0,1)$ for which $\sum_{u_i\in V}\mu_{ij}(u_i)\le s_1$ and $\sum_{u_i\in V}(1-\nu_{ij}(u_i))\le s_2$, $\forall 1\le i\le m, 1\le j\le n$ implies T is known by locally minimal IFT of IFTHG. The set containing locally minimal IFT of IFTHG is denoted as $T\curlyvee^*(\mathbb{H}_{\mathbb{G}})$.

Theorem 5.4.5. If T is an IFT of IFTHG $\mathbb{H}_{\mathbb{G}}=(U,\varepsilon;s_1,s_2)$ then $\hbar_t(T) \ge \hbar_t(\varepsilon_j)$for $\varepsilon_j \in \varepsilon$. And, if T is a minimal IFT of IFTHG, implies $\hbar_t(T)=\left\{\max\left(\min\left(\mu_{ij}\right)\right),\max\left(\max\left(\nu_{ij}\right)\right)|\mu_{ij},\nu_{ij}\in\varepsilon\right\}=\hbar_t(\mathbb{H}_{\mathbb{G}})$.

Theorem 5.4.6. Each IFTHG has a nonempty IFT.

Note: Each IFT of IFTHG contains a minimal IFT. (i.e.,) $T\curlyvee(\mathbb{H}_{\mathbb{G}}) \subseteq T(\mathbb{H}_{\mathbb{G}})$.

Theorem 5.4.7. If $T' \in T\Upsilon(\mathbb{H}_{\mathbb{G}})$ and for each $u \in U$, $T'(\mathbb{H}_{\mathbb{G}}) \in \mathcal{F}(\mathbb{H}_{\mathbb{G}})$, then $\mathcal{F}\,T\Upsilon(\mathbb{H}_{\mathbb{G}}) \subseteq \mathcal{F}(\mathbb{H}_{\mathbb{G}})$.

Theorem 5.4.8. $T\Upsilon(\mathbb{H}_{\mathbb{G}})$ is sectionally elementary.

Proof: Let $\mathcal{F}(T\Upsilon(\mathbb{H}_{\mathbb{G}})) = \{y_1, y_2, \ldots, y_k; z_1, z_2, \ldots, z_k;\}$. Assume that $T' \in T\Upsilon(\mathbb{H}_{\mathbb{G}})$ and some $\alpha, \beta \in (y_i, z_i)$ such that $T^{(y_i,z_i)} \subset T^{(\alpha,\beta)}$. Since $T\Upsilon(\mathbb{H}_{\mathbb{G}}^{(y_i,z_i)}) = T\Upsilon(\mathbb{H}_{\mathbb{G}}^{(\alpha,\beta)})$ $\exists$ some $\mathcal{A} \in T\Upsilon(\mathbb{H}_{\mathbb{G}})) \ni \mathcal{A}^{(y_i,z_i)} = T^{(\alpha,\beta)}$. Then $T^{(\alpha,\beta)} \subset \mathcal{A}^{(y_i,z_i)}$ implies the IFS $U(u_i)$ defined by

$$U(u_i) = \begin{cases} (\alpha,\beta)\, if\ u_i \in \mathcal{A}^{(y_i,z_i)} \setminus T^{(y_i,z_i)} \\ \mathcal{A} \text{ otherwise} \end{cases}$$

is an IFT of IFTHG. Here $U < \mathcal{A}, \Rightarrow$ minimality of $\mathcal{A}$, which is a contradiction.

Theorem 5.4.9. For each $\mathcal{A} \in T\Upsilon(\mathbb{H}_{\mathbb{G}})$, $\mathcal{A}^{(y_1,z_2)}$ is a minimal IFT of $\mathbb{H}_{\mathbb{G}}^{(y_1,z_2)}$.

Proof: For every IFTHG $\mathbb{H}_{\mathbb{G}} = (U, \varepsilon; s_1, s_2)$, consider a minimal IFT T of $(\mathbb{H}_{\mathbb{G}}^{(y_i,z_i)})$ such that $T \subset \mathcal{A}^{(y_1,z_2)}$. Define the intuitionistic fuzzy set $U(u_i)$ where

$$U(u_i) = \begin{cases} (y_2, z_2)\, if\ u_i \in \mathcal{A}^{(y_1,z_1)} \setminus T \\ \mathcal{A}\ A \text{otherwise} \end{cases}.$$

By the above theorem, U is an IFT of IFTHG, contradicting the minimality of $\mathcal{A}$.

Definition 5.4.10. Let IFTHG be $\mathbb{H}_{\mathbb{G}} = (U, \varepsilon; s_1, s_2)$. The intuitionistic fuzzy transversal core (IFTC) of $\mathbb{H}_{\mathbb{G}}$ is an IFTHG $\mathbb{H}_{\mathbb{G}}' = (U', \varepsilon'; s_1, s_2)$ then

1) $\wedge\, T\Upsilon(\mathbb{H}_{\mathbb{G}}') = \wedge\, T\Upsilon(\mathbb{H}_{\mathbb{G}})$,
2) $\cup \wedge\, T\Upsilon(\mathbb{H}_{\mathbb{G}}) = \mathbb{H}_{\mathbb{G}}'$
3) ε/ε' is completely the set containing vertices of $\mathbb{H}_{\mathbb{G}} \notin T\Upsilon(\mathbb{H}_{\mathbb{G}})$, and
4) an independent set $V \subseteq U$ has a set of all different combinations of a nonadjacent vertices in $\mathbb{H}_{\mathbb{G}} \Leftrightarrow \exists$ a threshold values s_1 & $s_2 > 0$ such that $\sum_{u_i \in V} \mu_{ij}(u_i) \le s_1$ and $\sum_{u_i \in V} (1 - \nu_{ij}(u_i)) \le s_2$.

Definition 5.4.11. Consider an IFTHG with $U = \{u_1, u_2, u_3, u_4, u_5, u_6\}$, $\varepsilon = \{\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4, \varepsilon_5\}$ where, $\varepsilon_1 = \{u_1\langle 0.3,0.4\rangle, u_6\langle 0.4,0.6\rangle\}$, $\varepsilon_2 = \{u_1\langle 0.3,0.4\rangle, u_2\langle 0.4,0.5\rangle, u_4\langle 0.3,0.6\rangle, u_6\langle 0.4,0.6\rangle\}$, $\varepsilon_3 = \{u_1\langle 0.3,0.4\rangle, u_3\langle 0.2,0.6\rangle, u_4\langle 0.3,0.6\rangle, u_5\langle 0.2,0.7\rangle, u_6\langle 0.4,0.5\rangle\}$, $\varepsilon_4 = \{u_3\langle 0.2,0.6\rangle, u_5\langle 0.2,0.7\rangle, u_7\langle 0.4,0.6\rangle\}$, and ε_5 $\{u_2\langle 0.4,0.5\rangle, u_6\langle 0.4,0.6\rangle\}$, as shown in Figure 5.3.

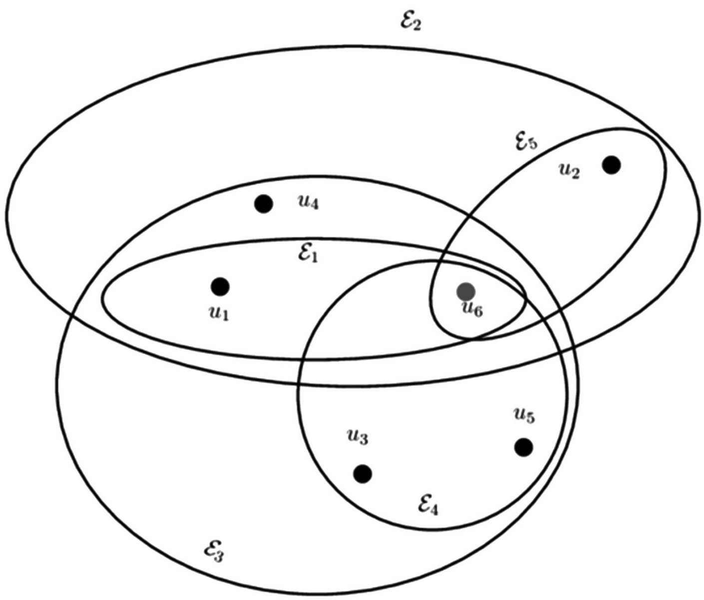

FIGURE 5.3 IFTHG ($\mathbb{H}_{\mathbb{G}}$).

The associated incidence matrix for $\mathbb{H}_{\mathbb{G}}$ is given as

$$\begin{array}{c} \\ u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \\ u_6 \end{array} \begin{pmatrix} \varepsilon_1 & \varepsilon_2 & \varepsilon_3 & \varepsilon_4 & \varepsilon_5 \\ \langle 0.3, 0.4\rangle & \langle 0.3, 0.4\rangle & \langle 0.3, 0.4\rangle & \langle 0, 1\rangle & \langle 0, 1\rangle \\ \langle 0, 1\rangle & \langle 0.4, 0.5\rangle & \langle 0, 1\rangle & \langle 0, 1\rangle & \langle 0.4, 0.5\rangle \\ \langle 0, 1\rangle & \langle 0, 1\rangle & \langle 0.2, 0.6\rangle & \langle 0.2, 0.6\rangle & \langle 0, 1\rangle \\ \langle 0, 1\rangle & \langle 0.3, 0.6\rangle & \langle 0.3, 0.6\rangle & \langle 0, 1\rangle & \langle 0, 1\rangle \\ \langle 0, 1\rangle & \langle 0, 1\rangle & \langle 0.2, 0.7\rangle & \langle 0, 1\rangle & \langle 0, 1\rangle \\ \langle 0.4, 0.6\rangle & \langle 0.4, 0.6\rangle & \langle 0.4, 0.6\rangle & \langle 0.4, 0.6\rangle & \langle 0.4, 0.6\rangle \end{pmatrix}.$$

The incidence matrix of IFTC $\mathbb{H}_{\mathbb{G}}'$ is given as

$$\begin{array}{c} \\ u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \\ u_6 \end{array} \begin{pmatrix} \varepsilon_1 & \varepsilon_2 \\ \langle 0.3, 0.4\rangle & \langle 0.3, 0.4\rangle \\ \langle 0.4, 0.5\rangle & \langle 0, 1\rangle \\ \langle 0, 1\rangle & \langle 0.2, 0.6\rangle \\ \langle 0.3, 0.6\rangle & \langle 0.3, 0.6\rangle \\ \langle 0, 1\rangle & \langle 0.2, 0.7\rangle \\ \langle 0.4, 0.6\rangle & \langle 0.4, 0.6\rangle \end{pmatrix}.$$

The transversal core of IFTHG is given in Figure 5.4.

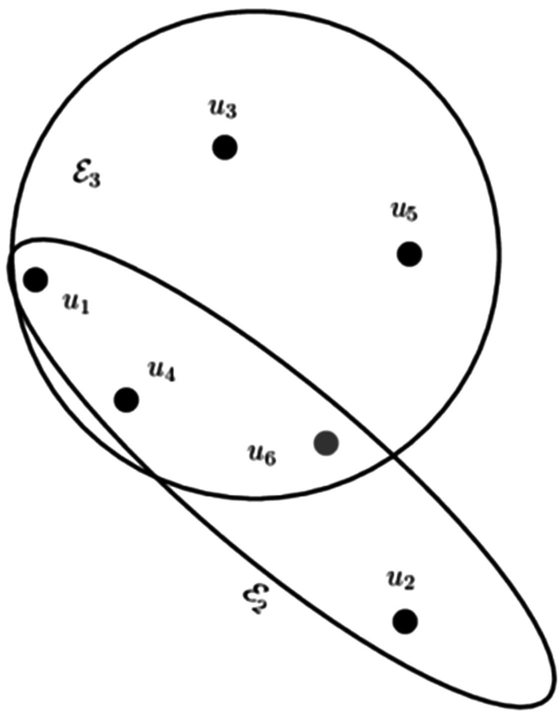

FIGURE 5.4 Transversal core of IFTHG ($\mathbb{H}_{\mathbb{G}}'$). ⏎

Result:

1. The transversal core exists and is unique for any IFTHG no spike hyperedges.
2. This definition also holds for IFTHGs among spike (a hyperedge including one vertex) hyperedges.

Definition 5.4.12. The *open neighborhood* for the minimal transversal on IFTHG of the vertex u_i is the set containing nearest vertices of u_i except itself in a hyperedge and is represented as $\mathcal{N}_h(u_i)$.

Example 5.4.13. Consider an IFTHG with $U = \{u_1,u_2,u_3,u_4,u_5,u_6,u_7\}$, $\varepsilon = \{\varepsilon_1,\varepsilon_2,\varepsilon_3,\varepsilon_4,\varepsilon_5\}$ where $\varepsilon_1 = \{u_1\langle 0.3,0.4\rangle, u_7\langle 0.4,0.6\rangle\}$, $\varepsilon_2 = \{u_2\langle 0.2,0.6\rangle, u_7 \langle 0.4,0.6\rangle\}$, $\varepsilon_3 = \{u_2\langle 0.2,0.6\rangle, u_4 \langle 0.5,0.3\rangle\}$, $\varepsilon_4 = \{u_2\langle 0.4,0.3\rangle, u_4 \langle 0.5,0.3\rangle, u_7 \langle 0.4,0.6\rangle\}$, ε_5 $\{u_5\langle 0.2,0.5\rangle, u_6 \langle 0.3,0.6\rangle, u_7 \langle 0.4,0.6\rangle\}$.

Here, u_2 and u_7 are the open neighborhood of the vertex u_1 in T_1.

Definition 5.4.14. The *closed neighborhood* for the minimal transversal on IFTHG of the vertex u_i is the set containing nearest vertices of u_i including the vertex in a hyperedge and is represented as $\mathcal{N}_h'(u_i)$.

Example 5.4.15. From the above example, it is shown that the closed neighborhood of the vertex u_1 is u_1, u_2 and u_7, in T_1.

Theorem 5.4.16. If $\mathbb{H}_{\mathbb{G}} = (U, \varepsilon; s_1, s_2)$ be an IFTHG, then the given conditions are similar

1) T is an IFT of IFTHG.
2) $T^{(y_i,z_i)} \cap \mathcal{A}^{(y_i,z_i)} \neq \varphi$, for each IF hyperedge $\mathcal{A} \in \varepsilon$ and each (y_i,z_i) with $0 < y_i \leq \hbar_{t\mu}(\mathbb{H}_{\mathbb{G}})$, $0 < z_i \leq \hbar_{t\nu}(\mathbb{H}_{\mathbb{G}})$.
3) $T^{(y_i,z_i)}$ is an IFT of $\mathbb{H}_{\mathbb{G}}^{(y_i,z_i)}$, for each (y_i,z_i) with $0 < y_i \leq \alpha$, $0 < z_i \leq \beta$.

Proof: By definition, "A minimal IFT T for IFTHG is a transversal of $\mathbb{H}_{\mathbb{G}}$ which satisfies the property that if $T_1 \subset T$, then T_1 is not an IFT of $\mathbb{H}_{\mathbb{G}}$" the proof is trivial.

Theorem 5.4.17. For a simple IFTHG $\mathbb{H}_{\mathbb{G}}$, $T\gamma(T\gamma(\mathbb{H}_{\mathbb{G}})) = \mathbb{H}_{\mathbb{G}}$.

Theorem 5.4.18. For any IFTHG $\mathbb{H}_{\mathbb{G}}$, $T\gamma(T\gamma(\mathbb{H}_{\mathbb{G}})) \subseteq \mathbb{H}_{\mathbb{G}}$.

Proof: From Definition 5.4.10, $\exists$ a partial IFTHG $\mathbb{H}_{\mathbb{G}}'$ of a simple IFTHG $\mathbb{H}_{\mathbb{G}}$, $\ni T\gamma(\mathbb{H}_{\mathbb{G}}') = T\gamma(\mathbb{H}_{\mathbb{G}})$. By Theorem 5.4.17, $T\gamma(T\gamma(\mathbb{H}_{\mathbb{G}})) = T\gamma(T\gamma(\mathbb{H}_{\mathbb{G}}')) = \mathbb{H}_{\mathbb{G}}' \subseteq \mathbb{H}_{\mathbb{G}}$.

Theorem 5.4.19. Let $\mathbb{H}_{\mathbb{G}} = (U, \varepsilon; s_1, s_2)$ be an IFTHG and assume

$T \in T\gamma(\mathbb{H}_{\mathbb{G}})$. If $\mathbb{H}_{\mathbb{G}}' \subseteq supp(T) \subseteq \mathbb{H}_{\mathbb{G}}$, then $\exists$ an IF threshold hyperedge $\mathcal{A}$, $(y_i,z_i) \in \mathcal{A}$ represent the membership and nonmembership values of $\mathcal{A} \ni$.

1) $(y_i, z_i) = \hbar_t(\mathcal{A}) = \hbar_t(T^{(y_i,z_i)}) > 0$.
2) $T_{\hbar t(\mathcal{A})} \cap \mathcal{A}_{\hbar t(\mathcal{A})} = \mathbb{H}_{\mathbb{G}}$.

Proof: Assume $0 < \hbar_t(T^{(y_i,z_i)}) \leq 1$ & suppose ε' be the set of IF threshold hyperedges where $\hbar_t(\tau^{(y_i,z_i)}) \geq \hbar_t(T^{(y_i,z_i)})$ for each $\tau \in \varepsilon'$ for which $\sum_{u_i \in V} \mu_{ij}(u_i) \leq s_1$ and $\sum_{u_i \in V} (1 - \nu_{ij}(u_i)) \leq s_2, \forall 1 \leq i \leq m, 1 \leq j \leq n$.

Since $T^{(y_i,z_i)}$ is an IFT of $\mathbb{H}_{\mathbb{G}}^{(y_i,z_i)}$ and $\mathbb{H}_{\mathbb{G}}' \subseteq T^{(y_i,z_i)}$ is nonempty. Further, for each $\tau \in \varepsilon'$, $\hbar_t(\tau) \geq (T^{(y_i,z_i)})$ is true. In addition, suppose that $T^{(y_i,z_i)}$ is the minimal IFT, then for each $\tau \in \varepsilon'$, $\hbar_t(\tau) \geq (T^{(y_i,z_i)})$ and there exists $\mathbb{H}_{\mathbb{G}\tau} \neq \mathbb{H}_{\mathbb{G}}$ with $\mathbb{H}_{\mathbb{G}\tau} \in \tau_{\hbar_t(\tau)} \cap T_{\hbar_t(\tau)}$.

Define an IFTHG $\mathbb{H}_{\mathbb{G}1} \ni$

$$\mathbb{H}_{\mathbb{G}_1}(u_i) = \begin{cases} \mathrm{T}(W) \text{ if } W \neq \mathbb{H}_{\mathbb{G}}{}' \\ \wedge(\hbar_t(\mathcal{A})/\hbar_t(\mathcal{A}) < \hbar_t(\mathrm{T}^{(y_i,z_i)})),\ \vee(\hbar_t(\mathcal{A})/\hbar_t(\mathcal{A}) < \hbar_t(\mathrm{T}^{(y_i,z_i)})) \text{ if } W = \mathbb{H}_{\mathbb{G}}{}' \end{cases}.$$

Clearly $\mathbb{H}_{\mathbb{G}1}$ is an IFT of IFTHG and $\hbar_t(\mathbb{H}_{\mathbb{G}1}{}^{(y_i,z_i)}) < \hbar_t(\mathrm{T}^{(y_i,z_i)})$, which contradicts the minimality of T. Assume every $\tau \in \varepsilon'$ satisfies part (i) & also contains $\mathbb{H}_{\mathbb{G}\tau} \neq \mathbb{H}_{\mathbb{G}}$ with $\mathbb{H}_{\mathbb{G}\tau} \in \tau_{\hbar_t(\tau)} \cap \mathrm{T}_{\hbar_t(\tau)}$. The process is repeated and the argument of (1) reaches a contradiction which completes the proof.

Theorem 5.4.20. Let $\mathbb{H}_{\mathbb{G}} = (U, \varepsilon; s_1, s_2)$ be an IFTHG. Then, $\exists$ $\mathrm{T} \in \mathrm{T}\Upsilon(\mathbb{H}_{\mathbb{G}})$ with $\mathbb{H}_{\mathbb{G}}{}' \subseteq \mathrm{supp}(\mathrm{T}) \subseteq \mathbb{H}_{\mathbb{G}}$, for $\mathcal{A} \in \varepsilon$ then

1) $(y_i, z_i) = \hbar_t(\mathcal{A})$,
2) (y_i, z_i)-level cut of $\hbar_t(\mathcal{A}')$ is not a subhypergraph of the (y_i, z_i)-level cut of $\hbar_t(\mathcal{A})$, for each $\mathcal{A}' \in \varepsilon$ with $\hbar_t(\mathcal{A}') > \hbar_t(\mathcal{A})$, and
3) the (y_i, z_i)-level cut of $\hbar_t(\mathcal{A})$ does not contain any other hyperedge of $\mathbb{H}_{\mathbb{G}\hbar_t(\mathcal{A})}$, where (y_i, z_i) represents membership and nonmembership values of $\mathcal{A}$.

Proof:
Necessary part:

1) Let $\mathrm{T} \in \mathrm{T}\Upsilon(\mathbb{H}_{\mathbb{G}})$ and $0 < \hbar_t(\mathrm{T}^{(y_i,z_i)}) \leq 1$. Then by Theorem 5.4.19, the result (i) follows.
2) Assume $\forall \mathcal{A}$ which meets the requirements of (i) $\exists$ $\mathcal{A}' \in \varepsilon \ni \hbar_t(\mathcal{A}') > \hbar_t(\mathcal{A})$ and $\mathcal{A}'_{\hbar_t(\mathcal{A}')} \subseteq \mathcal{A}_{\hbar_t(\mathcal{A})}$, then $\exists$ $u_i \neq \mathbb{H}_{\mathbb{G}}{}'$, with $U \in \mathcal{A}'_{\hbar_t(\mathcal{A}')} \cap \mathrm{T}_{\hbar_t(\mathcal{A}')} \subseteq \mathcal{A}_{\hbar_t(\mathcal{A})} \cap \mathrm{T}_{\hbar_t(\mathcal{A})}$ which contradicts Theorem 5.4.19.
3) Assume $\forall \mathcal{A}$ satisfying (1) and (2) then $\exists$ $\mathcal{A}' \in \varepsilon$ so that $\emptyset \neq \mathcal{A}'_{\hbar_t(\mathcal{A}')} \subset \mathcal{A}_{\hbar_t(\mathcal{A})}$. Since $\mathcal{A}'_{\hbar_t(\mathcal{A})} \neq \emptyset$ and by (2), implies $\hbar_t(\mathcal{A}') = \hbar_t(\mathcal{A}) = (y_i, z_i)$.

If $(y_i, z_i) = \hbar_t(\mathcal{A}')$ & $\mathcal{A}'' \in \varepsilon \ni \emptyset \neq \mathcal{A}''_{\hbar_t(\mathcal{A})} \subset \mathcal{A}'_{\hbar_t(\mathcal{A})} \subset \mathcal{A}_{\hbar_t(\mathcal{A})}$. Continuing the procedure the chain must end infinitely many steps so without loss of abstraction suppose $(y_i, z_i) < \hbar_t(\mathcal{A})$. But, $\exists$ $U \neq \mathbb{H}_{\mathbb{G}}{}' \ni U \in \mathcal{A}'_{\hbar_t(\mathcal{A})} \cap \mathrm{T}_{\hbar_t(\mathcal{A})} \subseteq \mathcal{A}_{\hbar_t(\mathcal{A})} \cap \mathrm{T}_{\hbar_t(\mathcal{A})}$, this contradicts to Theorem 5.4.19.

Sufficient Part:

Assume $\mathcal{A} \in \varepsilon$ satisfies the conditions (1) and (2). From (1), $\hbar_t(\mathcal{A}) = (y_i, z_i)$ for some member of $\mathcal{F}(\mathbb{H}_{\mathbb{G}})$. From (2) and (3) $\exists$ $U \in \mathcal{A}'_{\hbar_t(\mathcal{A}')} \backslash \mathcal{A}_{\hbar_t(\mathcal{A})}$, $\forall$ $\mathcal{A}' \in \varepsilon \ni \mathcal{A}' \neq \mathcal{A}$ & $\hbar_t(\mathcal{A}') \geq \hbar_t(\mathcal{A})$. Suppose $V_{\mathcal{A}}$ be the set of all vertices of $\mathbb{H}_{\mathbb{G}}$ $\ni \mathrm{V}_{\mathcal{A}} \cap \mathcal{A}_{\hbar_t(\mathcal{A})} = \emptyset$.

Construct the initial sequence of transversals $\tau_s \subseteq U$ for each s, $1 \leq s < i$ and $\tau_s \subseteq U_{\mathcal{A}} \cup U_i$. Clearly, $U_i \in \tau_i$, $\forall_i$. Repeating the procedure it goes to a minimal IFT with $(y_i, z_i) = \hbar_t(\mathcal{A}) = \hbar_t\,(\mathrm{T}^{y_i, z_i})$.

Theorem 5.4.21. Let $\mathbb{H}_{\mathbb{G}} = (U, \varepsilon; s_1, s_2)$ be an IFTHG with $\mathcal{F}(\mathbb{H}_{\mathbb{G}}) = \{y_1, y_2, \ldots, y_k;\, z_1, z_2, \ldots, z_k\}$ so that $0 \leq y_i \leq \hbar_{t\mu}(\mathbb{H}_{\mathbb{G}}), 0 = \leq z_i \leq \hbar_{t\nu}(\mathbb{H}_{\mathbb{G}})$. Also, $\mathbb{H}_{\mathbb{G}}^{(y_i, z_i)}$ be the elementary IFTHG repeating $\mathcal{A}' \Leftrightarrow \hbar_t(\mathcal{A}') = (y_i, z_i)$ & $\operatorname{supp}(\mathcal{A}')$ is a hyperedge of $\mathbb{H}_{\mathbb{G}}^{(y_i, z_i)}$. So $\mathrm{T}\Upsilon\,(\mathrm{T}\Upsilon\,(\mathbb{H}_{\mathbb{G}}))$ is a partial IFTHG of $\mathbb{H}_{\mathbb{G}}^{(y_i, z_i)}$.

Proof: By Theorem 5.4.9 and from the construction of minimal IFT, the (y_i, z_i)-level IFTHG of $\mathrm{T}\Upsilon\,(\mathbb{H}_{\mathbb{G}})$ is $\mathrm{T}\Upsilon\,(\mathbb{H}_{\mathbb{G}}^{(y_i, z_i)})$ which implies $(\mathrm{T}\Upsilon\,(\mathbb{H}_{\mathbb{G}}))^{(y_i, z_i)} = \mathrm{T}\Upsilon\,(\mathbb{H}_{\mathbb{G}}^{(y_i, z_i)})$. Let $\tau \in \mathrm{T}\Upsilon\,(\mathrm{T}\Upsilon\,(\mathbb{H}_{\mathbb{G}}))$. By Theorem 5.4.19, $\hbar_t\,(\tau\,(U_i) > 0$, this implies that $\exists\, \mathrm{T} \in \mathrm{T}\Upsilon\,(\mathbb{H}_{\mathbb{G}})$ with $\hbar_t\,(\tau\,(U_i) = \hbar_t\,(\mathrm{T})$. By Theorem 5.4.5, $\hbar_t\,(\mathrm{T}) = \{\max\,(\min(\mu_{ij})), \max(\max(\nu_{ij})) \mid \mu_{ij}, \nu_{ij} \in \varepsilon\} = \hbar_t\,(\mathbb{H}_{\mathbb{G}})$, for each minimal IFT T. Hence τ is elementary with height (y_i, z_i). Since $\operatorname{supp}(\tau) = \tau^{(y_i, z_i)}$, Theorem 5.4.9 suggests that $\operatorname{supp}(\tau)$ is a minimal IFT of $(\mathrm{T}\Upsilon\,(\mathbb{H}_{\mathbb{G}}))^{(y_i, z_i)}$. It is obvious that $\operatorname{supp}(\tau)$ is a hyperedge of $\mathbb{H}_{\mathbb{G}}^{(y_i, z_i)}$. Hence τ is a hyperedge of $\mathbb{H}_{\mathbb{G}}^{(y_i, z_i)}$.

Theorem 5.4.22. Let $\mathbb{H}_{\mathbb{G}} = (U, \varepsilon; s_1, s_2)$ be an IFTHG with $\mathbb{H}_{\mathbb{G}}^{(y_i, z_i)}$ is a simple. Then $\mathrm{T}\Upsilon\,(\mathrm{T}\Upsilon\,(\mathbb{H}_{\mathbb{G}})) = \mathbb{H}_{\mathbb{G}}^{(y_i, z_i)}$.

Proof: By the above theorem, $\mathrm{T}\Upsilon\,(\mathrm{T}\Upsilon\,(\mathbb{H}_{\mathbb{G}})) \subseteq \mathbb{H}_{\mathbb{G}}^{(y_i, z_i)}$. Let τ be elementary with $\hbar_t(\mathrm{T}) = (y_i, z_i)$ and $\operatorname{supp}(\tau) \in \mathbb{H}_{\mathbb{G}}^{(y_i, z_i)}$. By Theorem 5.4.21, $\operatorname{supp}(\tau)$ is a minimal IFT of $(\mathrm{T}\Upsilon\,(\mathbb{H}_{\mathbb{G}}))^{(y_i, z_i)}$. Since every minimal IFT of $\mathrm{T}\Upsilon\,(\mathbb{H}_{\mathbb{G}})$ is elementary by minimal IFT definition the procedure terminates at (y_i, z_i) -level & $\tau \in \mathrm{T}\Upsilon\,(\mathrm{T}\Upsilon\,(\mathbb{H}_{\mathbb{G}}))$. Hence $\mathbb{H}_{\mathbb{G}}^{(y_i, z_i)} \subseteq \mathrm{T}\Upsilon\,(\mathrm{T}\Upsilon\,(\mathbb{H}_{\mathbb{G}}))$ which implies $\mathbb{H}_{\mathbb{G}}^{(y_i, z_i)} = \mathrm{T}\Upsilon\,(\mathrm{T}\Upsilon\,(\mathbb{H}_{\mathbb{G}}))$.

5.5 APPLICATION

Imagine a large agricultural farm that employs drip irrigation to water its crops. Drip irrigation systems use a network of pipes and hoses to deliver water directly to the root zone of plants, minimizing water wastage compared to traditional irrigation methods. However, managing such a system efficiently is challenging due to varying crop types, soil conditions, and environmental factors that affect the water requirements of different areas within the farm.

To address this challenge, the farm decides to utilize IFTHGs. These mathematical structures provide a way to model and analyze the complex relationships between different factors that influence water distribution, such as crop types, soil moisture levels, and weather conditions. Each factor is denoted as a vertex in IFTHG, and hyperedges between vertices indicate dependencies and interactions.

In this context, transversals come into play as a means to identify optimal water distribution strategies. A transversal of the hypergraph represents a selection of factors or areas that, when irrigated, ensure that all critical dependencies are met. By finding the minimal transversals, the farm can determine the most efficient way to distribute water while satisfying the various constraints and requirements of different crops and soil conditions. The farm's irrigation system is equipped with sensors and actuators that can adjust water flow rates and schedules in real-time. By employing transversals in the hypergraph, the system can make intelligent decisions about, where and when to allocate water resources.

For example:

- **Resource Allocation:** The hypergraph analysis can identify which areas of the farm require water at a given time, taking into account crop-specific needs and soil moisture levels.
- **Fault Tolerance:** If a section of the irrigation system experiences a malfunction or blockage, then the system can use transversals to quickly reroute to ensure that all essential areas receive adequate irrigation.
- **Adaptation to Weather Conditions:** By considering weather forecasts as factors in the hypergraph, the system can adjust irrigation plans to respond to anticipated rainfall or drought conditions.

5.6 CONCLUSION

In this chapter, some interesting concepts, such as, IFT, minimal IFT, locally minimal IFT, and IFTC of IFTHGs were discussed. It is important to note that IFTC exists for both spike and nonspike intuitionistic fuzzy threshold hyperedges. Finally, the study of transversals and their properties of IFTHG offers valuable insights for various applications, including drip irrigation. By applying these concepts, we can optimize resource allocation and decision-making processes in irrigation systems, leading to more efficient water usage and improved crop yields.

KEYWORDS

- **intuitionistic fuzzy transversal**
- **minimal IFT**
- **locally minimal IFT**
- **IFTC of IFTHG**

REFERENCES

1. Alain, B. (2013). *Hypergraph Theory: An Introduction*. Springer International Publishing: Switzerland.
2. Bondy. J. A., & Murty, U. S. R. (1976). *Graph Theory with Applications*. Elsevier Science Publishing Co.: Newyork.
3. Choudum, S. A. (2000). *A First Course in Graph Theory*. Laxmi Publications, Macmillan India.
4. Vaclav, C., & Hammer, P. L. (1977). Aggregation of inequalities in integer programming. In: *Annals of Discrete Mathematics*, North-Holland: Amsterdam, Vol. 1, pp. 145–162.
5. Berge, C. (1973). *Graphs and Hypergraphs*. North-Holland Publishing Company: Amsterdam.
6. Berge, C. (1989). *Hypergraphs: Combinatorics of Finite Sets*. Elsevier Science Publishing Company: New York.
7. Mordeson, J. N., & Nair, P. S. (2012). *Fuzzy Graphs and Fuzzy Hypergraphs*. Physica-Verlag.
8. Atanassov, K. T. (2012). *On Intuitionistic Fuzzy Set Theory*. Springer-Verlag Berlin Heidelberg.
9. Atanassov, K. T. (1999). *On Intuitionistic Fuzzy Sets: Theory and Applications*. Springer-Verlag: Berlin Heidelberg.
10. Yang, L., & Mao, H. (2019). Intuitionistic fuzzy threshold graphs. *Journal of Intelligent & Fuzzy Systems*, *36*, 6641–6651.
11. Euler, L. (1763). Solution of a problem in the geometry of position. *The Journal Commentaries of the St. Petersburg Academy of Sciences,* Mathematical Association of America.
12. Pal, M., Samanta, S., & Ghorai, G. (2020). *Modern Trends in Fuzzy Graph Theory*. Springer Nature Singapore Pvt. Ltd.
13. Mahadev, N. V. R., & Peled, U. N. (1995). *Threshold Graphs and Related Topics*. Elsevier Science, Amsterdam: The Netherlands.
14. Mohammad, A. B., & Mateja, S. (2015). Connection and separation in hypergraphs. *Theory and Applications of Graphs, 2*(2), 1–25.
15. Muhammad, A., & Dudek, W. A. (2013). Intuitionistic fuzzy hypergraphs with applications. *Information Sciences, 218*, 182–193.

16. Myithili, K. K., Parvathi, R., & Akram, M. (2016). Certain types of intuitionistic fuzzy directed hypergraphs. *International Journal of Machine Learning and Cybernetics*, *7*(2), 287–295.
17. Myithili, K. K., & Parvathi, R. (2016). Properties of transversals of intuitionistic fuzzy directed hypergraphs. *Advances in Fuzzy Sets ans Systems, 21*(1), 93–105.
18. Parvathi, R., Thilagavathi, S., & Karunambigai, M. G. (2009). Intuitionistic fuzzy hypergraphs, Bulgarian Academy of Sciences. *Cybernetics and Information Technologies, 9*(2), 6641–6651.
19. Mathew, S., Mordeson, J. N., & Malik, D. S. (2018). *Fuzzy Graph Theory*. Springer International Publishing: Switzerland**.**
20. Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*, 338–353.

CHAPTER 6

Applications of Intuitionistic Fuzzy Sets and Fuzzy Logic in Mathematics and Allied Domains

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ABSTRACT

The present chapter focuses on the theoretical and practical potential of intuitionistic fuzzy set (IFS) and fuzzy logic in addressing uncertainty and hesitation. An IFS proposed by Atanassov extends classical fuzzy sets by incorporating degrees of membership, nonmembership, and hesitation; thus providing a richer framework to handle uncertainty. Fundamental concepts of IFS are introduced highlighting their significance in handling ambiguity beyond classical fuzzy sets. The chapter examines the applications of IFS in various domains. The significance of IFS in mathematical disciplines such as algebraic structures and topological spaces is presented. This chapter includes application of IFS in decision-making systems, where its ability to model hesitations and uncertainties is illustrated through a case study on supplier selection in manufacturing. In addition, it further provides integration of IFS with computer science, showcasing its contributions to expert systems, pattern recognition, risk assessment, and control systems. This chapter underscores the relevance of intuitionistic fuzzy set and fuzzy logic in bridging mathematical theory with practical challenges. It invites readers to explore the transformative potential of IFS in emerging fields, fostering innovative solutions for complex problems.

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6.1 INTRODUCTION

6.1.1 BACKGROUND OF FUZZY LOGIC AND INTUITIONISTIC FUZZY SETS (IFS)

Zadeh [46] introduced the concept of fuzzy sets (FS) in the 20th century to deal with uncertain and imprecise data. The conventional logic understood by the computer is strictly binary, whereas fuzzy logic is multivalued logic taking intermediate values between [0,1] where 0 and 1 are extreme cases. Basically, the FS provides partial membership, that is, the members of the set could have varying degrees of membership. As a result, Zadeh considered classes of objects having relative concepts that are expressed in natural languages, such as, weight, color, age, size, height, and temperature.

The IFS proposed by Atanassov [7] in the 1980s is a generalization of classical FS where each element of the set has degrees of membership, nonmembership, and hesitation. It was designed to enhance the ability of FSs to better capture uncertainty and vagueness in decision-making and reasoning processes.

During the initial two decades of their establishment, Atanassov [8] and a small group of researchers associated with him made advancements in IFSs. Their work focused predominantly on the mathematical logic and mathematics underlying the concept, particularly in the areas of analysis, algebra, geometry, and related fields. Subsequently, there has been a notable shift in the landscape due to advancements in information technology and decision science. There has been a substantial surge in the utility of IFSs, with many research papers being published each year in prestigious journals and conferences across the disciplines of mathematics and other fields. The community of theoretical researchers is expanding, along with the group of practitioners applying the theoretically created notion in various fields such as medicine, expert and control systems, industry, economics, artificial intelligence, and others.

After the FSs were introduced, many researchers worked to advance the sets arising from the extensions of FSs. The relationship among the FSs and their extensions has been illustrated in Figure 6.1.

IFSs, a concept that emerged ahead of its time, now provide us with vital tools to manage intrinsic uncertainty and impreciseness. Figure 6.2 shows the development and expansion of the FSs.

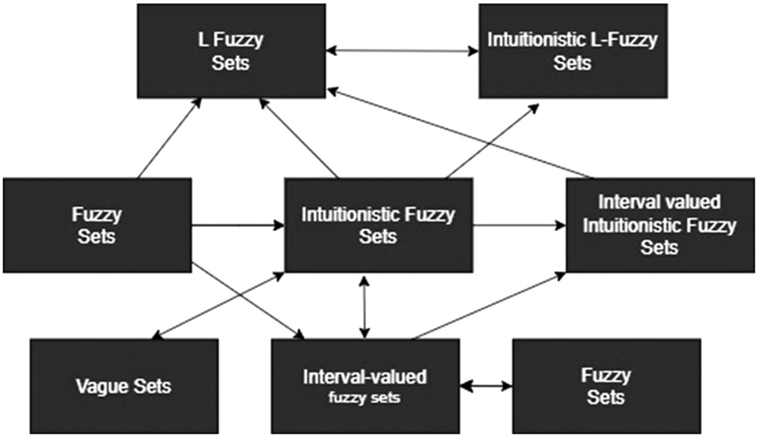

FIGURE 6.1 Relationship among fuzzy sets and other sets. ⏎

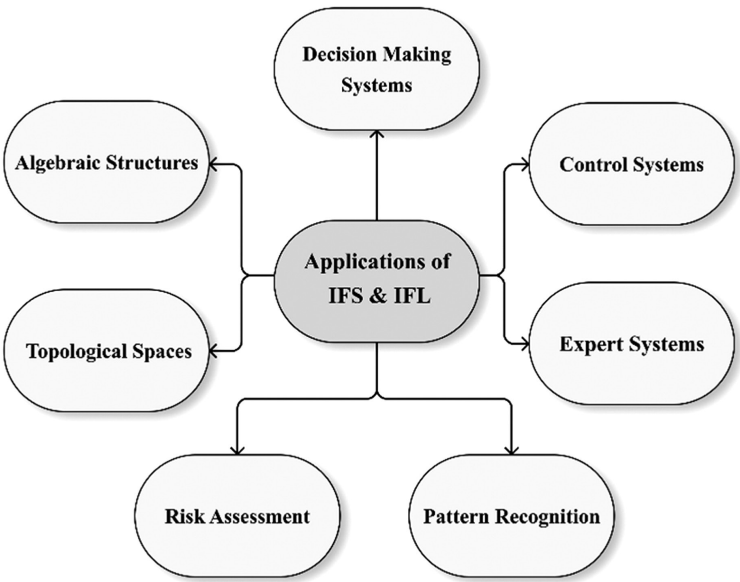

FIGURE 6.2 Applications of IFS. ⏎

6.1.2 SIGNIFICANCE OF INTUITIONISTIC FUZZY LOGIC (IFL)

The IFL provides an adaptable model to manage the impreciseness in the decision-making process. Operations on IFSs are useful for solving real-life problems. These are suitable for situations when the existence of a membership function does not seem enough. IFS could be utilized as a tool for demonstrating the hesitation degree, which is part of both the degree of membership and nonmembership of an element in a set.

These sets have applications in various fields, such as, artificial intelligence, sales analysis, new product marketing, career determination, financial services, decision making, and negotiation processes. They are particularly relevant in fields related to computer science where data may be incomplete or uncertain, such as image processing, machine learning, and pattern recognition. Figure 6.2 shows applications in various fields.

6.2 FUNDAMENTALS OF IFS

An IFS is a type of FS defined in the discourse domain where each member of the FS is denoted as a four tuple, consisting of the membership degree, nonmembership degree, and hesitation degree. The hesitation degree is a component of either the degree of membership or the nonmembership or both.

6.2.1 DEFINITION

IFS A in the domain of discourse, U is defined as a nonempty set of four-tuple elements, that is,

$$A = \left\{ \left\langle e, \mu_A(e), \pi_A(e), \nu_A(e) \right\rangle \mid e \in U \right\}, e \in U$$

where the notation where the notation μ_A, π_A, and ν_A denote the membership function μ_A: $U \rightarrow [0,1]$, hesitation function π_A: $U \rightarrow [0,1]$, and nonmembership function ν_A: $U \rightarrow [0,1]$, respectively. Here, $\mu_A(e)$, $\pi_A(e)$, and $\nu_A(e)$ represent the membership degree, hesitation degree, and nonmembership degree of $e \in U$, respectively, to the IFS A. We can represent μ_A (membership), π_A (nonmembership), and ν_A (hesitation) degrees with the help of the diagram shown in Figure 6.3.

For every $e \in U$, $\mu_A(e) + \pi_A(e) + \nu_A(e) = 1$, and $0 \leq \mu_A(e), \pi_A(e), \nu_A(e) \leq 1$. For example, if we know degrees of $\mu_A(e)$ and $\nu_A(e)$, we can calculate the degree of $\pi_A(e)$, that is, $\pi_A(e) = 1\ \mu_A(e) - \nu_A(e)$ $(e \in U)$.

For our convenience, we may denote each element of the IFS A as a three-tuple element, that is, $\left\langle \mu_A(e), \pi_A(e), \nu_A(e) \right\rangle$, and so the IFS A can be written as: $A = \left\{ t_i \middle| t_i = \langle \mu_A(e_i), \pi_A(e_i), \nu_A(e) \rangle \;\&\; e_i \in U \right\}$ or simply $A = \left\{ t_i \middle| t_i = \langle \mu_i, \pi_i, \nu_i \rangle \right\}$ where $\mu_i = \mu_A(e_i), \pi_i = \pi_A(e_i), \pi_i = \pi_A(e_i),$ and $\nu_i = \nu_A(e_i), \forall\ e_i \in U$.

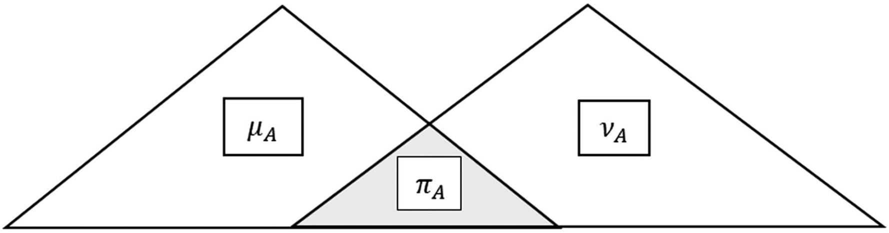

FIGURE 6.3 Illustration of membership, nonmembership, and hesitation degrees. ⏎

6.2.2 PROPERTIES

Let A and B be two IFSs. We define some operations and relations on A and B as follows:

1) Inclusion: $A \subseteq B \leftrightarrow \mu_A(e) \leq \mu_B(e)\ and\ \nu_A\ (e) \geq \nu_B(e)\ \forall\ e \in U$
2) Equality: $A = B \leftrightarrow \mu_A(e) = \mu_B(e)\ and\ \nu_A(e) = \nu_B(e)\ \forall\ e \in U$
3) Negation: $\overline{A} = \{\langle e, \nu_A(e), \mu_A(e)\rangle | e \in U\}$
4) Union: $A \cup B = \{\langle e, max(\mu_A(e), \mu_B(e)), min(\nu_A(e), \nu_B(e))\rangle; e \in U\}$
5) Intersection: $A \cap B = \{\langle e, min(\mu_A(e), \mu_B(e)), max(\nu_A(e), \nu_B(e))\rangle; e \in U\}$
6) Symmetric difference: $$A\ \Delta\ B = \{\langle e, max[min(\mu_A, \nu_B), min(\mu_B, \nu_A)], \\ min[max(\nu_A, \mu_B), max(\nu_B, \mu_A)] : e \in U\}$$
7) Cartesian Product: $A \times B = \{\langle \mu_A(e)\mu_B(e), \nu_A(e)\ \nu_A(e)\rangle : e \in U\}$

6.3 APPLICATIONS IN MATHEMATICS

6.3.1 ALGEBRAIC STRUCTURES

There has been research on the lattice and algebraic structures of the IFSs [44]. Additionally, there have been studies on the algebraic structures of IFSSs. One paper discusses the algebraic structures of complex IFSSs linked with groups and subgroups [33]. Another study demonstrates that the space of intuitionistic fuzzy values (IFVs), when equipped with a linear order determined by a score and accuracy function, exhibits a similar algebraic structure as the space generated by a linear order based on a similarity function and an accuracy function. Furthermore, this space is both a topological space and a lattice [41].

6.3.2 TOPOLOGICAL SPACES

In the context of topological spaces, IFSs can be used to define Intuitionistic fuzzy topological spaces, the generalized form of classical topological spaces. Near sets have been used as a tool to study extensions of topological spaces [26, 36]. Intuitionistic fuzzy topological spaces have uses in fields like decision-making, image processing, and recognition.

6.4 APPLICATIONS IN DECISION-MAKING SYSTEMS

IFL and IFSs are often used in decision-making processes where decision-makers are uncertain about the belongingness degree of an element in a set. They provide a more flexible framework to represent and reason with uncertain information.

6.4.1 MODELING HESITATIONS AND UNCERTAINTIES

IFSs are particularly suitable for situations where the decision-maker is not certain of the development of a particular condition, and where uncertain data needs to be modeled [29]. The nonmembership degree can be used to represent hesitation or uncertainty in decision-making [25]. IFSs have various applications in various fields, including multiattribute group decision-making [31], multiobjective optimization problems [12], and decision-making based on measure-based granular uncertainty [42].

6.4.2 CASE STUDY: DECISION-MAKING IN SUPPLIER SELECTION FOR A MANUFACTURING COMPANY

Context

A manufacturing company must identify the best suppliers for its production operations. The organization must consider different factors like price, quality, reliability, and lead time. Management seeks to make a well-informed judgment considering the inherent uncertainty in the supplier selection process.

Application of IFSs

1. *Evaluation of criteria:* The company's procurement team assigns intuitionistic fuzzy values to the different criteria for every possible supplier.

For example, they might assess the cost of Supplier A using a degree of membership of 0.8 and a hesitation degree of 0.2.

2. *Criteria for ranking suppliers:* The procurement team establishes regulations based on their expertise and the company's objectives. These guidelines consider the imprecise values supplied to each criterion.

   A rule can be defined as follows: if the supplier's cost is deemed extremely acceptable (with a membership degree more than 0.7) and the quality is considered moderately decent (with a membership degree greater than 0.5), then the supplier is preferred.
3. *Assessment of rules:* By considering the membership and hesitation degrees as per the conditions of the rules, the supplier ranking rules are implemented for every possible provider.
4. *Defuzzification:* It refers to the process of converting FSs into crisp values. The outcomes derived from the rules are de-fuzzified to provide a precise supplier ranking that indicates the most appropriate suppliers according to the specified criteria.

Results

By incorporating IFSs into the supplier selection process, the company can generate a prioritized roster of potential suppliers. Supplier B may have the highest ranking, with a confidence level of 0.75. The degree of reluctance reflects the level of ambiguity that the management has regarding this decision, which may be 0.1 in this scenario.

Conclusion

This case study showcases the application of IFSs in the context of supplier selection in manufacturing. It highlights the adaptability of IFS in decision-making procedures. By factoring in ambiguity and incorporating specialized expertise, the company may make more knowledgeable supplier selection choices that align with its objectives and priorities. Implementing this strategy can enhance the efficiency of the supply chain and the quality of the products while reducing the potential risks linked to the process of choosing suppliers.

6.5 APPLICATIONS IN COMPUTER SCIENCE

6.5.1 EXPERT SYSTEMS

IFSs include not only a membership degree but also a nonmembership and hesitation degree. This added information can be particularly useful in functioning expert systems [6] designed to emulate human expertise and decision-making processes. Here are some applications of IFSs in expert systems:

1. *Medical diagnosis:* In medical expert systems, IFSs can be used to represent the uncertainty associated with diagnosing a patient's condition. Dhiman et al. [19] describe the development of an intuitionistic fuzzy fractional knowledge-based expert system for medical diagnosis. It allows experts to indicate their degree of confidence in a diagnosis and the extent to which they believe it does not belong to a particular category.
2. *Financial decision support:* In financial expert systems, IFS can handle imprecise data and expert opinions when making investment decisions. Intuitionistic fuzzy models are developed for time series prediction related to finance [15] for simultaneously modeling the linear and nonlinear relationships in financial time series, making them useful for complex prediction problems.
3. *Environmental management*: IFSs can accommodate the vagueness and hesitations when assessing environmental impact or risk. Adamu [1] proposed an application of IFS in environmental management to determine the type of erosion. A hybrid MCDM technique based on the intuitionistic fuzzy EM-SWARA-TOPSIS approach given by Alkan and Kahraman [2] has been used to analyze medical waste treatment techniques concerning social, environmental, economic, and technical criteria.
4. *Natural language processing*: IFS can be employed in natural language understanding, such as, for text classification, representation of linguistic variables and rules, sentiment analysis [20], etc., within expert systems. Sidiropoulos et al. [35] represent text classification using IFS measures such as distance and similarity measures. They can help to handle the inherent uncertainty and ambiguity of human language, improving the system's ability to interpret and respond to user queries.
5. *Quality control:* In manufacturing and quality control expert systems, IFS can be used to assess and review product quality, considering both the degree of conformity to quality standards and the degree of nonconformity.
6. *Supply chain management:* In supply chain optimization and logistics expert systems, IFS can be employed to handle uncertain demand, lead times, and inventory levels.

7. *Human resources (HRs):* In HR expert systems, IFS can help in the recruitment and selection process by accommodating the imprecision and hesitation associated with candidate evaluations. For example, a method based on interval-valued IFSs known as the fuzzy analytic hierarchy process [21] is used for the selection criteria of the people enrolled for a position at some university.

In these applications, IFSs can provide a more realistic and nuanced representation of uncertainty and expert knowledge, enabling expert systems to make better-informed decisions in complex and uncertain environments. These systems can use IFS to not only handle imprecision but also to capture experts' degrees of belief and disbelief in various possibilities.

6.5.2 PATTERN RECOGNITION

IFSs have found significant applications in pattern recognition due to their ability to handle uncertainty, vagueness, and ambiguity in data. Given below are some key applications of IFSs in pattern recognition:

1. *Image recognition*: In image recognition tasks, objects, or patterns in images are often subject to variations in size, orientation, and lighting. Images in the intuitionistic fuzzy environment are comprised of components that correspond to membership and hesitancy functions, linked with image properties. These functions model the uncertainty of images from various departure points. IFSs are particularly useful in recognizing partially occluded objects or objects with unclear edges, as they can capture the uncertainty associated with the presence or absence of features [13, 16, 28]. IFSs are also used in digital image classification [32].
2. *Handwriting and character recognition:* Handwriting and character recognition systems benefit from IFS when dealing with handwritten characters that vary in style and quality. IFS measures are used for text classification and pattern recognition [35]. Many research studies describe handwritten Arabic words for recognition using intuitionistic fuzzy information [10, 11]. IFS represents the imprecision in the shape of characters, making recognition more robust, particularly where traditional FSs may not be sufficient.
3. *Biometric recognition:* Biometric systems, such as, facial recognition and fingerprint identification, involve capturing biometric features that may exhibit variations due to factors like aging, lighting, or

pose. A process for evaluating the fingerprint equivalence of two fingerprints uses intuitionistic fuzzy evaluations [14].

4. *Object detection and tracking:* In computer vision and object detection, IFS can be applied to detect and track objects in video sequences. In Giveki et al. [22], a novel and effective approach for detecting moving objects by using IFS theory is introduced. IFL is applied in [34] for the object detection method.
5. *Texture recognition:* Recognizing materials or patterns in images are a common task in texture analysis. Tripathy et al. [37] present a texture retrieval system that uses IFS theory. The authors use a combination of color and texture features to represent images and apply the IFS theory to measure the similarity between images. Method for texture feature extraction using an intuitionistic fuzzy local binary pattern (IFLBP) [4], shows that IFLBP is effective in texture recognition.
6. *Emotion recognition:* In affective computing, emotion recognition from facial expressions, speech, or physiological signals can benefit from IFS by handling the uncertainty and subtlety of emotional cues. Yang et al. [43] introduced a novel speech-emotion recognition scheme based on the IFS and discrimination information measures. Emotions that are not expressed clearly or those affected by some factors like cultural differences can be upgraded with approaches based on IFS.

In all these applications, IFSs enable pattern recognition systems to be more adaptive and robust, as they can handle imprecise and uncertain data, making them suitable for real-world scenarios where exact and crisp boundaries are often hard to define.

6.5.3 RISK ASSESSMENT

IFSs are valuable tools in risk assessment [9] due to their ability to handle and represent various forms of uncertainty, including vagueness and ambiguity. Figure 6.4 presents some applications of IFS in risk assessment.

Some other applications of IFS and IFL in risk assessment are as follows:

1) *Environmental risk assessment:* Intuitionistic fuzzy values are valuable in environmental risk assessment to evaluate the impact of pollutants [5], climate change, and defining risk factors including aggregation operators for combining the opinions of multiple experts on the severity of every risk factor [38].

By using IFS, environmental scientists can better analyze and communicate the uncertainties associated with potential risks to the ecosystem.

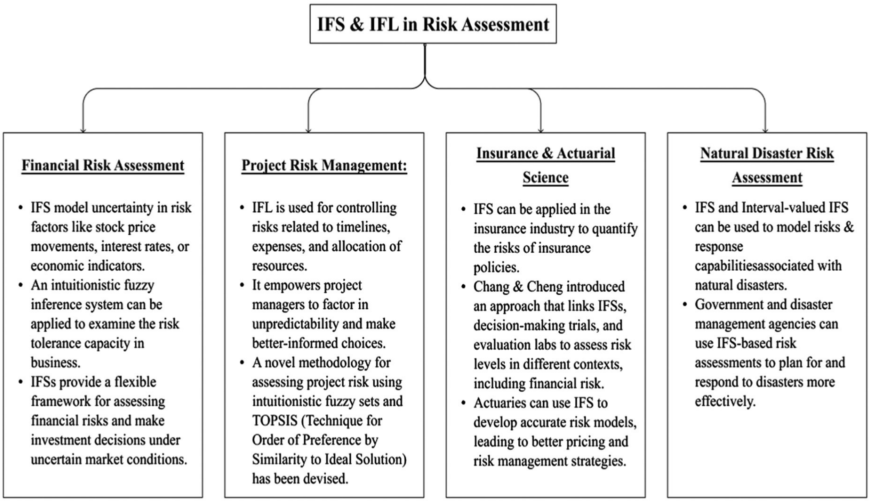

FIGURE 6.4 IFS and IFL in risk assessment. ⏎

2) *Medical and healthcare risk assessment:* In healthcare, IFS can help assess patient risks by incorporating uncertain data related to diagnosis, treatment outcomes, and patient conditions. For instance, Yousefnejad et al. [45] integrated the hazard and operability (HAZOP) method with IFSs to enhance decision-making under the inherent ambiguity associated with traditional HAZOP. This approach provided a more accurate assessment of risk levels, leading to a more realistic view of the situation. Another study [18] used an interval-valued intuitionistic fuzzy method to assess the likelihood of resumption during COVID-19 prevention, using decision-making trial and evaluation laboratory. The proposed method yielded more precise results than the usual method in a complex system.

   Summarizing, the above applications, we could state that the IFS approach gives a better insight into the level of risks in real-world problems and can be used to evaluate risks in medical and healthcare systems.

In all the above applications, IFSs model an adjustable framework for risk assessment. They allow the decision-makers to deal with uncertain and imprecise data, leading to more comprehensive, realistic, and robust risk assessment.

6.5.4 CONTROL SYSTEMS

IFL and IFSs are significantly useful in control systems for handling imprecise or uncertain data. Figure 6.5 presents some applications of IFS in control systems.

Some other applications of IFS and IFL in risk assessment are as follows:

1) *Fuzzy logic control:* IFSs can handle more complex uncertainty in fuzzy logic control systems. A domain expert often provides the inference rules employed in a fuzzy logic controller. However, in systems that utilize IFSs, these rules are automatically induced as fuzzy association rules based on a training set [24].

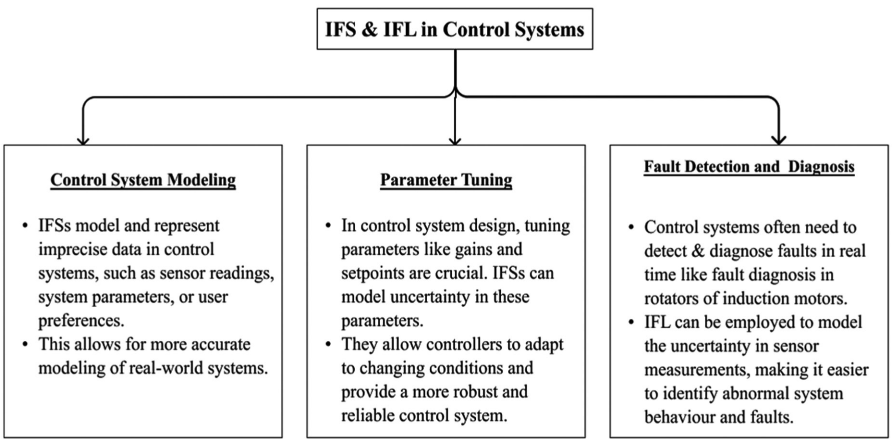

FIGURE 6.5 IFS in control systems. ⏎

2) *Optimization:* Intuitionistic fuzzy optimization techniques can be used to optimize control system parameters, considering both the satisfaction of control objectives and the degree of uncertainty or hesitancy in decision-making. The solution to intuitionistic fuzzy optimization (IFO) problems can better fulfill the aim than the equivalent fuzzy optimization problem and the crisp one [3].

   IFSs provide a more comprehensive framework for dealing with hesitancy in control systems, making them valuable in applications where classical FSs may not capture the full extent of uncertainty and imprecision.

6.6 CONCLUSION

In conclusion, IFSs and IFL have found many diverse and valuable applications in Algebraic Structures, Topological Spaces, Decision-making Systems, Expert Systems, Pattern Recognition, Risk Assessment, and Control Systems across a wide spectrum of mathematics and allied domains These approaches have extended traditional mathematical and logical frameworks to effectively handle vagueness, uncertainty, and imprecision, making them essential tools for solving various real-world problems.

6.7 RECOMMENDATIONS FOR FUTURE RESEARCH

1) The study can be extended to create a sophisticated mathematical model using IFS to address the challenges in various domains.
2) Consider new algorithms and computational methods to use IFS for enhanced data analysis and problem solving.
3) Conduct comprehensive case studies across different sectors like healthcare, industry, and finance to demonstrate the practicality of IFS.

KEYWORDS

- **intuitionistic fuzzy sets**
- **intuitionistic fuzzy logic**
- **intuitionistic fuzzy values**
- **hazard and operability method**

REFERENCES

1. Adamu, I. M. (2021). Application of intuitionistic fuzzy sets to environmental management. *Notes on Intuitionistic Fuzzy Sets*, *27*(3), 40–50. https://doi.org/10.7546/nifs.2021.27.3.40-50.

2. Alkan, N., & Kahraman, C. (2022). An intuitionistic fuzzy multi-distance based evaluation for aggregated dynamic decision analysis (IF-DEVADA): Its application to waste disposal location selection. *Engineering Applications of Artificial Intelligence*, *111*, 104809. https://doi.org/10.1016/j.engappai.2022.104809
3. Angelov, P. P. (1997). Optimization in an intuitionistic fuzzy environment. *Fuzzy Sets and Systems*, *86*(3) 299–306. https://doi.org/10.1016/S0165-0114(96)00009-7
4. Ansari, M. D., Ghrera, S. P., & Mishra, A. R. (2020). Texture feature extraction using intuitionistic fuzzy local binary pattern. *Journal of Intelligent Systems*, *29*(1). https://doi.org/10.1515/jisys-2016-0155
5. Ashraf, S., Ali, M., Sohail, M., & Eldin, S. M. (2023). Assessing the environmental impact of industrial pollution using the complex intuitionistic fuzzy ELECTREE method: A case study of pollution control measures. *Frontiers in Environmental Science*, *11*. https://doi.org/10.3389/fenvs.2023.1171701
6. Atanassov, K. T. (n.d.). A generalized net model of an intuitionistic fuzzy expert system. In: *Notes on Intuitionistic Fuzzy Sets, 26*(1), 46–68. https://doi.org/10.7546/nifs.2020.26.1.46-68
7. Atanassov, K. T. (1986). Intultionistic fuzzy sets. In: *Fuzzy Sets and Systems*. Vol. 20.
8. Atanassov, K. T. (2007). Remark on intuitionistic fuzzy numbers. In *NIFS*. Vol. 13, pp. 29–32.
9. Aven, T. (2016). Risk assessment and risk management: Review of recent advances on their foundation. In *European Journal of Operational Research*. Vol. 253, pp. 1–13. https://doi.org/10.1016/j.ejor.2015.12.023
10. Baccour, L., & Alimi, A. M. (2009). A comparison of some intuitionistic fuzzy similarity measures applied to handwritten Arabic sentences recognition. In: *IEEE International Conference on Fuzzy Systems*. https://doi.org/10.1109/FUZZY.2009.5276877
11. Baccour, L., Kanoun, S., Maergner, V., & Alimi, M. A. (2008). An application of intuitionistic fuzzy information for handwritten Arabic word recognition. In *NIFS*. Vol. 14.
12. Bharati, S. K. (2022). Hesitant intuitionistic fuzzy algorithm for multiobjective optimization problem. *Operational Research*, *22*(4), 3521–3547. https://doi.org/10.1007/s12351-021-00685-8
13. Bouchet, A., Montes, S., & Díaz, I. (2021). Intuitionistic fuzzy sets applied to color image processing. In: *CEUR Workshop Proceedings*, 3074.
14. Bureva, V., Yovcheva, P., & Sotirov, S. (2018). Generalized net model of fingerprint recognition with intuitionistic fuzzy evaluations. In: *Advances in Intelligent Systems and Computing*. Springer: Cham, p. 641. https://doi.org/10.1007/978-3-319-66830-7_26
15. Cagcag Yolcu, O., & Yolcu, U. (2023). A novel intuitionistic fuzzy time series prediction model with cascaded structure for financial time series. *Expert Systems with Applications*, *215*, 119336. https://doi.org/10.1016/j.eswa.2022.119336
16. Chaira, T. (2019). Application of fuzzy/intuitionistic fuzzy set in image processing. In *Fuzzy Set and Its Extension*. Wiley, pp. 237-257. https://doi.org/10.1002/9781119544203.ch9
17. Chang, K. H., & Cheng, C. H. (2010). A risk assessment methodology using intuitionistic fuzzy set in FMEA. *International Journal of Systems Science*, *41*(12), 1457–1471. https://doi.org/10.1080/00207720903353633
18. Chen, Z. Hui, Wan, S. Ping, & Dong, J. Ying. (2023). An integrated interval-valued intuitionistic fuzzy technique for resumption risk assessment amid COVID-19 prevention. *Information Sciences*, *619*, 695–721. https://doi.org/10.1016/j.ins.2022.11.028

19. Dhiman, N., Gupta, M. M., Singh, D. P., Vandana, Mishra, V. N., & Sharma, M. K. (2022). On Z-Intuitionistic fuzzy fractional valuations for medical diagnosis: an intuitionistic fuzzy knowledge-based expert system. *Fractal and Fractional*, *6*(3), 151. https://doi.org/10.3390/fractalfract6030151
20. Dhyani, M., Kushwaha, G. S., & Kumar, S. (2022). A novel intuitionistic fuzzy inference system for sentiment analysis. *International Journal of Information Technology (Singapore)*, *14*(6), 3193–3200. https://doi.org/10.1007/s41870-022-01014-8
21. Fahmi, A., Derakhshan, A., & Kahraman, C. (2015). Human resources management using interval valued intuitionistic fuzzy analytic hierarchy process. In: *IEEE International Conference on Fuzzy Systems*. November, 2015. https://doi.org/10.1109/FUZZ-IEEE.2015.7338094
22. Giveki, D., Montazer, G. A., & Soltanshahi, M. A. (2017). Atanassov's intuitionistic fuzzy histon for robust moving object detection. *International Journal of Approximate Reasoning*, *91,* 80–95. https://doi.org/10.1016/j.ijar.2017.08.014
23. Guo, Z., & Zhang, Q. (2009). A new approach to project risk evaluation based on intuitionistic fuzzy sets. In *6th International Conference on Fuzzy Systems and Knowledge Discovery*, FSKD 2009, 6. https://doi.org/10.1109/FSKD.2009.683
24. Iancu, I., Gabroveanu, M., & Cosulschi, M. (2013). Intuitionistic fuzzy control based on association rules. In: *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *8083 LNAI*. https://doi.org/10.1007/978-3-642-40495-5_24
25. Jana, B., & Mohanty, S. N. (2017). An intuitionistic fuzzy logic models for multicriteria decision making under uncertainty. *Journal of the Institution of Engineers (India): Series C*, *98*(2), 197–201. https://doi.org/10.1007/s40032-016-0299-9
26. Khare, M., & Singh, R. (2008). Complete ξ-grills and (L, n)-merotopies. *Fuzzy Sets and Systems*, *159*(5), 620–628. https://doi.org/10.1016/j.fss.2007.10.007
27. Kumar, V., Gupta, S. K., Kaushik, R., Verma, S. K., & Sakovska, O. (2023). An intuitionistic fuzzy approach to analysis financial risk tolerance with MATLAB in business. In: *International Conference on IoT, Intelligent Computing and Security. Lecture Notes in Electrical Engineering*, Vol. 982. https://doi.org/10.1007/978-981-19-8136-4_26
28. Michalíková, A. (2019). Intuitionistic fuzzy sets and their use in image classification. *Notes on Intuitionistic Fuzzy Sets*, *25*(2), 60–66. https://doi.org/10.7546/nifs.2019.25.2.60-66
29. Milovanović, V., Aleksić, A., Sokolović, V., & Milenkov, M. (2021). Uncertainty modeling using 929 intuitionistic fuzzy numbers. *Vojnotehnicki Glasnik*, *69*(4), 905–929. https://doi.org/10.5937/vojtehg69-33301
30. Otay, I., & Jaller, M. (2020). Multi-expert disaster risk management response capabilities assessment using interval-valued intuitionistic fuzzy sets. *Journal of Intelligent and Fuzzy Systems*, *38*(1), 835–852. https://doi.org/10.3233/JIFS-179452
31. Pal, N. R., Bustince, H., Pagola, M., Mukherjee, U. K., Goswami, D. P., & Beliakov, G. (2013). Uncertainties with Atanassov's intuitionistic fuzzy sets: Fuzziness and lack of knowledge. *Information Sciences*, *228,* 61–74. https://doi.org/10.1016/j.ins.2012.11.016
32. Peters, J. F., Tiwari, S., Singh, R., & Peters, J. (2013). Approach Merotopies and associated near sets. In *Theory and Applications of Mathematics & Computer Science*. Vol. 3, Issue 1. https://www.researchgate.net/publication/236162604
33. Quek, S. G., Selvachandran, G., Davvaz, B., & Pal, M. (2019). The algebraic structures of complex intuitionistic fuzzy soft sets associated with groups and subgroups. *Scientia Iranica E, 26*(3), 1898–1912. https://doi.org/10.24200/sci.2018.50050.1485

34. Revathi, R., & Hemalatha, M. (2013). Moving and immovable object in video processing using intuitionistic fuzzy logic. In: *2013 4th International Conference on Computing, Communications and Networking Technologies, ICCCNT 2013*. https://doi.org/10.1109/ICCCNT.2013.6726746
35. Sidiropoulos, G. K., Diamianos, N., Apostolidis, K. D., & Papakostas, G. A. (2022). Text classification using intuitionistic fuzzy set measures—an evaluation study. *Information (Switzerland)*, *13*(5), 235. https://doi.org/10.3390/info13050235
36. Singh, R., & Umrao, A. K. (2019). On finite order nearness in soft set theory. *WSEAS Transactions on Mathematics*, *18*.
37. Tripathy, S. S., Shekhar, R., & Kumar, R. S. (2011). Texture retrieval system using intuitionistic fuzzy set theory. In: *2011 International Conference on Devices and Communications, ICDeCom 2011—Proceedings*. https://doi.org/10.1109/ICDECOM.2011.5738490
38. Uzhga-Rebrov, O., & Grabusts, P. (2023). Methodology for environmental risk analysis based on intuitionistic fuzzy values. *Risks*, *11*(5), 88. https://doi.org/10.3390/risks11050088
39. Wang, J., & Sun, Y. (2012). The intuitionistic fuzzy sets on evaluation of risks in projects of energy management contract. *Systems Engineering Procedia*, *3,* 30–35. https://doi.org/10.1016/j.sepro.2011.11.004
40. Wu, C., Zou, H., & Barnes, D. (2023). A supply risk perspective integrated sustainable supplier selection model in the intuitionistic fuzzy environment. *Soft Computing*, *27*(20), 15133–15151. https://doi.org/10.1007/s00500-023-08336-0
41. Wu, X., Wang, T., Liu, Q., Liu, P., Chen, G., & Zhang, X. (2021). Topological and algebraic structures of Atanassov's Intuitionistic Fuzzy-Values Space. http://arxiv.org/abs/2111.12677
42. Xue, Y., & Deng, Y. (2021). Decision making under measure-based granular uncertainty with intuitionistic fuzzy sets. *Applied Intelligence*, *51*(8), 6224–6233. https://doi.org/10.1007/s10489-021-02216-6
43. Yang, T., Yang, J., & Bi, F. K. (2009). Emotion statuses recognition of speech signal using intuitionistic fuzzy set. In: *2009 WRI World Congress on Software Engineering,* Xiamen: China, 2009, pp. 204–207. https://doi.org/10.1109/WCSE.2009.237
44. Yin, Y., Li, H., & Jun, Y. B. (2012). On algebraic structure of intuitionistic fuzzy soft sets. *Computers and Mathematics with Applications*, *64*(9), 2896–2911. https://doi.org/10.1016/j.camwa.2012.05.004
45. Yousofnejad, Y., Afsari, F., & Es'haghi, M. (2023). Dynamic risk assessment of hospital oxygen supply system by HAZOP and intuitionistic fuzzy. *PLoS One*, *18*(2), e0280918. https://doi.org/10.1371/journal.pone.0280918
46. Zadeh, L. A. (1965). Fuzzy Sets*. In *INFOR~ATIO~ AND CONTROL,* Vol. 8.
47. Zhang, T., & Zhi, H. (2023). A fuzzy set theory-based fast fault diagnosis approach for rotators of induction motors. *Mathematical Biosciences and Engineering*, *20*(5), 9268–9287. https://doi.org/10.3934/mbe.2023406
48. Zhou, S., Hu, C., Xie, Y., & Chang, W. (2016). Research on supply chain risk assessment with intuitionistic fuzzy information. *Journal of Intelligent and Fuzzy Systems*, *30*(6), 3367–3372. https://doi.org/10.3233/IFS-152084

CHAPTER 7

Applications of MCDM Aggregation Operator in the Selection of Suitable Site for the Manufacturing Plant

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ABSTRACT

The development of multicriteria decision-making (MCDM) techniques helps in the decision-making process and addresses many real-life problems. In this chapter, an intuitionistic fuzzy-based MCDM decision-making technique has been proposed for the selection of a suitable site for a manufacturing plant. Dynamic intuitionistic fuzzy weighted averaging operator has been used for decision-making under an intuitionistic fuzzy environment. The method is demonstrated by the help of a case study, comprised of the selection of suitable sites among the 11 sites on the basis of 5 factors and the opinion of 3 domain experts. The proposed model may help the decision makers to taking better decisions under uncertainty.

7.1 INTRODUCTION

To run a successful enterprise, site selection is very critical and depends on many factors including the type of plant, requirement of raw material, supply of furnished goods, etc. It is a very complex task that needs critical

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thinking and some unforeseen things that may happen during and after the establishment of a plant. Therefore, the factors that influence selection need to be identified first and a thorough intervention of domain experts is required for the suitable selection of a site. On the basis of the identified factors, domain experts provide the foundation knowledge required to select the optimal location. The generalization of fuzzy set (FS) theory helps in the development of decision support systems that allow decision-makers to tackle these problems. Real-life problems are uncertain in nature as they contain incomplete information that could be overlooked by human reasoning. These challenges attract researchers to do research in this discipline to develop handheld support systems to tackle the problems of vagueness. Generally, real-life situations are nondeterministic in nature and many challenges have been faced in outcome such situations, as these situations are not clearly defined. Zadeh [18] coined the concept of FSs, which is the generalized version of the classical set theory and has the potential to deal with uncertain situations. The intuitionistic fuzzy set (IFS) was proposed by Atanassov [1], which is the generalization of fuzzy theory, which is characterized by both membership and nonmembership grades. IFSs are the special version of FSs that describe fuzziness more comprehensively and have a variety of applications in real-life scenarios. The complexity of many problems may not be discussed through traditional methods unless uncertainty in these systems has been addressed precisely in some measurable way. FSs and their generalizations provide computational support to the problems at hand for dealing with the imprecision and uncertainty of human reasoning. The main feature of fuzzy theory is that it interprets verbal as well as linguistic information and describes them by simple rules. This factor is very much beneficial to establish relationships. Information can be gathered from various sources that contain some sort of uncertainty in it. Therefore, multiple factors are involved in the decision-making process to address real-life problems. Multicriteria decision-making (MCDM) problem is a trade-off between the set of alternatives and the evaluating factors in which a set of domain experts is involved in providing domain knowledge to establish some decision mechanism on the basis of certain performance indicators. Some approximation techniques have been developed by Krassimir [8] to address MCDM problems with fuzzy information. To deal with MCDM problems, Xu and Yager [14] developed certain aggregation operators in the IFS environment. In this chapter, the MCDM technique for the selection of a suitable site for the manufacturing plant has been discussed.

7.2 LITERATURE REVIEW

MCDM problems when taken up with fuzzy theory, provide strength to the concept. These problems are interdisciplinary and capture the attention of researchers to address the issue of multiple opinions under one situation. The domains of fuzzy as well as IF sets are discrete for dealing with imperfect and incomplete information. Wang and Zhang [9] explained MCDM problems by defining the expected values of the fuzzy information in the form of intuitionistic trapezoidal fuzzy number (ITrFN). Wang and Zhang [10], Guorong [5], and Wan and Dong [11] established certain aggregation operators by defining the expected values in ITrFN and investigated that aggregation operators work well in MCDM problems. To aggregate the information received from the domain experts , aggregation operators have been deployed to understand the priority. Wei [12] presented the generalization of aggregation operators proposed by Yager [16, 17] and developed some hesitant fuzzy aggregation operators. Fuzzy as well as IF-based MCDM models have been proposed by several researchers, such as, Chen and Hwang [3], Kacprzyk [7], Herrera [6], and Bordogna [2]. Researchers, such as, Chen and Hwang [3], Kacprzyk [7], Fodor and Runens [4], Herrera [6], and Bordogna [2] proposed certain fuzzy MCDM techniques. In this chapter, an aggregation operator DIFWG has been used for the selection of a suitable site for a manufacturing plant. The main objective of the work is to establish a decision support system that not only helps the decision-makers to take optimal decision but also provides some logical solutions. The given system gathered initial information from the three domain experts and performed the decision-making with the help of an algorithm to rank the sites.

7.3 PRELIMINARIES

Let X = $\{x_1, x_2, \ldots, x_n\}$be a discrete universe of discourse. The following preliminaries are defined as

7.3.1 FSS

Zadeh [18] defined FSs as: A FS A is defined as: $A = \{< x, \phi_A(x) > \; : \; x \in X\}$ where, $\phi_A : X \to [0,1]$ and $\phi_A(x)$ be the membership function and membership grade, respectively, of $x \in X$ in A.

It is the generalization of the classical notion of set.

7.3.2 IFSS

Atanassov [1], IFS is a generalization of FSs and is defined as

$$A = \{< x, \phi_A(x), \psi_A(x) > | \, x \in X\}$$

where, $\phi_A(x), \psi_A(x) : X \to [0, 1]$ are the membership and nonmembership function of $x \in X$ with $\pi_A(x) = 1 - \phi_A(x) - \psi_A(x)$ as the intuitionistic index or hesitation index of A in A.

7.3.3 INTUITIONISTIC FUZZY VARIABLE

For a time variable t, $\zeta(t) = (\phi_{\zeta(t)}, \psi_{\zeta(t)})$ is called the intuitionistic fuzzy variable.

In general, If $t = t_1, t_2, \ldots, t_p$, then $\zeta(t_1), \ldots, \zeta(t_p); (\phi_{\zeta(t)}, \psi_{\zeta(t)}) \in [0, 1]$ be the intuitionistic fuzzy numbers (IFNs) collected at different periods.

The concept was proposed by Xu and Yager [15].

7.3.4 ITrFN

Wang [13] applied the concept of ITrFN and defined as:

Let A be an IFS in $\Re$, whose membership and nonmembership functions are defined as follows:

$$\phi_A = \begin{cases} \dfrac{(x - t_1)\tilde{\phi}_A}{t_2 - t_1}, t_1 \le x \le t_2 \\ \tilde{\phi}_A, \ t_2 \le x \le t_3 \\ \dfrac{(t_4 - x)\tilde{\phi}_A}{t_4 - t_3}, t_3 \le x \le t_4 \\ 0, \ \ otherwise \end{cases} ; \psi_A = \begin{cases} \dfrac{(t_2 - x) + \tilde{\psi}_A(x - t_{11})}{t_2 - t_{11}}, & t_{11} \le x \le t_2 \\ \tilde{\psi}_A, & t_2 \le x \le t_3 \\ \dfrac{(x - t_3) + \tilde{\psi}_A(t_{14} - x)}{t_{14} - t_3}, & t_3 \le x \le t_{14} \\ 1, & otherwise \end{cases}$$

where, $0 \le \phi_A + \psi_A \le 1$, $\tilde{\phi}_A$ and $\tilde{\psi}_A$ are maximum and minimum values, respectively, and $t_1, t_2, t_3, t_4, t_{11}, t_{14} \in \Re$. Then A is called ITrFN and is denoted by

$$A = \langle ([t_1, t_2, t_3, t_4]; \phi_A), ([t_{11}, t_2, t_3, t_{14}]; \psi_A) \rangle$$

7.3.5 DYNAMIC INTUITIONISTIC FUZZY WEIGHTED AVERAGING (DIFWA) OPERATOR

Xu and Yager [15], let $\zeta(t_1),\ldots,\zeta(t_q)$ be a collection of IFNs collected at q different periods and τ be the weight vector of the periods t_k, then $DIFWA_{\tau(t)}$ $(\zeta(t_1),\ldots,\zeta(t_q)) = \tau(t_1)\zeta(t_2) \oplus \ldots\ldots\ldots \oplus \tau(t_q)\zeta(t_q)$ is called DIFWA operator.

$$DIFWA_{\lambda(t)}(\zeta(t_1),\ldots,\zeta(t_q))$$
$$= \left(1 - \prod_{k=1}^{q}(1-\phi_{\zeta(t_k)})^{\tau(t_k)}, \prod_{k=1}^{q}\psi_{\zeta(t_k)}^{\tau(t_k)}, \prod_{k=1}^{q}(1-\phi_{\zeta(t_k)})^{\tau(t_k)} - \prod_{k=1}^{q}\psi_{\zeta(t_k)}^{\tau(t_k)}\right)$$

where, $\tau(t_k) \geq 0\,;\ \sum_{k=1}^{q}\tau(t_k) = 1$

In this chapter, information is taken in the form of ITrFN and decision-making is taking with the help of DIFWA operator.

7.4 MAIN CONCEPT

The idea of MCDM has been used by many researchers to discuss real-life situations encountered in day-to-day life. In this chapter, an algorithmic approach of the DIFWA operator proposed by Xu and Yagar [15] has been discussed by taking information as ITrFN for the selection of a suitable site for the manufacturing plant under certain attributes. The attributes considered for the decision are given in the form of IFNs. A hypothetical case study has been developed to explain the algorithm. In this study, five factors have been considered that are responsible for the selection of a suitable site for the manufacturing plant and are given in Figure 7.1.

7.4.1 ALGORITHM

Following hypothesis has been considered and are given as:

I: Let $\Theta = \{\theta_1,\ldots,\theta_n\}$ be the set of n alternatives.

II: Let $MP = \{MP_1,\ldots,MP_m\}$ be the finite set of attributes articulated in IFNs, with weight vector as $\omega = (\omega_1,\ldots,\omega_m)^T$

where $\omega_j \geq 0\ \ \sum_{j=1}^{m}\omega_j = 1$

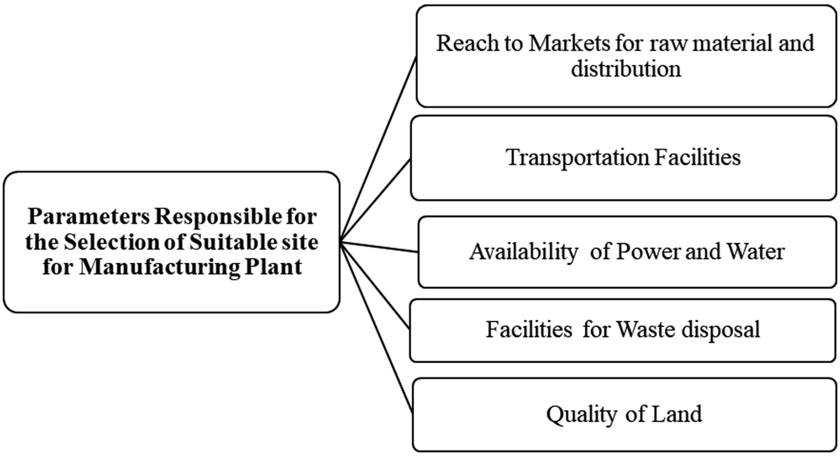

FIGURE 7.1 Parameters responsible for the selection of suitable site for manufacturing Plant. ⏎

III: Let t_k having q periods with weight vector is $\zeta(t) = (\zeta(t_1),\ldots,\zeta(t_q))^T$, where $\zeta(t_k) \geq 0; \sum_{k=1}^{q} \zeta(t_k) = 1$

IV: Let $\Re(t_k) = (r_{ij}(t_k))_{n\times m}$ be an IF decision matrix of the period t_k, where $r_{ij}(t_k) = (\phi_{r_{ij}}(t_k), \psi_{r_{ij}}(t_k), \pi_{r_{ij}}(t_k)); (i, j = 1,\ldots,n)$ is the attribute value defined in the form of IFN.

The steps of the algorithm are given as:

Step I: Using the DIFWA operator, defined in Section 7.3

$$r_{ij} = DIFWA_{\zeta(t)}\left(r_{ij}(t_1),\ldots,r_{ij}(t_q)\right)$$

$$= \left(1 - \prod_{k=1}^{q}(1-\phi_{r_{ij}(t_k)})^{\zeta(t_k)}, \prod_{k=1}^{q}\psi_{r_{ij}(t_k)}^{\zeta(t_k)}, \prod_{k=1}^{q}(1-\phi_{r_{ij}(t_k)})^{\zeta(t_k)} - \prod_{k=1}^{q}\psi_{r_{ij}(t_k)}^{\zeta(t_k)}\right)$$

To aggregate all the IF decision matrix

$$\Re(t_k) = \left(r_{ij}(t_k)\right)_{m\times n}$$

where, $r_{ij} = (\phi_{ij}, \psi_{ij}, \pi_{ij}); \phi_{ij} = 1 - \prod_{k=1}^{k=q}\left(1-\phi_{r_{ij}(t_k)}\right)^{\zeta(t_k)}; \psi_{ij} = \prod_{k=1}^{k=q}\psi_{r_{ij}(t_k)}^{\zeta(t_k)};$

Step II: Let $\overset{+}{\Phi}_i = (\overset{+}{\Phi}_1,\ldots,\overset{+}{\Phi}_m)^T$ and $\overline{\Phi}_i$, $(\overline{\Phi}_1,\ldots,\overline{\Phi}_m)^T$ be the IF positive and ideal solutions, respectively, where $\overset{+}{\Phi}_i = (0,1,0)$ and $\overline{\Phi}_i = (0,1,0)$ be the m largest and m smallest IFNs, respectively. Furthermore, let $\theta_i = (r_{i1},\ldots r_{im})^T$.

Step III: Determine IF positive and negative ideals: IFPIS($\overset{+}{\Phi}_i$) and IFNIS ($\overset{-}{\Phi}_i$)from the alternatives θ_i as

$$\delta(\theta_i,\overset{+}{\Phi}_i)=\sum_{j=1}^{m}\omega_j\delta(r_{ij},\overset{+}{\Phi}_i)=\sum_{j=1}^{m}\omega_j(1-\phi_{ij})$$

$$\delta\left(\theta_i,\overset{-}{\Phi}_i\right)=\sum_{j=1}^{m}\omega_j\delta\left(r_{ij},\overset{-}{\Phi}_i\right)=\sum_{j=1}^{m}\omega_j\left(1-\psi_{ij}\right)$$

where, $r_{ij} = (\phi_{ij}, \psi_{ij}, \pi_{ij})$

Step IV: Calculate the closeness coefficient of each alternative:

$$C(\theta_i)=\frac{\delta(\theta_i,\overset{-}{\Phi}_i)}{\delta(\theta_i,\overset{+}{\Phi}_i)+\delta(\theta_i,\overset{-}{\Phi}_i)}$$

Since, $\delta(\theta_i,\overset{+}{\Phi}_i)+\delta(\theta_i,\overset{-}{\Phi}_i)=\sum_{j=1}^{m}\omega_j(1+\pi_{ij})$

$$\therefore \qquad C\left(\theta_i\right)=\frac{\sum_{j=1}^{m}\omega_j\left(1-\psi_{ij}\right)}{\sum_{j=1}^{m}\omega_j\left(1+\pi_{ij}\right)}$$

Step V: On the basis of closeness coefficients $C(\theta_i)$, rank the alternative θ_i. Greater the $C(\theta_i)$, better the alternative.

Step VI: End.

7.4.2 EVALUATION OF CASE STUDY

Let MP_i (i = 1,2,…,11) be the available set of sites for the manufacturing plant. The selection of site for the plant can be identified on the basis of the certain factors $\Theta = (\theta_1,\ldots,\theta_5)$ as shown in Figure 7.1. Also, the decision for the final selection of site can be made by considering the inputs received from the three decision-makers as $D = (d_1,d_2,d_3)$. Let $\tau(t) = (0.16, 0.33, 0.5)^T$ be the weight vector of the experts t_k and $\omega(t) = (0.1,0.15,0.2,0.25, 0.3, 0.4)^T$ be the weight vector of the factors θ_j (j = 1, …,5). The decision for the selection of site for manufacturing plant among the available sites has been made on the basis of Algorithm 7.4.1. The opinion collected from various experts has been articulated in the form of IFNs and are given in Tables 7.1–7.3.

The collective result received from the set of experts is presented in Table 7.4.

TABLE 7.1 IFN Information Provided by the Expert d_1 ⏎

Site/Factor	θ_1	θ_2	θ_3	θ_4	θ_5
MP_1	(0,8,0.1,0.1)	(0.9,0.1,0.0)	(0.7,0.2,0.1)	(0.7,0.2,0.1)	(0.2,0.4,0.4)
MP_2	(0.7,0.3,0.0)	(0.6,0.2,0.2)	(0.6,0.3,0.1)	(0.5,0.2,0.3)	(0.2,0.7,0.1)
MP_3	(0.5,0.4,0.1)	(0.7,0.3,0.0)	(0.6,0.1,0.3)	(0.4,0.6,0.2)	(0.1,0.8,0.1)
MP_4	(0.9,0.1,0.0)	(0.7,0.1,0.2)	(0.8,0.2,0.0)	(0.7,0.1,0.2)	(0.5,0.1,0.4)
MP_5	(0.6,0.1,0.3)	(0.8,0.2,0.0)	(0.5,0.1,0.4)	(0.2,0.4,0.4)	(0.4,0.5,0.1)
MP_6	(0.3,0.6,0.1)	(0.5,0.4,0.1)	(0.4,0.5,0.1)	(0.2,0.7,0.1)	(0.5,0.5,0.0)
MP_7	(0.5,0.2,0.3)	(0.4,0.6,0.0)	(0.5,0.5,0.0)	(0.1,0.8,0.1)	(0.8,0.2,0.0)
MP_8	(0,8,0.1,0.1)	(0.9,0.1,0.0)	(0.7,0.2,0.1)	(0.7,0.2,0.1)	(0.5,0.4,0.1)
MP_9	(0.7,0.3,0.0)	(0.6,0.2,0.2)	(0.6,0.3,0.1)	(0.5,0.2,0.3)	(0.4,0.6,0.0)
MP_{10}	(0.5,0.4,0.1)	(0.7,0.3,0.0)	(0.6,0.1,0.3)	(0.4,0.6,0.0)	(0.6,0.1,0.3)
MP_{11}	(0.9,0.1,0.0)	(0.7,0.1,0.2)	(0.8,0.2,0.0)	(0.7,0.1,0.2)	(0.3,0.6,0.1)

TABLE 7.2 IFN Information Provided by the Expert d_2 ⏎

Site/Factor	θ_1	θ_2	θ_3	θ_4	θ_5
MP_1	(0.9,0.1,0.0)	(0.8,0.2,0.0)	(0.8,0.1,0.1)	(0.6,0.3,0.1)	(0.4,0.3,0.3)
MP_2	(0.8,0.2,0.0)	(0.5,0.1,0.4)	(0.7,0.2,0.1)	(0.4,0.3,0.3)	(0.7,0.1,0.2)
MP_3	(0.5,0.5,0.0)	(0.7,0.2,0.1)	(0.8,0.2,0.0)	(0.7,0.1,0.2)	(0.3,0.5,0.2)
MP_4	(0.9,0.1,0.0)	(0.9,0.1,0.0)	(0.7,0.3,0.0)	(0.3,0.5,0.2)	(0.7,0.2,0.1)
MP_5	(0.5,0.2,0.3)	(0.6,0.3,0.1)	(0.6,0.2,0.2)	(0.6,0.1,0.3)	(0.8,0.2,0.0)
MP_6	(0.4,0.6,0.0)	(0.3,0.4,0.3)	(0.5,0.5,0.0)	(0.2,0.3,0.5)	(0.7,0.3,0.0)
MP_7	(0.3,0.5,0.2)	(0.5,0.3,0.2)	(0.6,0.4,0.0)	(0.1,0.5,0.4)	(0.5,0.1,0.4)
MP_8	(0.9,0.1,0.0)	(0.8,0.2,0.0)	(0.8,0.1,0.1)	(0.6,0.3,0.1)	(0.7,0.2,0.1)
MP_9	(0.8,0.2,0.0)	(0.5,0.1,0.4)	(0.7,0.2,0.1)	(0.4,0.3,0.3)	(0.9,0.1,0.0)
MP_{10}	(0.5,0.5,0.0)	(0.7,0.2,0.1)	(0.8,0.2,0.0)	(0.7,0.1,0.2)	(0.5,0.5,0.0)
MP_{11}	(0.9,0.1,0.0)	(0.9,0.1,0.0)	(0.7,0.3,0.0)	(0.3,0.5,0.2)	(0.9,0.1,0.0)

TABLE 7.3 IFN Information Provided by the Expert θ_1 ⏎

Site/Factor	θ_1	θ_2	θ_3	θ_4	θ_5
MP_1	(0.7,0.1,0.2)	(0.9,0.1,0.0)	(0.9,0.1,0.0)	(0.6,0.1,0.3)	(0.4,0.5,0.1)
MP_2	(0.9,0.1,0.0)	(0.6,0.2,0.2)	(0.5,0.2,0.3)	(0.5,0.2,0.3)	(0.7,0.1,0.2)
MP_3	(0.4,0.5,0.1)	(0.8,0.1,0.1)	(0.7,0.1,0.2)	(0.3,0.3,0.4)	(0.8,0.2,0.0)
MP_4	(0.8,0.1,0.1)	(0.7,0.2,0.1)	(0.9,0.1,0.0)	(0.4,0.4,0.2)	(0.5,0.4,0.1)
MP_5	(0.6,0.3,0.1)	(0.8,0.2,0.0)	(0.7,0.2,0.1)	(0.5,0.5,0.0)	(0.9,0.1,0.0)
MP_6	(0.2,0.7,0.1)	(0.5,0.1,0.4)	(0.3,0.1,0.6)	(0.1,0.4,0.5)	(0.6,0.1,0.3)
MP_7	(0.4,0.6,0.0)	(0.7,0.3,0.0)	(0.5,0.5,0.0)	(0.2,0.3,0.5)	(0.3,0.6,0.1)
MP_8	(0.5,0.4,0.1)	(0.7,0.3,0.0)	(0.6,0.1,0.3)	(0.4,0.6,0.2)	(0.1,0.8,0.1)
MP_9	(0.9,0.1,0.0)	(0.7,0.1,0.2)	(0.8,0.2,0.0)	(0.7,0.1,0.2)	(0.5,0.1,0.4)
MP_{10}	(0.6,0.1,0.3)	(0.8,0.2,0.0)	(0.5,0.1,0.4)	(0.2,0.4,0.4)	(0.4,0.5,0.1)
MP_{11}	(0.3,0.6,0.1)	(0.5,0.4,0.1)	(0.4,0.5,0.1)	(0.2,0.7,0.1)	(0.5,0.5,0.0)

TABLE 7.4 Collective IFN Information Provided by the Experts $D = (d_1, d_2, d_3)$

Site/Factor	$\boldsymbol{\theta_1}$	$\boldsymbol{\theta_2}$	$\boldsymbol{\theta_3}$	$\boldsymbol{\theta_4}$	$\boldsymbol{\theta_5}$
MP_1	0.806,0.1,0.094	0.874,0.126,0.0	0.849,0.112,0.039	0.619,0.162,0.219	0.371,0.406,0.223
MP_2	0.849,0.151,0.0	0.569,0.159,0.272	0.594,0.214,0.192	0.469,0.229,0.302	0.647,0.138,0.215
MP_3	0.452,0.482,0.066	0.755,0.151,0.094	0.725,0.126,0.149	0.486,0.233,0.281	0.610,0.342,0.048
MP_4	0.859,0.1,0.041	0.792,0.141,0.067	0.838,0.162,0.0	0.437,0.342,0.221	0.578,0.252,0.170
MP_5	0.569,0.218,0.213	0.748,0.229,0.023	0.640,0.178,0.181	0.498,0.282,0.220	0.830,0.165,0.005
MP_6	0.289,0.648,0.063	0.441,0.2,0.359	0.390,0.224,0.386	0.151,0.399,0.450	0.623,0.189,0.189
MP_7	0.387,0.470,0.143	0.601,0.337,0.063	0.536,0.464,0.0	0.151,0.419,0.430	0.492,0.275,0.233
MP_8	0.749,0.200,0.051	0.782,0.218,0.0	0.697,0.112,0.190	0.533,0.397,0.070	0.434,0.449,0.117
MP_9	0.849,0.151,0.0	0.627,0.112,0.261	0.743,0.214,0.043	0.588,0.162,0.250	0.699,0.135,0.167
MP_{10}	0.553,0.215,0.232	0.755,0.214,0.031	0.645,0.126,0.229	0.450,0.270,0.280	0.472,0.382,0.145
MP_{11}	0.735,0.245,0.020	0.731,0.200,0.069	0.603,0.362,0.035	0.350,0.452,0.197	0.691,0.301,0.008

Using sections steps 2–5 of the Algorithm 7.4.1, the values of Closeness Coefficients $C(S_i)$ against each kind of site for manufacturing plant is given in Table 7.5.

TABLE 7.5 Closeness Coefficients of Various Type of Sites for Manufacturing Plant ⏎

Type of Site	Closeness Coefficients $C(MP_i)$
MP_1	0.690
MP_2	0.672
MP_3	0.654
MP_4	0.692
MP_5	0.705
MP_6	0.539
MP_7	0.518
MP_8	0.630
MP_9	0.727
MP_{10}	0.622
MP_{11}	0.625

The largest value of the closeness coefficient $C(MP_i)$ represents the preference to the type of the Site.

7.5 RESULT AND DISCUSSION

On the basis of the values of the closeness coefficient given in Table 7.5 are presented graphically in Figure 7.2.

From Figure 7.2, it is observed that the site no. MP_9 is the most suitable one and the ranking is given below as

$$MP_9 \succ MP_5 \succ MP_4 \succ MP_1 \succ MP_2 \succ MP_3 \succ MP_8 \succ MP_{11} \succ MP_{10} \succ MP_6 \succ MP_7$$

The decision is made on the basis of the collective information received from the decision-makers $D = (d_1,d_2,d_3)$. IF information used with the aggregation operator gives promising results to develop support system for the selection of suitable site for the manufacturing plant on the basis of the factors.

7.6 CONCLUSION

MCDM technique has been used in this chapter for the selection of suitable site for the manufacturing as per the desired requirement.

The information given is in the form of ITrFNs, which is aggregated using DIFWA operator. Further, the opinion of three domain experts is considered while taking the decision. Decision-making is made and the alternatives are ranked on the basis of the calculated value of closeness coefficient. More the value of closeness coefficient, more the preference will be given to the alternative. This model can be utilized for other such situations to avoid the unnecessary expenditure on surveys. The model is more suitable to perform initial investigation of the problem in hand under uncertainty.

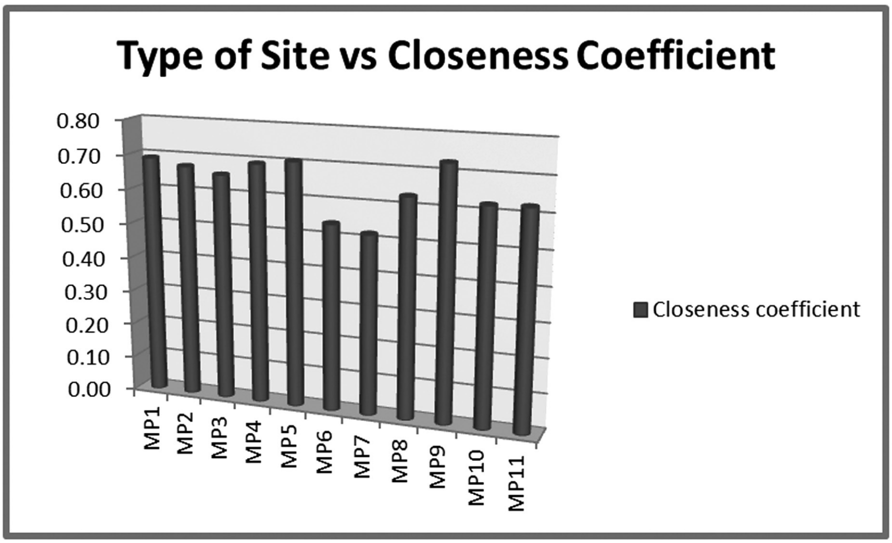

FIGURE 7.2 Closeness coefficients for the sites. ⏎

KEYWORDS

- **intuitionistic fuzzy number**
- **intuitionistic fuzzy sets**
- **aggregation operator**
- **dynamic intuitionistic fuzzy weighted averaging operator**

REFERENCES

1. Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, *20*(1), 87–96.
2. Bordogna, G., Fedrizzi, M., & Pasi, G. (1997). A linguistic modeling of consensus in group decision making based on OWA operators. *IEEE Transactions on Systems Man and Cybernetics*, *27*(1), 126–132.
3. Chen, S. J., & Hwang, C. L. (1992). *Fuzzy Multiple Attribute Decision Making*. Springer-Verlag: New York.
4. Fodor, J. C., & Rubens, M. (1994). *Fuzzy Preference Modelling and Multicriteria Decision Support*. Kluwer Academic Publisher: Dordrecht.
5. Guorong, X. (2011). Models for multiple attribute decision making with intuitionistic trapezoidal information. *International Journal of Advancement in Computing Technology*, *3*(6), 21–25.
6. Herrera, F., Herrera-Viedma, E., & Verdegay, J. L. (1996). A linguistic decision process in group decision making. *Group Decision and Negotiation*, *5*, 165–176.
7. Kacprzyk, J., Fedrizzi, M., & Nurmi, H. (1992). Group decision making and consensus under fuzzy preferences and fuzzy majority. *Fuzzy Sets and Systems*, *49*, 21–31.
8. Krassimir, A., Gabriella, P., & Ronald, Y. (2005). Intuitionistic fuzzy interpretations of multi-criteria multi-person and multi-measurement tool decision making. *International Journal of Systems Science*, *36*(14), 859–868
9. Wang, J. Q., & Zhang, Z. H. (2008). Programming method of multi-criteria decision-making based on intuitionistic fuzzy number with incomplete certain information. *Control and Decision*, *23*, 1145–1148.
10. Wang, J. Q., & Zhang, Z. H. (2009). Aggregation operators on intuitionistic trapezoidal fuzzy number and its application to multi-criteria decision-making problems. *Journal of Systems Engineering and Electronics*, *20*, 321–326.
11. Wan, S. P., & Dong, J. Y. (2010). Method of trapezoidal intuitionistic fuzzy number for multi-attribute group decision. *Control and Decision*, *25*(5), 773–776.
12. Wei, G. W. (2012). Hesitant fuzzy prioritized operators and their application to multiple attribute decision making. *Knowledge-Based Systems*, *31*, 176–182.
13. Wang, J. Q. (2008). Overview on fuzzy multi-criteria decision-making approach. *Control and Decision*, *23*, 601–606.
14. Xu, Z. S., & Yager, R. R. (2006). Some geometric aggregation operators based on intuitionistic fuzzy sets. *International Journal of General Systems*, *35*, 417–433.
15. Xu, Z., & Yager, R. R. (2008). Dynamic intuitionistic fuzzy multi-attribute decision making. *International Journal of Approximate Reasoning*, *48*, 246–262.
16. Yager, R. R. (2004). OWA aggregation over a continuous interval argument with applications to decision making. *IEEE Transactions on Systems, Man, and Cybernetics –Part B*, *34*, 1952–1963.
17. Yager, R. R. (2009). Prioritized OWA aggregation. *Fuzzy Optimization and Decision Making*, *8*, 245–262.
18. Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*, 338–353.

CHAPTER 8

Fuzzy Logic in Industrial IoT for Smart Manufacturing

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ABSTRACT

The convergence of fuzzy logic and the Industrial Internet of Things (IIoT) has led to a new age of smart manufacturing, giving unprecedented opportunities for efficiency, quality, and adaptability. This chapter analyses the crucial role of fuzzy logic within the context of IIoT in the quest for smart manufacturing. Fuzzy Logic's built-in capacity to hold uncertainty and imprecise data makes it a valuable mechanism for decision-making in complex and dynamic manufacturing situations. We delve into real-world applications where fuzzy logic is engaged to optimize processes, improve resource allocation, and enhance overall manufacturing performance. Additionally, we analyze the integration of fuzzy logic with IIoT sensors as well as platforms, highlighting how it enables real time, adaptive decision-making that is vital for achieving the objectives of smart manufacturing. By shedding light on the collaboration between fuzzy logic and IIoT, this chapter contributes insights into the transformative potential of these technologies in modern manufacturing and sets the stage for a more adaptive and responsive industrial landscape.

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8.1 INTRODUCTION

In the realm of Industry 4.0, the marriage of fuzzy logic and the Industrial Internet of Things (IIoT) is reshaping smart manufacturing paradigms. Fuzzy logic, grounded in the concept of handling uncertainty and imprecision, serves as a linchpin in navigating the complexities of modern industrial processes. As manufacturing facilities become increasingly interconnected through IIoT, the sheer volume and diversity of data generated demand intelligent solutions for decision-making. Fuzzy logic, with its capacity to model and control nonlinear and uncertain systems, seamlessly integrates with IIoT frameworks, offering a nuanced understanding of dynamic operational environments [1].

Figure 8.1 shows this integration empowers manufacturers to optimize processes, predict maintenance needs, ensure quality control, and implement adaptive automation. Real-world applications showcase the prowess of fuzzy logic in providing actionable insights from disparate and ambiguous data sources, thereby enhancing operational efficiency and responsiveness. However, the implementation of fuzzy logic in industrial settings necessitates a careful balance between precision and adaptability, acknowledging the need for robust, context-aware decision-making [2]. As industries embrace the symbiosis of fuzzy logic and IIoT, the trajectory toward intelligent, self-optimizing manufacturing systems in the Industry 4.0 era becomes increasingly tangible.

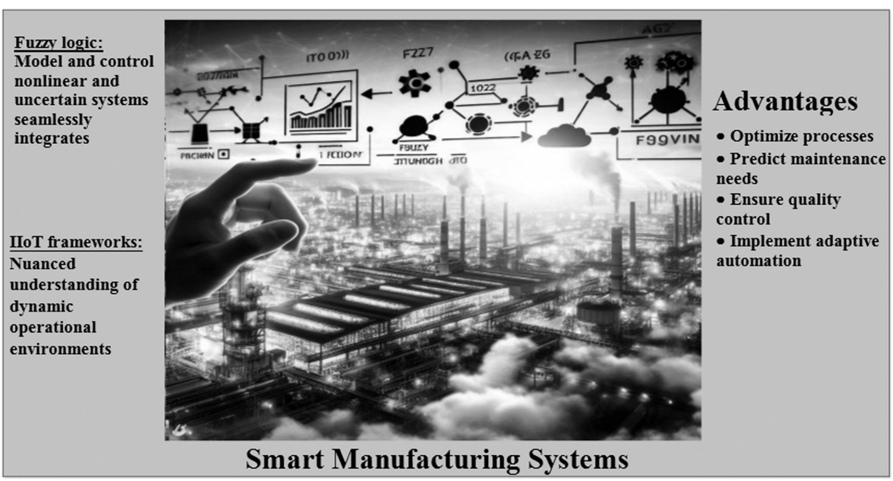

FIGURE 8.1 Concept of smart manufacturing systems. ⏎

8.1.1 BACKGROUND AND SIGNIFICANCE OF IIOT IN MANUFACTURING

The IIoT has emerged as a transformative force in the manufacturing sector, redefining traditional processes, and contributing to the advent of Industry 4.0. The introduction of cutting-edge sensors, actuators, and communication technologies into industrial machinery to create a network of linked devices is the foundation of IIoT in production [3]. The smooth interchange of data made possible by this interconnection makes it possible to monitor, analyze, and control production processes in real time. IIoT is significant in manufacturing in a number of ways.

First off, by offering never-before-seen visibility into every aspect of the production line, IIoT improves operational efficiency. Real-time data from sensors and devices provide proactive detection of inefficiencies or bottlenecks, improved workflow optimization, and improved decision-making. Consequently, this leads to increased output and efficient use of resources.

Second, IIoT is essential to predictive maintenance since it minimizes downtime and lowers the chance of equipment breakdowns. Machine sensors can gather performance metrics data, allowing predictive analytics to identify any problems early on and take appropriate action to prevent them from getting worse.

Furthermore, IIoT facilitates the evolution toward smart manufacturing by fostering connectivity not only within the factory floor but also across the entire supply chain. This interconnected ecosystem enables seamless communication between suppliers, manufacturers, and distributors, optimizing logistics, reducing lead times, and improving overall supply chain visibility.

In summary, the background and significance of IIoT in manufacturing lie in its capacity to revolutionize operational processes, improve efficiency, enable predictive maintenance, and foster a holistic, interconnected approach to smart manufacturing in the Industry 4.0 landscape. As industries increasingly embrace this transformative technology, the potential for innovation and competitiveness in the global market becomes ever more pronounced.

8.1.2 CHALLENGES IN HANDLING UNCERTAINTIES IN SMART MANUFACTURING

Smart manufacturing, driven by technologies like the IIoT, faces inherent challenges in handling uncertainties. These uncertainties stem from various sources within the complex and dynamic manufacturing environment [4]. Several key challenges are included in Table 8.1.

TABLE 8.1 Challenges in Smart Manufacturing ⏎

Challenges	Description
Data Variability and Quality	The sheer volume and diversity of data generated by sensors and devices in smart manufacturing introduce challenges related to data variability and quality. Inconsistencies, inaccuracies, or fluctuations in data quality can compromise the reliability of decision-making processes.
Environmental Changes	Manufacturing environments are subject to fluctuations in temperature, humidity, and other external factors. These environmental changes can impact the performance and reliability of sensors and devices, leading to uncertainties in the data they generate.
Complex System Interactions	In smart manufacturing, various interconnected systems and components collaborate to execute processes. The intricate interactions among these components introduce uncertainties, especially when unexpected events or disruptions occur.
Cybersecurity Risks	As manufacturing systems become more interconnected, the risk of cybersecurity threats increases. Cyber-attacks can introduce uncertainties by disrupting data integrity, system functionality, and overall manufacturing processes.
Human Factors	The involvement of human operators introduces a layer of uncertainty due to factors such as decision-making variability, skill levels, and response time. Human–machine interactions must be carefully managed to minimize uncertainties in smart manufacturing.
Supply Chain Dynamics	Smart manufacturing often relies on an interconnected supply chain. Uncertainties in the supply chain, such as delays, fluctuations in material availability, or unexpected demand spikes, can impact production schedules and overall efficiency.
Adaptability to Change	The dynamic nature of markets and technological advancements necessitates continuous adaptation in smart manufacturing. Uncertainties arise when systems struggle to keep pace with rapid changes in technology, regulations, or customer demands.

Addressing these challenges requires a holistic approach, incorporating advanced technologies such as machine learning, artificial intelligence (AI), and, notably, fuzzy logic to model and manage uncertainties effectively. Additionally, robust cybersecurity measures, data quality assurance protocols, and human–machine collaboration frameworks are essential components of a resilient smart manufacturing ecosystem. As industries struggle for greater efficiency and flexibility, understanding and mitigating uncertainties become crucial for the success of smart manufacturing initiatives.

8.1.3 ROLE OF FUZZY LOGIC AS A DECISION-MAKING TOOL

Fuzzy logic is an essential tool for decision-making in the context of smart manufacturing within Industry 4.0 [5]. It addresses the inherent complexities and uncertainties of contemporary industrial processes. Figure 8.2 shows the fuzzy logic's contribution to smart manufacturing which can be summed up as:

- **Handling Uncertain and Vague Information:** Sensors, machines, and other networked equipment produce enormous volumes of data in smart manufacturing settings. Fuzzy logic, which accepts degrees of truth rather than strict binary distinctions, is skilled at handling this ambiguous and frequently unclear data. This adaptability is necessary when making decisions based on faulty or insufficient information.
- **Adaptive Process Control:** Adaptive process control, where manufacturing conditions can change dynamically, is an area where fuzzy logic excels. It makes it possible to design control systems with the ability to instantly modify parameters in response to shifting inputs and external circumstances. This flexibility improves the robustness and efficiency of production operations.

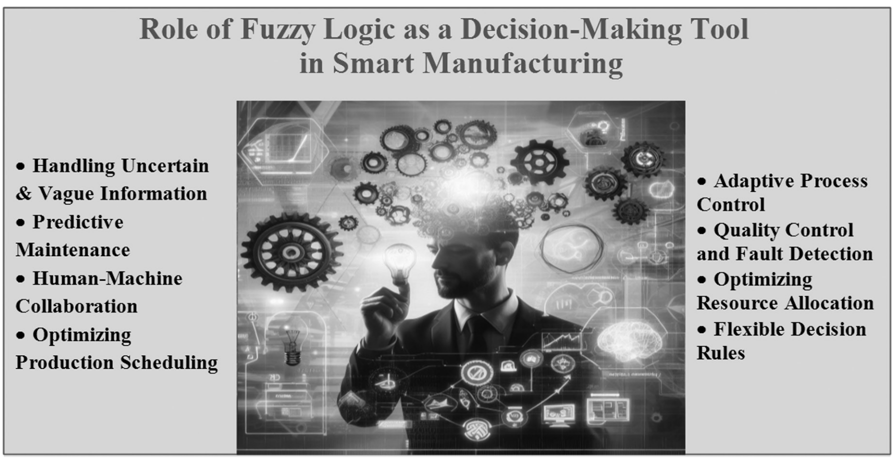

FIGURE 8.2 Role of fuzzy logic as a decision-making tool in smart manufacturing.

- **Quality Control and Fault Detection:** Smart manufacturing uses fuzzy logic to achieve fault detection and quality control. It makes it possible to create intelligent algorithms that can evaluate the quality of a product by taking into account multiple elements at once. To maintain product quality, fuzzy logic can also identify abnormalities or departures from expected parameters and initiate remedial action.

- **Optimizing Resource Allocation:** Smart manufacturing involves the optimization of resources such as energy, materials, and equipment. Fuzzy logic aids in decision-making by considering multiple factors and trade-offs simultaneously. This is mainly precious for allocating resources efficiently while considering changing production demands and operational constraints.
- **Predictive Maintenance:** Predictive maintenance solutions in smart manufacturing use fuzzy logic. Fuzzy logic models are able to anticipate possible malfunctions or maintenance requirements by evaluating both historical and current data from machinery and equipment. By being proactive, this strategy reduces downtime and increases the longevity of industrial assets.
- **Human–Machine Collaboration:** Fuzzy logic enables human–machine collaboration in smart manufacturing settings where human operators communicate with automated systems. It makes it possible to incorporate human judgment and experience into automated procedures, ensuring that choices are supported by both qualitative and quantitative information.
- **Flexible Decision Rules:** Decision rules that are more adaptable to various contexts can be created with fuzzy logic. This is essential in smart production since circumstances might change quickly and preset rules must be flexible enough to not require frequent reprogramming.
- **Optimizing Production Scheduling:** Fuzzy logic aids in production scheduling optimization by accounting for several factors, including equipment availability, production deadlines, and resource constraints. As a result, production schedules become more adaptable and effective, enabling businesses to quickly adapt to changing demand.

To sum up, fuzzy logic is a powerful tool for decision-making in smart manufacturing because it provides a framework for handling uncertainty, adapting to changing conditions, and streamlining processes for improved efficacy, quality, and resource efficiency. The incorporation of intelligent and self-optimizing manufacturing systems into Industry 4.0 considerably facilitates their realization.

8.2 FOUNDATIONS OF IIOT IN SMART MANUFACTURING

The IIoT in smart manufacturing is based on a combination of interrelated technologies that work together to drive industries into Industry 4.0. To create a complex network where machines can communicate, analyze, and react in real time, IIoT fundamentally depends on the smooth integration of smart sensors, actuators, and communication devices into the production ecosystem as shown in Figure 8.3. It also shows the idea of data-driven decision-making, which leverages the constant flow of data from many sources to get insights into operational effectiveness, predictive maintenance, and quality control, is fundamental to this foundation. Scalability and accessibility are made possible by the infrastructure that cloud computing and edge computing platforms offer to handle and process this flood of data. Another essential pillar that protects the confidentiality and integrity of sensitive data traveling over the IIoT network is security protocols. The integration of advanced analytics, AI, and ML strengthens the foundations of IIoT as it develops, enabling intelligent, self-optimizing, and adaptive industrial processes that characterize smart manufacturing [6].

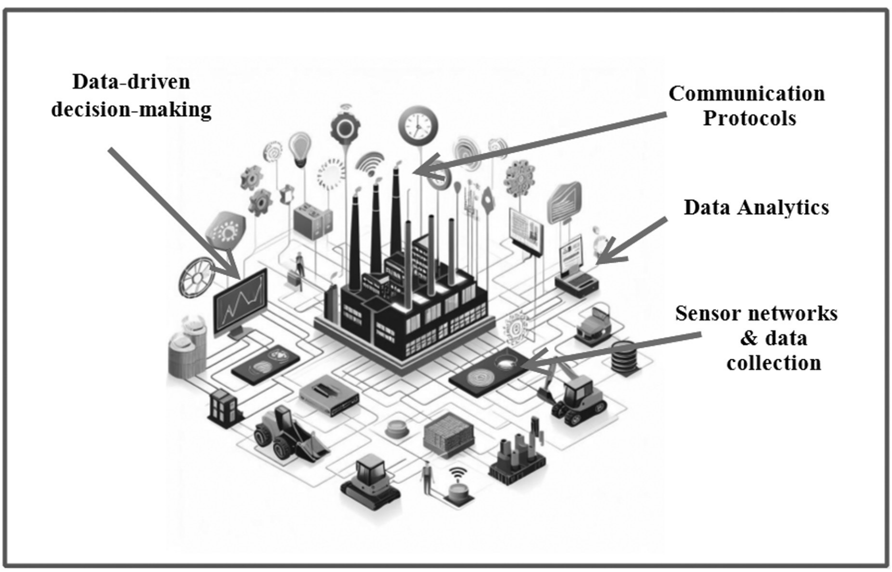

FIGURE 8.3 Concept of IIoT in smart manufacturing. ⏎

8.2.1 SENSOR NETWORKS AND DATA COLLECTION

In the context of smart manufacturing, sensor networks and data gathering are the foundation of the IIoT. These technologies are essential to the transformation of manual production processes into data-driven, flexible ecosystems. Sensor networks are made up of many intelligent sensors that are placed strategically throughout the production environment to gather data in real time on a variety of parameters, including vibration, temperature, pressure, humidity, and machine status. By gathering a thorough picture of the operational environment, these sensors act as the IIoT's eyes and ears.

In the context of the IIoT, data collection refers to the methodical acquisition and transfer of data from these sensors to centralized platforms for analysis. Manufacturers can measure production indicators, keep an eye on the condition of their equipment, and evaluate the overall effectiveness of the manufacturing process thanks to this deluge of data. In addition, the use of edge computing facilitates on-site data processing, which lowers latency and speeds up decision-making.

Sensor networks and data collecting are important because they can yield insights that can be put to use. By using this data, manufacturers may put predictive maintenance plans into place, preventing downtime by anticipating possible equipment breakdowns. Continuous monitoring improves quality control by guaranteeing that goods fulfill strict requirements. Additionally, the data makes it easier to optimize production schedules, energy efficiency, and resource utilization, all of which increase overall efficiency.

Security and privacy are critical considerations in the context of sensor networks and data collection. Robust cybersecurity measures are implemented to safeguard sensitive data, preventing unauthorized access and ensuring the integrity of the manufacturing process.

In conclusion, sensor networks and data collection in IIoT for smart manufacturing epitomize the transition from conventional to intelligent production systems. By harnessing real-time data from diverse sources, manufacturers gain unprecedented visibility and control over their operations, paving the way for enhanced efficiency, predictive capabilities, and adaptive decision-making in the Industry 4.0 landscape.

8.2.2 COMMUNICATION PROTOCOLS AND DATA ANALYTICS

In the domain of smart manufacturing within the IIoT, effective communication protocols and advanced data analytics are integral components that drive connectivity, collaboration, and informed decision-making.

8.2.2.1 COMMUNICATION PROTOCOLS

Communication protocols serve as the foundation for the seamless exchange of data among the myriad devices and systems in smart manufacturing. Protocols such as MQTT (Message Queuing Telemetry Transport), Constrained Application Protocol, and OPC UA (Open Platform Communications Unified Architecture) facilitate efficient, low-latency communication between sensors, machines, and control systems [7]. These protocols support the real-time transmission of data, ensuring that critical information is delivered promptly for analysis and decision-making. The standardized communication enabled by these protocols promotes interoperability, allowing diverse devices from different manufacturers to communicate effectively within the IIoT ecosystem.

8.2.2.2 COMMUNICATION PROTOCOLS

Data analytics is the driving force behind the transformative potential of IIoT in smart manufacturing. Advanced analytics techniques, including machine learning and AI, process the vast volumes of data generated by sensors and devices to extract meaningful insights. Predictive analytics is applied to anticipate equipment failures and schedule maintenance proactively, minimizing downtime. Prescriptive analytics provides actionable recommendations for optimizing production processes, resource allocation, and energy efficiency. Descriptive analytics offers historical perspectives, aiding in performance analysis and continuous improvement. Edge analytics, performed closer to the data source, reduces latency and allows for real-time decision-making. The synergy of communication protocols and data analytics empowers manufacturers to create intelligent, adaptive systems that optimize efficiency, enhance quality, and respond dynamically to changing operational conditions.

In conclusion, the effective integration of communication protocols and data analytics in IIoT for smart manufacturing forms a symbiotic relationship that underpins the evolution toward Industry 4.0. These technologies collectively enable the creation of connected, intelligent ecosystems, where data-driven insights propel manufacturing processes to new heights of efficiency, resilience, and innovation.

8.2.3 THE NEED FOR REAL-TIME DECISION-MAKING

The need for real-time decision-making in the IIoT within smart manufacturing is paramount, shaping a paradigm shift in the way industries operate and optimize their processes. Several factors underscore the significance of real-time decision-making in this context:

- **Dynamic Operational Environment:** Smart manufacturing environments are dynamic and subject to constant changes. Real-time decision-making allows for swift adaptations to fluctuations in demand, equipment conditions, and unforeseen events. It ensures that responses are immediate, enhancing the agility of the manufacturing process.
- **Optimizing Efficiency and Productivity:** A live image of the production line is provided by real-time data coming from sensors and gadgets. Manufacturers can find bottlenecks, streamline processes, and improve overall operational efficiency by real-time data analysis. Lead times are shortened and productivity is raised as a result of this agility.
- **Predictive Maintenance:** Predictive maintenance plans are made possible by timely insights into the health of the equipment. With the use of real-time data analytics, manufacturers may plan maintenance before problems get worse by identifying anomalies or trends suggestive of impending failures. This lowers maintenance costs, increases equipment lifespan, and minimizes downtime.
- **Quality Control:** It is critical to maintain product quality in smart manufacturing. The ability to monitor and analyze production data in real time facilitates the prompt detection of deviations from quality requirements. This guarantees that remedial measures can be implemented without delay, averting the manufacturing of faulty products and reducing wastage.
- **Supply Chain Coordination:** Throughout the whole supply chain, decisions are made in real time, not only on the manufacturing floor. Manufacturers may better respond to market demands, optimize supply chain efficiency, and cut lead times by regularly evaluating data pertaining to inventory levels, demand predictions, and logistics.
- **Customer Responsiveness:** Demands from customers and the market might shift quickly. Making decisions in real time enables producers to react quickly to changes in consumer preferences or industry trends. Retaining competitiveness and satisfying customer expectations require this flexibility.
- **Emergency Response:** Unexpected incidents that call for quick action, like supply chain interruptions or equipment failures, must be addressed right away. Making decisions in real time reduces the impact of emergencies on production schedules by facilitating quick responses and the execution of backup plans.

- **Reducing Information Latency:** Decision-making that is not well-informed can be impeded by information delay. By lowering this latency, real-time processing makes sure that decision-makers have access to the most recent and pertinent data. This is especially important in manufacturing settings that move quickly.

In conclusion, the need for real-time decision-making in IIoT-driven smart manufacturing arises from the dynamic nature of industrial processes, the quest for operational excellence, and the imperative to respond promptly to changing conditions. By harnessing the power of real-time data analytics, manufacturers can not only optimize their current operations but also position themselves for agility and competitiveness in the rapidly evolving landscape of Industry 4.0.

8.3 FUZZY LOGIC BASICS

Fuzzy logic, conceived by Lotfi A. Zadeh in the 1960s, revolutionizes traditional binary logic by introducing a nuanced approach to decision-making and system control. At its core are fuzzy sets, allowing for partial membership and degrees of truth between 0 and 1. Membership functions define the extent of belonging to a set, portraying the inherent uncertainty in real-world data. Fuzzy logic operations, including AND, OR, and NOT, manipulate these fuzzy sets to handle imprecision and uncertainty. Expressed through if-then rules, fuzzy logic enables the incorporation of expert knowledge and human-like reasoning [8]. The inference mechanism combines rules to derive conclusions, and defuzzification converts fuzzy outputs into actionable results. With applications ranging from control systems to AI, fuzzy logic stands as a powerful tool for modeling complex, uncertain systems, providing a bridge between crisp, deterministic logic and the intricacies of the real world.

8.3.1 FUZZY SETS AND MEMBERSHIP FUNCTIONS

Basic ideas in fuzzy logic, a mathematical framework that enables the representation of uncertainty and imprecision in decision-making and system control, including fuzzy sets and membership functions. An extension of a classical set, a fuzzy set has items that have a degree of membership between 0 and 1, indicating how much they belong to the set, as opposed to strictly belonging or not belonging.

These degrees of membership are defined in large part by membership functions. These functions indicate how much a particular element belongs to the fuzzy set by mapping the input values to a range between 0 and 1. The fuzzy set's properties are determined by the membership function's form, and it can take a variety of forms such as triangular, trapezoidal, Gaussian, or more complex shapes as shown in Figure 8.4.

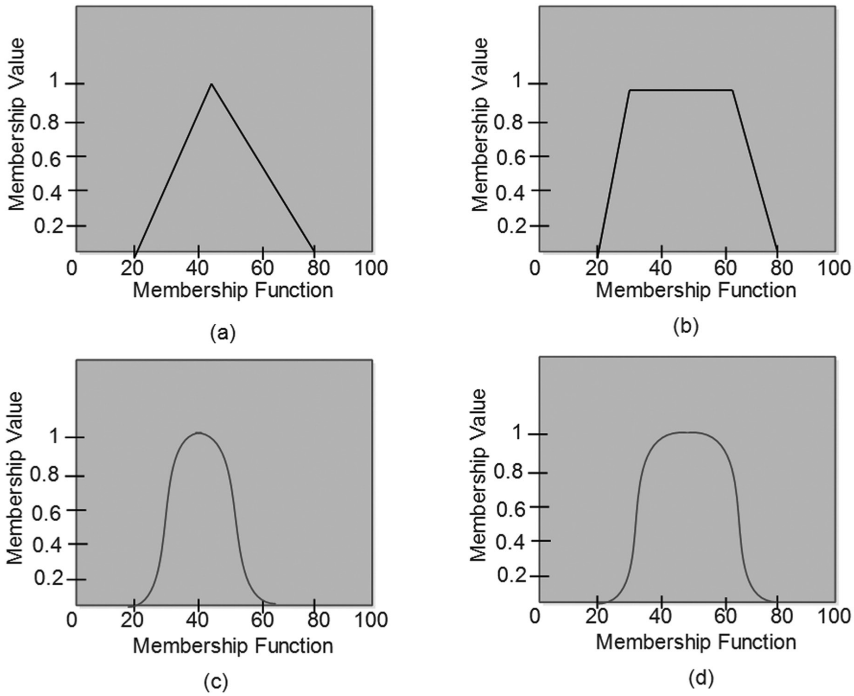

FIGURE 8.4 Examples of four classes of parameterized MFs: (a) triangular; (b) trapezoidal; (c) Gaussian; and (d) bell. ⏎

For example, in modeling the linguistic variable "temperature" in a fuzzy set "warm," the membership function might assign a high degree of membership (close to 1) to temperatures around 25°C, and this degree gradually decreases as the temperature deviates from this central value. This allows fuzzy logic to represent and manipulate linguistic terms and human-like reasoning in decision-making processes where precise, binary distinctions are inadequate. Fuzzy sets and membership functions are crucial components in constructing rule-based systems that emulate human decision-making in complex and uncertain environments.

8.3.2 FUZZY INFERENCE SYSTEMS (FIS)

A FIS shown in Figure 8.5 is a computational model in fuzzy logic that mimics the human decision-making process by using fuzzy set theory. FIS involves a set of rules and a reasoning mechanism that makes decisions based on fuzzy logic principles. The key components and concepts of FISs are given in below section.

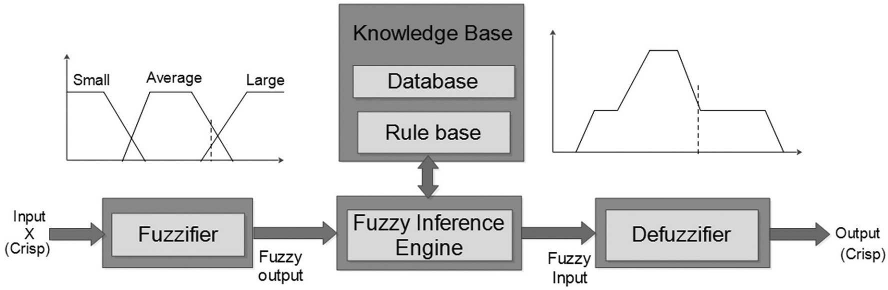

FIGURE 8.5 Fuzzy inference system. ⏎

8.3.2.1 FUZZIFICATION

Fuzzification is the first step of FIS when membership functions are used to convert crisp input values into fuzzy sets. In this step, the degree to which the input values fall into different language categories is determined.

8.3.2.2 RULE BASE

The relationship between the fuzzy input and fuzzy output values is defined by a collection of IF–THEN rules. Every rule usually prescribes a fuzzy output action and relates to a certain set of input conditions.

8.3.2.3 INFERENCE ENGINE

The central element of FIS is the inference engine, which combines fuzzy input values in accordance with the rule basis to produce fuzzy output values. Typical inference techniques are Sugeno and Mamdani. Sugeno inference generates a sharp output based on a certain input, whereas Mamdani inference yields fuzzy results.

8.3.2.4 AGGREGATION

To create a comprehensive fuzzy output, aggregation is the process of integrating the fuzzy outputs produced by various rules. To aggregate the fuzzy sets, a variety of techniques can be applied, including maximum and average.

8.3.2.5 DEFUZZIFICATION

The final step is defuzzification, where the fuzzy output is transformed into a crisp output. This process involves converting the fuzzy output sets into a single, actionable value. Common defuzzification methods include centroid, mean of maximum, and weighted average.

FISs find applications in diverse fields, including control systems, decision support systems, and pattern recognition. They excel in scenarios where precise mathematical models are challenging to define, and human expertise and linguistic reasoning play a crucial role. FIS gives a flexible and intuitive technique for modeling complex systems in the existence of uncertainty and imprecision, providing the achievement of fuzzy logic applications in real-world problems.

8.3.3 RULE-BASED REASONING WITH FUZZY LOGIC

FISs are built on the foundation of rule-based reasoning with fuzzy logic, which entails drawing inferences from a set of if–then rules using the ideas of fuzzy logic. Fuzzy logic excels at modeling and managing complex systems with uncertainty and imprecision because these rules capture expert knowledge and human-like reasoning. Rule-based reasoning proceeds through a number of crucial steps:

- **Fuzzification:** Using membership functions, the input variables are converted from sharp, numerical values into fuzzy sets. This stage makes it possible to depict the uncertainty and imprecision contained in real-world data.
- **Rule Base:** The rule base consists of a set of if–then rules that relate fuzzy input variables to fuzzy output variables. Each rule articulates a linguistic relationship between certain input conditions and the resulting output action. For example, a rule might state "IF temperature is high THEN air conditioning is strong."

- **Inference Engine:** The inference engine evaluates the fuzzy rules based on the current fuzzy input values. The degree to which each rule is satisfied is determined by the membership functions associated with the input variables. The inference engine combines these rule strengths to generate fuzzy output values.
- **Aggregation:** To create a thorough fuzzy output, the fuzzy output values from several rules are combined. This entails merging the distinct fuzzy sets that each rule generates, frequently utilizing methods like maximum or average aggregation.
- **Defuzzification:** Defuzzification, the last stage, transforms the fuzzy output into a clear, useful outcome. In this process, the combined fuzzy output set is usually summarized into a single numerical number. The centroid, mean of maximum, and weighted average defuzzification are popular techniques.

Fuzzy logic is a valuable tool for control systems, expert systems, smart manufacturing, robotics, and decision-making because it uses a rule-based reasoning process to account for the inherent uncertainties in real-world systems. Because fuzzy logic can capture the complexity of human-like decision-making due to rule-based reasoning's flexibility, it is especially useful in scenarios when more exact and deterministic approaches are insufficient.

8.4 INTEGRATION OF FUZZY LOGIC IN IIoT

Fuzzy logic's incorporation into the IIoT is a major development for control systems and smart manufacturing. Because fuzzy logic can deal with uncertainty and imprecision, it fits very well with the dynamic nature of IIoT contexts. Fuzzy logic principles can be integrated into IIoT frameworks [9] to improve decision-making capabilities for industries confronting real-world complexity. By allowing for a more sophisticated interpretation of the massive volumes of data produced by networked devices and sensors, fuzzy logic advances data analytics. Manufacturing systems may now respond instantly to changing conditions, streamlining workflows and boosting overall effectiveness thanks to this integration. Whether applied to predictive maintenance, quality control, or adaptive automation, the marriage of fuzzy logic and IIoT fosters intelligent, self-optimizing systems that define the essence of smart manufacturing in the Industry 4.0 era. This synergy not only augments the robustness of control systems but also underscores the transformative potential of integrating human-like reasoning into the fabric of interconnected industrial ecosystems.

8.4.1 FUZZY LOGIC CONTROLLERS (FLCS) FOR MANUFACTURING PROCESSES

FLCs have emerged as instrumental tools in optimizing manufacturing processes, providing a flexible and adaptive approach to control systems in the industrial landscape. Unlike traditional control systems, FLCs excel in managing complex, nonlinear, and uncertain manufacturing environments. These controllers leverage linguistic rules and human-like reasoning to make decisions based on imprecise or incomplete information, characteristics often inherent in industrial processes. In manufacturing, FLCs find application in various domains such as temperature control, pressure regulation, and quality assurance [10].

FLCs operate by translating expert knowledge into a rule-based system. For instance, in a temperature control system, rules may dictate that "IF the temperature is high AND the pressure is increasing, THEN decrease the heat input." FLCs continuously evaluate these rules in real time, adjusting control parameters based on the current state of the system. This adaptability enables FLCs to respond dynamically to fluctuations, enhancing process stability and efficiency.

The integration of FLCs with sensors and actuators in the manufacturing environment as shown in Figure 8.6 contributes to improved precision and reliability. FLCs are particularly valuable in scenarios where mathematical models are difficult to establish due to the complexity or variability of the manufacturing process. Their ability to handle imprecise inputs and adapt to changing conditions positions FLCs as key components in the pursuit of intelligent, self-optimizing manufacturing systems within the Industry 4.0 framework. As industries continue to embrace advanced technologies, the role of FLCs in enhancing control and decision-making processes remains integral to the evolution of smart manufacturing.

8.4.2 FUZZY CONTROL IN PREDICTIVE MAINTENANCE

Predictive maintenance for manufacturing processes using fuzzy control is a novel way to maximize equipment dependability and reduce unscheduled downtime. Fuzzy logic is used in this situation to deal with the uncertainty and imprecision that come with foretelling and averting equipment failures. The process starts with sensors built into manufacturing equipment continuously measuring a variety of characteristics.

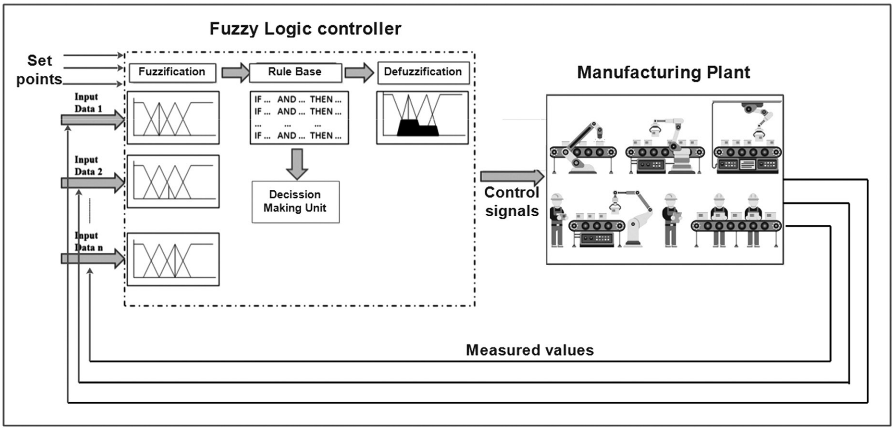

FIGURE 8.6 Integration of fuzzy logic controller (FLC) in manufacturing processes. ⏎

In the context of predictive maintenance, fuzzy control refers to the development of fuzzy rules that identify the connections between sensor data and possible equipment faults. Frequently, historical data, expert knowledge, or a mix of the two are used to create these rules. Fuzzy logic makes use of language variables like "high," "medium," and "low" to describe the likelihood and seriousness of prospective problems in a way that is more reminiscent of human speech.

The fuzzy control system determines the danger or possibility of a future failure by evaluating the real-time sensor data and applying the fuzzy rules while the manufacturing equipment is in operation. Because the statistics are ambiguous, this assessment takes membership degrees into account rather than a binary approach. Fuzzy inference mechanisms combine these degrees of membership to generate a comprehensive evaluation of the equipment's health status.

Based on the fuzzy logic analysis, the predictive maintenance system can then make decisions regarding the optimal timing for maintenance activities [11]. If the fuzzy control system indicates a high risk of failure, it may recommend immediate maintenance to prevent critical issues. Conversely, if the risk is deemed low, the system may schedule maintenance during a planned downtime window, optimizing resource utilization.

The integration of fuzzy control in predictive maintenance enhances the adaptability and responsiveness of manufacturing processes. It enables a more nuanced and context-aware approach to maintenance scheduling, aligning with the dynamic nature of modern industrial environments. Ultimately, fuzzy control in predictive maintenance contributes to increased operational efficiency, reduced downtime, and improved overall equipment effectiveness in smart manufacturing systems. As Industry 4.0 principles continue to evolve, the application of fuzzy control in predictive maintenance stands as a key enabler of intelligent, self-optimizing manufacturing processes.

8.4.3 QUALITY CONTROL WITH FUZZY LOGIC

Quality control using fuzzy logic in manufacturing processes is a sophisticated and adaptive approach to ensure product quality in the face of uncertainties and variations. Fuzzy logic provides a framework that accommodates imprecise and ambiguous information, making it particularly suitable for modeling and improving complex manufacturing systems. In quality control applications, fuzzy logic is employed to handle the inherent variability in raw materials, production conditions, and environmental factors. Here is how fuzzy logic enhances quality control in manufacturing:

- **Fuzzy Rule-Based Systems:** Fuzzy logic utilizes rule-based systems that encapsulate expert knowledge and operational experience. These rules define the relationships between input variables (such as dimensions, temperatures, or material properties) and the corresponding quality output. To indicate the levels of adherence to quality standards, linguistic variables such as "high," "medium," and "low" are used.
- **Fuzzification of Data:** The first step in fuzzy logic is to fuzz clean input data, which transforms numerical measurements into linguistic variables with corresponding membership functions. In this step, information that is imprecise and uncertain can be represented in a format that fuzzy logic systems can process.
- **Inference Mechanism:** Fuzzy logic uses an inference engine to assess fuzzy rules by using fuzzified input data. By combining these guidelines, it produces fuzzy output values that indicate the product's quality level. A complex and context-aware evaluation of product quality is made possible by this procedure.
- **Aggregation and Defuzzification:** The process of combining fuzzy output values and then de-fuzzifying them yields a clear, practical

decision from the fuzzy quality assessment. The product's quality level is clearly indicated in this last step, enabling the proper course of action to be followed.

- **Adaptive Decision-Making:** In dynamic production contexts, quality control relies heavily on fuzzy logic's capacity to adjust to changing situations. It ensures consistent product quality even in the face of uncertainty by enabling real-time modifications in reaction to fluctuations in production parameters.
- **Integration with Sensors and Automation:** Automation systems and sensor data are easily integrated with fuzzy logic. Key quality indicators are continuously monitored by sensors, and fuzzy logic analyses this data to make decisions about the quality state of the product. Automation systems can then use these imprecise data to make correctional decisions.
- **Multicriteria Decision-Making:** Fuzzy logic is mainly good at handling several criteria at once. Fuzzy logic allows for a comprehensive evaluation of quality control when multiple factors influence the final product quality. This is achieved by considering the interdependencies of various quality parameters.

Manufacturing processes can attain greater levels of precision, adaptability, and robustness by utilizing fuzzy logic for quality control. This method is especially useful for producing consistently high-quality products in industries where fluctuation is a given.

8.5 FUZZY LOGIC APPLICATIONS IN ADAPTIVE MANUFACTURING

Applications of fuzzy logic in adaptive manufacturing are a prime example of how this mathematical framework has revolutionized the contemporary industrial scene. Fuzzy logic is essential to control systems and decision-making in adaptive manufacturing, where the capacity to react quickly to changing circumstances is critical. Adaptive processes that easily adapt to changes in production parameters, demand fluctuations, and unanticipated events are made possible by fuzzy logic's capacity to handle imprecise information and uncertainty [12]. Applications are numerous and include dynamic scheduling based on shifting priorities, real-time quality assurance, adaptive control of manufacturing gear, and more. Manufacturing systems can mimic human-like reasoning by using fuzzy logic to incorporate linguistic variables and expert knowledge to make sophisticated judgments. Within the larger context of Industry 4.0, this adaptability improves operational efficiency, reduces downtime, and helps to realize intelligent, self-optimizing manufacturing environments [13]. The adoption of adaptive manufacturing by various industries has led to the growing significance of fuzzy logic applications in establishing production ecosystems that are sensitive, agile, and efficient.

8.5.1 ADAPTIVE PRODUCTION SCHEDULING

Taking into account uncertainties, changing priorities, and real-time adjustments, adaptive production scheduling is a flexible and adaptable method of planning and arranging manufacturing operations. Adaptive production scheduling, in contrast to conventional static scheduling techniques, makes use of cutting-edge technologies and clever algorithms to continuously optimize production plans in response to changes in the industrial environment [14]. The notion of adaptive production scheduling is defined by many essential components:

- **Real-Time Data Integration:** Throughout the manufacturing ecosystem, real-time data from several sources must be seamlessly integrated in order for adaptive production scheduling to work. Information from sensors, manufacturing equipment, inventory levels, and outside variables like consumer demand are all included in this.
- **Predictive Analytics:** By predicting future interruptions or modifications to the production environment, predictive analytics is essential to adaptive scheduling. Predicting future events and trends entails using data analytics, machine learning, and other predictive modeling techniques.
- **Dynamic Rescheduling:** Adaptive production scheduling refers to the capacity to modify production schedules dynamically in reaction to evolving conditions. This could involve unforeseen equipment failures, shifts in demand, or adjustments to the availability of resources.
- **Machine Learning and AI Algorithms:** Algorithms for AI and machine learning are used to examine past data, spot trends, and enhance the adaptive scheduling model over time. These algorithms improve the system's capacity for deliberative decision-making by adapting to and learning from fresh inputs.
- **Optimization Objectives:** Production plans are optimized by adaptive scheduling based on predetermined objectives, such as maximizing resource utilization, minimizing production costs, meeting delivery

deadlines, or maximizing energy efficiency. These goals can be adjusted to fit the particular aims of the production process.

- **Human–Machine Collaboration:** A certain amount of human–machine collaboration is frequently involved in adaptive production scheduling. Although algorithms manage the data analysis and decision-making process, human operators provide subject knowledge, deal with unforeseen difficulties, and make strategic choices that support overarching company objectives.
- **Integration with Industry 4.0 Principles:** Adaptive production scheduling emphasizes the use of interconnected technologies, Internet of Things (IoT) devices, and cyber-physical systems, which is in line with the principles of Industry 4.0. An automated, adaptable, and intelligent manufacturing environment is promoted by this integration.
- **Agile Manufacturing Concepts:** A key component of adaptive production scheduling is the idea of agility. Because of the system's quick response time to changes, producers can stay adaptable in the face of shifting market dynamics and operational difficulties.

One of the main components of smart manufacturing is adaptive production scheduling, which opens the door to higher productivity, shorter lead times, and improved responsiveness to market fluctuations. In the end, it helps to achieve the main objective of creating a robust and competitive manufacturing environment. It symbolizes a change from strict, preset timetables to more flexible and adaptive production processes.

8.5.2 DYNAMIC RESOURCE ALLOCATION

A planned and flexible method for effectively managing and optimizing resources in real time inside a system or environment is dynamic resource allocation. This idea is especially important in environments that are dynamic and change quickly, like manufacturing, cloud computing, or project management, where the supply and demand for resources might change regularly. Table 8.2 shows the essential features of dynamic resource allocation:

In contexts marked by unpredictability and variability, dynamic resource allocation is essential to strike a balance between resource efficiency and flexibility. In the context of Industry 4.0 and beyond, this flexibility aligns with the principles of agility by making systems more resilient, responsive, and economical.

TABLE 8.2 Characteristics of Dynamic Resource Allocation ⏎

Dynamic Resources	Characteristics
Real-Time Adaptability	Flexibility to real-time reallocation of resources in response to shifting demands, priorities, or situations.
Data-Driven Decision-Making	Leveraging real-time information and analytics to make informed choices about resource allocation.
Optimization Objectives	To enhance efficiency, reduce costs, and meet specific operational or business objectives.
Automation and Algorithms	To evaluate data, forecast future resource requirements, and make allocation choices.
Scalability	To change resource requirements, workload variations, and shifts in the size of activities.
Integration with IoT and Sensors	To collect data in real time on resource utilization, environmental conditions, and other pertinent elements, dynamic resource allocation frequently interacts with sensor technologies and the Internet of Things (IoT).
Task Prioritization	Depending on the urgency, significance, and dependencies of various activities or processes, resources are assigned based on task prioritization.
Adaptation to Uncertainty	To deal with unforeseen circumstances and uncertainties by constantly evaluating the system's present state and adjusting resource allocation accordingly.
Application in Various Fields	Used in a variety of contexts where effective and flexible resource allocation is required, like manufacturing, cloud computing, project management, traffic control, and other settings.
Human-In-The-Loop	Human decision-makers are frequently involved in dynamic resource allocation to set parameters, provide strategic advice, and make important judgments.

8.5.3 SUPPLY CHAIN OPTIMIZATION

The goal of supply chain optimization is to improve the supply chain's overall performance, flexibility, and efficiency using a strategic and data-driven strategy. In order to optimize value and save expenses, supply chain activities must be systematically analyzed, planned, and carried out. Supply chain optimization is characterized by a few essential elements:

- **Demand Forecasting:** The basis of supply chain optimization is precise demand forecasting. Organizations can anticipate future demand and allocate resources proactively by utilizing market trends, historical data, and predictive analytics.

- **Inventory Management:** Proper inventory control guarantees that the appropriate quantity of items is accessible at the appropriate time and place. Optimizing the supply chain attempts to achieve a balance between reducing holding costs and averting stockouts.
- **Logistics and Transportation Optimization:** Simplifying transportation routes, choosing the most economical carriers, and cutting down on transit times are all examples of logistics optimization. Real-time tracking, the use of route optimization technologies, and cooperation with logistics partners can all be part of this.
- **Supplier Relationship Management:** Resilient and effective supply chains depend on having strong connections with their suppliers. In this case, optimization entails working with dependable suppliers, negotiating advantageous conditions, and cooperating on projects aimed at ongoing improvement.
- **Technology Integration:** Utilizing cutting-edge technologies like AI, blockchain, and the IoT may automate procedures, give real-time supply chain visibility, and facilitate data-driven decision-making for optimization.
- **Risk Management:** Identifying and reducing risks that could impair operations is a key component of supply chain optimization. This entails assessing externalities that can affect the supply chain, such as natural disasters and geopolitical events.
- **Multi-Echelon Optimization:** When optimizing a supply chain, suppliers, manufacturers, distributors, and retailers are just a few of the organizations that are taken into account. The goal of multi-echelon optimization is to maximize information and material flow throughout the whole supply chain.
- **Sustainability Considerations:** A key component of contemporary supply chain optimization is sustainability. This entails cutting waste, implementing eco-friendly practices, and minimizing the negative effects of supply chain operations on the environment.
- **Collaborative Planning:** For optimization, cooperation and communication between supply chain participants are essential. Information sharing is facilitated by collaborative planning platforms and tools, which assist all stakeholders in coordinating their efforts with the overall objectives of the supply chain.
- **Continuous Improvement:** Monitoring, analysis, and improvement are all part of the continuous process that is supply chain optimization. Organizations can pinpoint areas for improvement by routinely evaluating key performance indicators and performance metrics.

Organizations may improve their supply chain optimization and become more resilient, efficient, and responsive by taking a comprehensive and integrated strategy. This is especially important in the fast-paced business climate of today, when supply chain strategies must be flexible and optimized due to the influence of global markets, shifting consumer expectations, and technology breakthroughs.

8.6 CASE STUDIES IN SMART MANUFACTURING

Smart manufacturing case studies provide insightful examples of how Industry 4.0 technologies are being applied in real-world settings and how they are changing the industry. These studies frequently show how businesses use cutting-edge technologies to transform their industrial processes, including robotics, AI, machine learning, and the IIoT. They demonstrate the use of smart devices to build intelligent and networked industrial ecosystems, the integration of sensors for real-time data collecting, and predictive analytics for preventive maintenance. Case studies also show how smart manufacturing increases overall operating efficiency, decreases downtime, maximizes resource utilization, and promotes agility. These real-world examples offer insightful information to other businesses considering Industry 4.0, providing concrete proof of the advantages and difficulties related to the implementation of smart manufacturing practices.

8.6.1 CASE STUDY 1: FUZZY LOGIC IN PREDICTIVE MAINTENANCE

In a case study that shows how fuzzy logic is used in predictive maintenance, a manufacturing facility wanted to increase the production machinery's dependability and efficiency. Reactive maintenance and unscheduled downtime presented difficulties for the business, which raised operating expenses [16]. To solve these problems, the development of a fuzzy logic predictive maintenance system was started.

Numerous sensors were integrated into the predictive maintenance system to track vital indicators including vibration, temperature, and equipment performance in real time. The sensor data was analyzed using fuzzy logic, which took into consideration the uncertainty and imprecision present in the equipment circumstances. Based on past data and expert knowledge, fuzzy rules were developed to evaluate the machinery's health as shown in Figure 8.7.

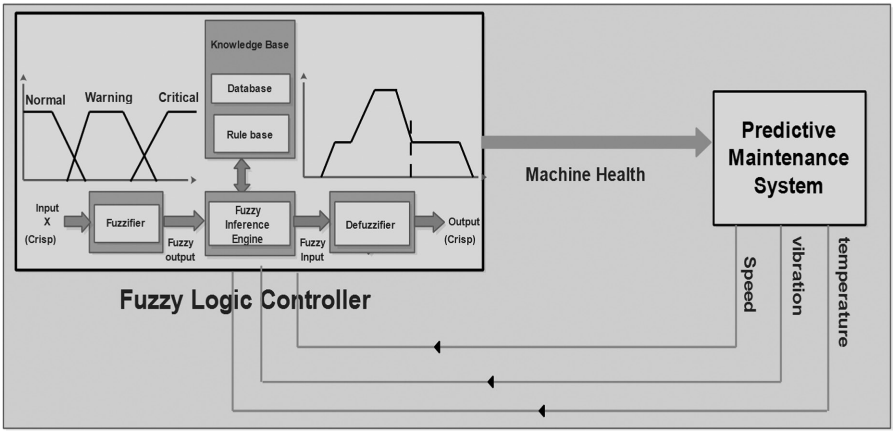

FIGURE 8.7 Concept of the utilization of fuzzy logic in predictive maintenance of machinery. ⏎

For example, different equipment conditions were described using linguistic variables like "normal," "warning," and "critical." These linguistic factors were taken into account by FISs, which combined them to predict the probability of an upcoming failure. Comparing this complex evaluation to conventional binary procedures, a more accurate forecast was possible.

Because of this, the fuzzy logic predictive maintenance system could spot minute changes in the behavior of the machinery and provide early alerts for possible problems. Because fuzzy logic is adaptable, the system was able to modify its analysis in response to changing circumstances, resulting in a more precise and context-aware forecast of maintenance requirements.

Because maintenance tasks could be proactively scheduled during scheduled downtimes, the installation led to a significant decrease in unscheduled downtime. This decreased overall maintenance costs, prolonged the equipment's lifespan, and minimized production disruptions. The predictive maintenance system using fuzzy logic exhibited its efficacy in managing the intricacy and fluctuations of actual industrial settings, highlighting the pragmatic advantages of fuzzy logic in enhancing equipment dependability and refining maintenance approaches.

8.6.2 CASE STUDY 2: ADAPTIVE PRODUCTION CONTROL WITH FUZZY LOGIC

A manufacturing facility sought to improve its production processes by implementing a system that could dynamically adapt to changing conditions and optimize production in real time, as demonstrated in a case study showcasing the use of fuzzy logic in adaptive production control. Enhancing productivity, cutting lead times, and accounting for changes in demand and resource availability were the objectives [16].

Fuzzy logic was used by the adaptive production control system to manage the complexity and inherent uncertainties of the manufacturing environment. Based on historical data and expert knowledge, fuzzy rules were developed to define correlations between desired production outputs and input variables including machine speeds, production rates, and inventory levels.

To illustrate, terms such as "high," "medium," and "low" were employed to characterize the rates of production and the consumption of resources. These linguistic factors were integrated by fuzzy inference methods to help them decide how to change production parameters like machine speeds or the order in which to complete specific tasks.

The industrial machinery's embedded sensors provide real-time data to the system, which utilized fuzzy logic as shown in Figure 8.8 to dynamically modify production schedules. The production plan might be quickly and intelligently adjusted by the fuzzy logic adaptive control system to maximize throughput and resource utilization, for instance, if demand unexpectedly surged or a machine temporarily slowed down.

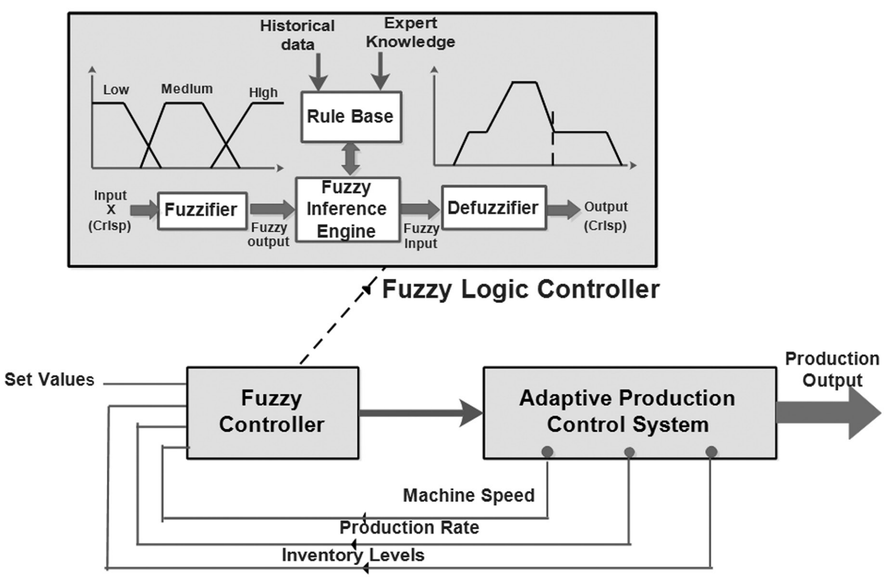

FIGURE 8.8 Enhancement of productivity in adaptive production control system using FLC.
⏎

Significant gains in responsiveness, flexibility, and production efficiency were shown in the case study. The adaptive production control system, which utilized fuzzy logic, successfully mitigated the effects of unanticipated disruptions, minimized idle hours, and optimized resource allocation. Because of its flexibility, the manufacturing plant was able to respond more quickly to changing production needs, which improved overall operational efficiency.

Fuzzy logic was successfully incorporated into adaptive production control, demonstrating this method's capacity to offer a clever and adaptable response to the dynamic character of contemporary manufacturing environments. The case study demonstrated how fuzzy logic-based control systems can help realize manufacturing processes that are both Industry 4.0 compliant and flexible.

8.6.3 CASE STUDY 3: QUALITY ASSURANCE IN SMART MANUFACTURING

In an Industry 4.0 case study showcasing smart manufacturing's incorporation of quality assurance, an innovative automotive manufacturing facility aimed to improve its production processes through the application of state-of-the-art technologies [17]. Enhancing product quality, lowering faults, and guaranteeing a more streamlined and effective production line were the main goals.

Using AI, computer vision, and machine learning, among other technologies, the smart manufacturing solution integrated sophisticated quality assurance methods. This system allows for the strategic placement of sensors throughout the manufacturing line to gather data in real time on a variety of quality characteristics, such as assembly precision, surface finish, and dimensions.

One important part of the quality assurance system that was used to address the inherent imprecision and unpredictability of manufacturing processes was fuzzy logic. Fuzzy rules that established correlations between input variables (sensor data) and intended quality outcomes were developed using expert knowledge and historical data.

To describe the quality of particular components, for example, linguistic variables such as "acceptable," "borderline," and "defective" were employed. The sensor data was processed by fuzzy inference algorithms, which then calculated the level of quality standard conformance as shown in Figure 8.9. An assessment of product quality that was more precise and contextually aware was made possible by this nuanced review.

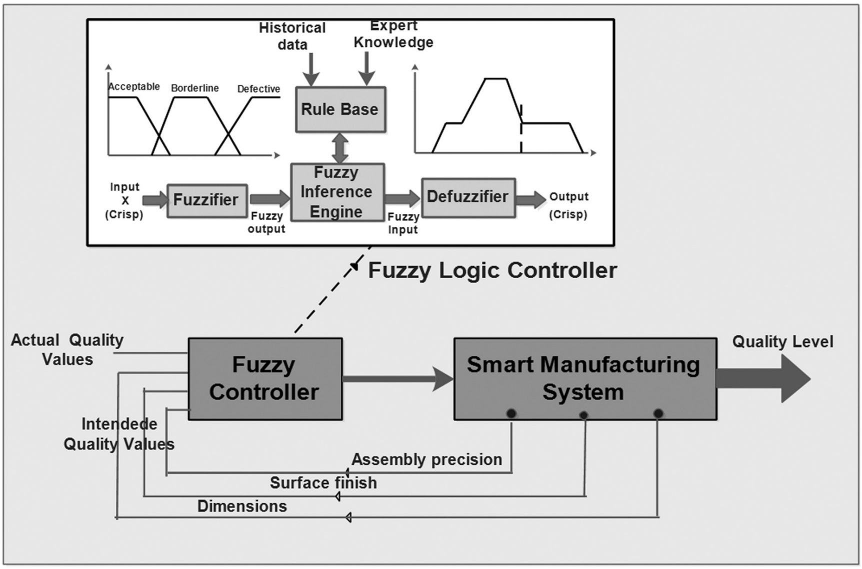

FIGURE 8.9 Quality assurance in smart manufacturing using FLC. ⏎

The quality assurance system's ability to adapt allowed it to change in response to changes in the production environment. For instance, if a sensor finds a difference between the intended and actual quality requirements, the fuzzy logic system may make real-time modifications to the production process to address the problem.

The implementation resulted in a significant reduction in defects, improved overall product quality, and minimized the need for postproduction inspections. The smart manufacturing quality assurance system not only enhanced the reliability of the manufacturing process but also contributed to cost savings by reducing rework and waste.

This case study demonstrated the practical benefits of integrating fuzzy logic and smart technologies into quality assurance processes. It showcased how a holistic approach to quality control, combining real-time data analytics, adaptive decision-making, and fuzzy logic, can revolutionize manufacturing practices, aligning with the goals of Industry 4.0.

8.7 CHALLENGES AND CONSIDERATIONS

Smart manufacturing, while promising enhanced efficiency and innovation, confronts a spectrum of challenges that demand thoughtful consideration.

Interoperability issues stemming from diverse technologies, data security concerns, and privacy considerations necessitate robust strategies [18]. Bridging skill gaps and training a workforce adept in data analytics and automation is pivotal, as is addressing the substantial upfront costs associated with deploying smart technologies. Integrating legacy systems and establishing standardized frameworks for seamless collaboration pose additional hurdles. Efficient data management, change management strategies to navigate organizational shifts, and ensuring the reliability and resilience of digital systems are critical considerations. Regulatory compliance within evolving frameworks adds complexity to the implementation process. Navigating these challenges requires a holistic and adaptive approach, emphasizing the importance of investing in both technology and human capital to unlock the full potential of smart manufacturing.

8.7.1 SCALABILITY AND REAL-TIME PERFORMANCE

Scalability and real-time performance are critical considerations in the realm of smart manufacturing, reflecting the ability of systems to handle increasing workloads and deliver timely responses. A smart manufacturing infrastructure must be scalable in order to adapt to changes in demand or the addition of new equipment and procedures. This flexibility is necessary to meet the changing demands of a production setting. Conversely, real-time performance is essential to guarantee minimal delay in data processing and decision-making, enabling prompt responses to changing conditions on the factory floor. Real-time performance and scalability go hand in hand because a scalable system needs to continue operating at peak efficiency even as it expands. Utilizing cutting-edge technology like edge computing, which processes data closer to the source to minimize latency and improve real-time capabilities, is necessary to achieve this balance [19]. Establishing resilient communication networks, data analytics platforms, and flexible control systems helps smart manufacturing achieve the scalability and real-time performance required in the Industry 4.0 environment.

8.7.2 DATA INTEGRATION AND INTEROPERABILITY

Fundamental concepts of smart manufacturing, data integration, and interoperability are necessary to build an effective ecosystem inside the Industry 4.0 framework. Throughout the manufacturing process, data integration refers to the smooth transfer and aggregation of information from many sources. This comprises information produced by devices such as machines, sensors, and enterprise resource planning systems, among other things. Conversely, interoperability makes sure that these different systems can coexist peacefully by following common guidelines and conventions.

A comprehensive understanding of the production process is made possible by efficient data integration in smart manufacturing, which makes it easier to monitor, analyze, and make decisions in real time. Process optimization in general, quality assurance, and predictive maintenance can all benefit from this integrated data. However, due to the variety of devices, protocols, and standards, ensuring smooth interoperability is frequently difficult.

Organizations use data-sharing formats like MQTT, communication standards like OPC UA, and IIoT protocols to overcome these issues. These standards give systems and devices a common language, guaranteeing compatibility and promoting easy data sharing.

Moreover, by processing data closer to the source, lowering latency, and facilitating faster replies, edge computing significantly improves data integration and interoperability. By enabling centralized platforms for data sharing and communication between heterogeneous systems, cloud-based solutions also aid with interoperability.

Strategic planning, investment in compatible technology, and cooperation with industry partners are necessary for the successful implementation of data integration and interoperability in smart manufacturing. By establishing standardized communication protocols and adopting technologies that support seamless data exchange, manufacturers can unlock the full potential of smart manufacturing, driving efficiency, innovation, and agility in their operations.

8.7.3 SECURITY AND PRIVACY CONCERNS

Security and privacy concerns are paramount considerations in the implementation of smart manufacturing, as the increased connectivity and data exchange introduce new vulnerabilities and risks [20]. Several key challenges in this regard include:

- **Cybersecurity Threats:** The interconnected nature of smart manufacturing systems makes them susceptible to cyber threats such as hacking, malware, and ransomware attacks. Securing industrial control systems and preventing unauthorized access to critical infrastructure are critical priorities.

- **Data Integrity and Confidentiality:** Ensuring the integrity and confidentiality of sensitive data is crucial. Unauthorized access or tampering with production data, intellectual property, or trade secrets can have severe consequences.
- **Supply Chain Risks:** Smart manufacturing often involves global supply chains, introducing security risks at various points. Securing the digital supply chain, from design to production, is essential to prevent compromises or counterfeiting.
- **Interoperability Challenges:** Integrating diverse technologies and systems may lead to interoperability challenges, potentially creating security gaps. Ensuring that all components adhere to robust security standards is essential to prevent vulnerabilities.
- **Employee Awareness and Training:** Human factors play a significant role in security. Insufficient awareness and training among employees can lead to unintentional security breaches. Educating the workforce about cybersecurity best practices is crucial.
- **Regulatory Compliance:** Compliance with data protection and privacy regulations is a complex challenge, particularly in regions with stringent laws. Navigating diverse regulatory landscapes while maintaining operational efficiency requires careful attention.
- **Legacy System Vulnerabilities:** Many manufacturing facilities still operate with legacy systems that may lack modern security features. Retrofitting or securing these systems is crucial to prevent exploitation of vulnerabilities.
- **Physical Security:** Protecting the physical infrastructure, including machinery and data storage facilities, is vital. Unauthorized physical access to critical components can compromise the entire manufacturing process.
- **Data Ownership and Sharing:** Establishing clear policies regarding data ownership and sharing is essential. Balancing the need for collaboration with the protection of proprietary information is crucial for smart manufacturing ecosystems.
- **Continuous Monitoring and Incident Response:** Implementing continuous monitoring and incident response mechanisms is vital for identifying and mitigating security threats promptly. Timely response to security incidents minimizes the potential impact on operations.

Addressing these security and privacy concerns requires a comprehensive cybersecurity strategy. This includes regular risk assessments, the implementation of robust encryption protocols, continuous employee training, and collaboration with cybersecurity experts. Manufacturers must stay vigilant, adapt to evolving threats, and prioritize security to fully realize the benefits of smart manufacturing while safeguarding their operations and sensitive information.

8.8 FUTURE TRENDS IN FUZZY LOGIC AND IIOT

The future trends in the integration of fuzzy logic and the IIoT promise to redefine decision-making processes and enhance operational efficiency across industrial landscapes. Fuzzy logic, with its ability to handle uncertainty and imprecision, is poised to play a pivotal role in optimizing IIoT applications. Advanced fuzzy logic systems will evolve to incorporate more sophisticated machine learning algorithms, enabling adaptive decision-making in dynamic manufacturing environments. The synergy between fuzzy logic and IIoT will extend beyond predictive maintenance and quality control, encompassing broader aspects of production, supply chain management, and human–machine interactions. The utilization of edge computing in conjunction with fuzzy logic will facilitate real-time analysis and decision-making at the source, reducing latency and enhancing responsiveness. Additionally, the future holds a shift toward more explainable AI, where fuzzy logic's inherently interpretable nature will contribute to building trust in autonomous decision-making systems [21]. As industries embrace the next wave of industrial transformation, the integration of fuzzy logic and IIoT is poised to unlock new dimensions of intelligence, adaptability, and resilience in smart manufacturing ecosystems.

8.8.1 EDGE COMPUTING AND DECENTRALIZED CONTROL

Edge computing and decentralized control are pivotal trends shaping the future of smart manufacturing, particularly in the context of Industry 4.0. Edge computing involves processing data closer to the source of generation, reducing latency, and enabling real-time analysis. In smart manufacturing, this means that data from sensors, devices, and machines can be processed at the edge of the network, allowing for quicker decision-making and more efficient use of resources [22]. Decentralized control, on the other hand, distributes decision-making authority across various components within the manufacturing system, enabling devices to make autonomous decisions based on local information.

The synergy between edge computing and decentralized control is transformative for smart manufacturing. By leveraging edge computing, the massive amounts of data generated in real time can be processed locally, reducing the need to transmit large volumes of data to centralized cloud servers. This not only minimizes network congestion but also enhances the system's responsiveness. Decentralized control complements edge computing by allowing devices and sensors to make independent decisions based on local data, fostering agility and adaptability in the manufacturing process.

Together, these trends enhance the efficiency, reliability, and scalability of smart manufacturing systems. They contribute to a more robust and resilient manufacturing ecosystem by reducing dependence on centralized processing, improving real-time decision-making, and facilitating the rapid deployment of adaptive and autonomous manufacturing processes. As Industry 4.0 continues to evolve, the integration of edge computing and decentralized control stands out as a key enabler for the future of smart manufacturing.

8.8.2 MACHINE LEARNING-FUZZY LOGIC HYBRID APPROACHES

The fusion of machine learning and fuzzy logic represents a cutting-edge approach to smart manufacturing, offering a powerful hybrid paradigm that combines the strengths of both methodologies. Machine learning excels in pattern recognition, data analytics, and complex modeling, while fuzzy logic provides a framework for handling imprecise and uncertain information through linguistic variables and rule-based reasoning [23]. In smart manufacturing, this hybridization manifests in several key applications:

- **Predictive Maintenance:** Machine learning models can analyze historical data to predict equipment failures, while fuzzy logic can interpret these predictions and make decisions based on the degree of certainty, allowing for more nuanced maintenance planning.
- **Quality Control:** Machine learning algorithms can learn from vast datasets to identify patterns associated with high-quality products, and fuzzy logic can then assess the quality of current products, considering imprecise factors and uncertainties in the manufacturing process.
- **Optimization of Processes:** Hybrid approaches can optimize manufacturing processes by leveraging machine learning to identify patterns in data and fuzzy logic to adaptively adjust control parameters based on real-time conditions, ensuring efficiency and quality.

- **Supply Chain Management:** Machine learning can analyze data to predict demand and optimize inventory levels, while fuzzy logic can handle uncertainties in supply chain variables, enabling adaptive decision-making in dynamic environments.
- **Energy Management:** Hybrid approaches can optimize energy consumption by using machine learning to identify energy-efficient patterns and fuzzy logic to adapt energy usage in response to varying production demands and environmental factors.
- **Human–Machine Interaction:** Machine learning models can be trained to understand human behavior and preferences, while fuzzy logic can interpret linguistic variables related to user satisfaction, leading to more intuitive and adaptive human–machine interfaces.

The integration of machine learning and fuzzy logic offers a synergistic solution that addresses the challenges of uncertainty and complexity in smart manufacturing. This hybrid approach leverages the learning capabilities of machine learning alongside the interpretability and rule-based reasoning of fuzzy logic, resulting in more robust, adaptive, and context-aware systems that contribute to the advancement of Industry 4.0.

8.8.3 INDUSTRY 4.0 AND THE FUTURE OF SMART MANUFACTURING

Industry 4.0 [24] signifies a paradigm shift in the manufacturing landscape, ushering in the era of smart manufacturing characterized by integrating digital technologies, automation, and data-driven decision-making [25]. Several transformative trends mark the future of smart manufacturing within the context of Industry 4.0:

- **Interconnectivity:** Industry 4.0 envisions a highly interconnected ecosystem where machines, devices, and systems communicate seamlessly. The IIoT facilitates real-time data exchange, enabling a holistic view of the entire production process.
- **Data Analytics and AI:** The future of smart manufacturing depends seriously on advanced data analytics and AI. Machine learning algorithms analyze large datasets to extract insights, improve processes, and permit predictive maintenance, contributing to improved efficiency and reduced downtime.
- **Edge Computing:** Edge computing is developing as an important enabler in smart manufacturing. Processing data closer to the source, at

the edge of the network, decreases latency, improves real-time decision-making, and enhances the burden on centralized cloud systems.

- **Digital Twins:** Digital twins, virtual duplications of physical assets and processes, play a vital role in smart manufacturing. They enable simulation, monitoring, and optimization of production processes, permitting proactive adjustments, and minimizing risks.
- **Decentralized Decision-Making:** Decentralized control mechanisms allow individual devices and components to make autonomous decisions based on local data, raising agility, adaptability, and flexibility in the face of dynamic manufacturing environments.
- **Cyber-Physical Systems:** Cyber-physical systems incorporate computational intelligence with physical processes, making intelligent, self-monitoring systems. This integration increases the ability to sense, adapt, and react to changes in real time.
- **Customization and Flexibility:** Smart manufacturing embraces customization and flexibility, allowing for the efficient production of smaller batches and even individualized products. This shift from mass production to more flexible and adaptive manufacturing aligns with changing consumer demands.
- **Sustainability and Energy Efficiency:** The future of smart manufacturing emphasizes sustainability and energy efficiency. Technologies such as smart grids, renewable energy integration, and resource optimization contribute to eco-friendly and cost-effective production.
- **Human–Machine Collaboration:** Collaborative robots, augmented reality interfaces, and intuitive human–machine interactions are integral to the future of smart manufacturing. Workers and machines collaborate synergistically, with automation handling routine tasks, and humans contributing creativity and problem-solving skills.
- **Security and Resilience:** With increased connectivity comes a heightened focus on cybersecurity. Future smart manufacturing systems prioritize robust security measures to safeguard against cyber threats, ensuring the resilience of critical industrial infrastructure.

As Industry 4.0 continues to evolve, the future of smart manufacturing is characterized by an increasingly interconnected, intelligent, and adaptive industrial ecosystem. Embracing these technological trends not only enhances operational efficiency but also positions manufacturing enterprises to thrive in the era of digital transformation.

8.9 CONCLUSION

In conclusion, the integration of fuzzy logic in IIoT for smart manufacturing represents a paradigm shift toward more intelligent, adaptive, and efficient industrial processes. Fuzzy logic's ability to handle uncertainties, imprecise data, and complex decision-making complements the dynamic and interconnected nature of the IIoT. Through real-time data analysis, predictive maintenance, and decision support, fuzzy logic contributes to optimizing manufacturing operations, reducing downtime, and enhancing overall productivity. The synergy between fuzzy logic and IIoT enables a nuanced understanding of manufacturing variables, fostering adaptive responses to changing conditions. Fuzzy logic integration is becoming increasingly important as smart manufacturing develops within the larger context of Industry 4.0 to handle the problems of unpredictability and variability in industrial settings. This combination of technologies creates the groundwork for manufacturing environments that are more robust, flexible, and intelligent in addition to improving operational efficiency. The significance of fuzzy logic in IIoT for navigating the details of contemporary industrial processes is validated by its place in the ever-changing field of smart manufacturing.

8.9.1 RECAP OF KEY INSIGHTS

In recap, the integration of fuzzy logic in IIoT for smart manufacturing brings forth key insights that shape the landscape of modern industrial processes:

- **Handling Uncertainty:** The power of fuzzy logic resides in its capacity to deal with ambiguity and inaccurate data. Fuzzy logic offers a strong framework for decision-making in an uncertain manufacturing environment, where variables cannot have exact values.
- **Real-time Decision Support:** Real-time data analysis and decision support are made possible by the combination of IIoT with fuzzy logic. This gives industrial systems the ability to adjust and decide intelligently in response to the constantly changing conditions on the factory floor.
- **Predictive Maintenance:** A key component of predictive maintenance techniques is fuzzy logic. Fuzzy logic models can forecast equipment failures and suggest preventive maintenance actions by evaluating both previous and current data. This minimizes downtime and maximizes operational efficiency.

- **Adaptive Manufacturing:** The combination of IIoT with fuzzy logic enhances manufacturing processes' adaptability. Rule-based reasoning in fuzzy logic enables adaptive reactions to shifting circumstances, guaranteeing that industrial systems can dynamically adapt to unanticipated events.
- **Nuanced Decision-making:** By adding linguistic factors and rule-based reasoning, fuzzy logic adds a degree of nuance to decision-making. More complicated and context-aware responses to the many and varied aspects influencing manufacturing are made possible by this nuanced approach.
- **Integration Challenges:** Fuzzy logic has many advantages, but there are drawbacks as well. These include issues with standardization, interoperability, and the requirement for qualified personnel. Unlocking the full potential of fuzzy logic in smart manufacturing requires overcoming these obstacles.
- **Future Trends:** Future directions for fuzzy logic and IIoT include continuing development of adaptive decision-making systems, edge computing, and decentralized control. These developments highlight the need for localized and more effective data processing to improve real-time performance and lower latency.
- **Industry 4.0 Transformation:** IIoT's use of fuzzy logic is consistent with Industry 4.0's more general revolution. In order to develop more intelligent and connected manufacturing ecosystems, this transformation places a strong emphasis on connectivity, data-driven insights, and the convergence of digital technologies.

Fuzzy logic adoption in IIoT for smart manufacturing is essentially a proactive strategy to deal with the uncertainties and complexity prevalent in contemporary industrial processes. It is evidence of the continuous evolution toward greater adaptability, effectiveness, and resilience.

8.9.2 IMPLICATIONS FOR THE FUTURE OF MANUFACTURING

The integration of fuzzy logic in IIoT for smart manufacturing holds profound implications for the future of the manufacturing industry. These implications encompass technological advancements, operational enhancements, and strategic considerations:

- **Increased Efficiency and Productivity:** Fuzzy logic's ability to make nuanced decisions based on imprecise data contributes to increased operational efficiency. This leads to optimized production processes, reduced downtime, and enhanced overall productivity.

- **Predictive and Proactive Maintenance:** The use of fuzzy logic in predictive maintenance enables manufacturing facilities to shift from reactive to proactive maintenance strategies. By predicting equipment failures, organizations can schedule maintenance activities in advance, minimizing disruptions and extending the lifespan of machinery.
- **Adaptive and Agile Manufacturing:** Fuzzy logic's adaptive decision-making capabilities, especially when integrated with IIoT, foster agile manufacturing processes. The ability to respond in real time to changing conditions ensures that manufacturing systems remain flexible and responsive to market demands and unforeseen disruptions.
- **Quality Improvement and Defect Reduction:** The application of fuzzy logic in quality control leads to better product quality by taking imprecise factors in the manufacturing process. This results in a reduction of defects and enhances the consistency and reliability of the end products.
- **Human–Machine Collaboration and User-Friendly Interfaces:** Fuzzy logic contributes to the development of more intuitive human–machine interfaces. This enables collaborative work environments where workers can interact effortlessly with smart manufacturing systems, enhancing the strengths of both human intuition and machine precision.
- **Resource Optimization and Sustainability:** The application of fuzzy logic to process optimization encompasses resource management, hence promoting sustainable industrial practices. Organizations can lower waste and energy consumption by dynamically modifying resource usage based on current conditions.
- **Technological Synergy and Industry 4.0 Integration:** Fuzzy logic and IIoT together are a natural fit for Industry 4.0, which is based on the idea that production may become intelligent, networked systems through the convergence of digital technologies. An industrial ecosystem that is more comprehensive and integrated is made possible by this integration.
- **Challenges in Implementation and Skill Development:** There are additional difficulties associated with the use of fuzzy logic in production, such as the requirement for standardization, interoperability, and

skill development. In order for companies to completely profit from fuzzy logic in smart manufacturing, these issues must be resolved.

The future of manufacturing will essentially be affected by a move toward more intelligent, data-driven, and adaptable systems. A key component of accomplishing these objectives is the integration of fuzzy logic with IIoT, which supports the continued development of the manufacturing sector in the age of digital transformation.

8.9.3 FINAL THOUGHTS ON THE ROLE OF FUZZY LOGIC IN IIOT FOR SMART MANUFACTURING

In summary, fuzzy logic plays a critical and revolutionary role in IIoT for smart manufacturing. Fuzzy logic offers a comprehensive framework for decision-making in dynamic situations, acting as a fulcrum in resolving the complexities and uncertainties inherent in contemporary industrial processes. Its capacity to process imprecise data, decipher linguistic nuances; and provide nuanced answers paves the way for intelligent and adaptable production systems.

Manufacturing processes become more than merely automated when fuzzy logic and IIoT are combined; they become responsive, nimble, and able to make context-aware decisions instantly. New heights of efficiency and efficacy are reached via predictive maintenance, quality control, and adaptive manufacturing, which boost output and save operating expenses.

The ramifications for the future are extensive, as they promise improved operational excellence as well as the advancement of resource-efficient and sustainable manufacturing techniques. The manufacturing environment is being significantly shaped by Industry 4.0, and one major facilitator of this transformation is the interplay between fuzzy logic and IIoT, which creates an ecosystem in which humans, machines, and processes work together harmoniously.

However, challenges such as interoperability and the need for skilled professionals underscore the importance of strategic planning and ongoing innovation. Overcoming these challenges will be instrumental in unlocking the full potential of fuzzy logic in smart manufacturing, propelling the industry toward a future characterized by resilience, adaptability, and intelligence. In this era of digital transformation, the role of fuzzy logic in IIoT stands as a testament to its significance in navigating the complexities of the manufacturing landscape and steering it toward a more efficient and intelligent future.

KEYWORDS

- **Fuzzy logic**
- **Industrial Internet of Things**
- **smart manufacturing**
- **decision-making**
- **adaptive control**

REFERENCES

1. Grace, J., Mahmoud, M. A., Mahdi, M. N., & Mostafa, S. A. (2022). An evaluation model of smart manufacturing system configurations prior to implementation using fuzzy logic. *Applied Science*, *12*(5), 2753.
2. Wang, B., Tao, F., Fang, X., Liu, C., Liu, Y., & Freiheit, T. (2021). Smart manufacturing and intelligent manufacturing: A comparative review. *Engineering*, 7(6), 738–757.
3. Hamdia, S. E., Oudania, M., Abouabdellahb, A., & Sebbar, A. (2019). Fuzzy approach for locating sensors in industrial internet of things. *Procedia Computer Science*, *160*, 772–777.
4. Yildizbasi, A., & Unlu, V. (2020). Performance evaluation of SMEs towards industry 4.0 using fuzzy group discussion making methods. *SN Applied Science*, *2*, 355.
5. Caiado, R., Scavarda, L. F., Gaviao, L., Ivson, P., Nascimento, D. L. D. M., & Garza-Reyes, J. A. (2020). A fuzzy rule-based industry 4.0 maturity model for operations and supply chain management. *International Journal of Production Economics*, *231*, 107883.
6. Yang, H., Kumara, S., Bukkapatnam, S. T. S., & Tsung, F. The internet of things for smart manufacturing: A review. *IIE Transactions*, 2019.
7. Mehbodniya, A., Webber, J. L., Rani, R., Ahmad, S. S., Wattar, I., Ali, L., & Nuagah, S. J. (2022). Energy-aware routing protocol with fuzzy logic in industrial internet of things with blockchain technology. In: *Wireless Communications and Mobile Computing*, pp. 1–15.
8. Sobrino, A. (2013). Fuzzy logic and education: Teaching the basics of fuzzy logic through an example (by Way of Cycling). *Education Sciences*, *3*(2), 75–97.
9. Kerimkhulle, S., Dildebayeva, Z., Tokhmetov, A., Amirova, A., Tussupov, J., Makhazhanova, U., Adalbek, A., Taberkhan, R., Zakirova, A., & Salykbayeva, A. (2023). Fuzzy logic and its application in the assessment of information security risk of industrial internet of things. *Symmetry*, 15(10).
10. Tashtoush, T., Alazzam, A., & Rodan, A. (2020). Utilizing fuzzy logic controller in manufacturing facilities design: Machine and operator allocation. *Cogent Engineering*, *7*(1), 1–16.
11. Mitrofani, I. A., Emiris, D. M., & Koulouiotis, D. E. (2020). An industrial maintenance decision support system based on fuzzy inference to optimize scope definition. *Procedia Manufacturing*, *51*, 1538–1543.

12. Moreno-Cabezali, B. M., & Fernandez-Crehuet, J. M. Application of a fuzzy-logic based model for risk assessment in additive manufacturing R&D projects. *Computer & Industrial Engineering*, *145*, 2020.
13. Al-Saadi, T., Rossiter, A., & Panoutsos, G. (2022). Fuzzy logic control in metal additive manufacturing: A literature review and case study. *IFAC-PapersOnline*, *55*(21), 37–42.
14. Azadegan, A., Porobic, L., Ghazinoory, S., Samouei, P., & Kheirkhah, A. S. (2011). Fuzzy logic in manufacturing: A review of literature and a specialized application. *International Journal of Production Economics*, *132*, (2), 258–270.
15. Baban, C. F., Baban, M., & Darius, S. M. (2016). Using a fuzzy logic approach for the predictive maintenance of textile machines. *Journal of Intelligent & Fuzzy Systems*, *30*(2), 999–1006.
16. Zou, M., Yi, J., Yang, C., Liao, Q., Xiong, W., & Wang, X. (2022). Adaptive fuzzy logic control for grinding process based on grinding sound trend. *IFAC-PapersOnline*, *55*(21), 120–125.
17. Galindo-Salcedo, M., Pertúz-Morenoa, A., Guzmán-Castillo, S., Gómez-Charrisa, Y., & Romero-Conradoa, A. R. (2022). Smart manufacturing applications for inspection and quality assurance processes. *Procedia Computer Science*, *198*, 536–541.
18. Phuyal, S., Bista, D., & Bista, R. (2020). Challenges, opportunities and future directions of smart manufacturing: A state of art review. *Sustainable Futures*, *2*, 100023.
19. Narwane, V. S., Raut, R. D., Gardas, B. B., Narkhede, B. E., & Awasthi, A. (2022). Examining smart manufacturing challenges in the context of micro, small and medium enterprises. *International Journal of Computer Integrated Manufacturing*, *35*(12), 1395–1412.
20. Tuptuk, N., & Hailes, S. (2018). Security of smart manufacturing systems. *Journal of Manufacturing Systems*, *47*, 93–106.
21. Qu, Y., Ming, X. G., Liu, Z. W., Zhang, X., & Hou, Z. T. (2019). Smart manufacturing systems: State of the art and future trends. *The International Journal of Advanced Manufacturing Technology, 103*(1), 3751–3768.
22. Protner, J., Pipan, M., Zupan, H., Resman, M., Simic, M., & Herakovic, N. (2021). Edge computing and digital twin based smart manufacturing. *IFAC-PapersOnLine*, *54*(1), 831–836.
23. Wang, J., Ma, Y., Zhang, L., Gao, R. X., & Wu, D. (2018). Deep learning for smart manufacturing: Methods and applications. *Journal of Manufacturing Systems*, *48*, 144–156.
24. Vaidya, S., Ambad, P., & Bhosle, S. (2018). Industry 4.0—a glimpse. *Procedia Manufacturing*, *20*, 233–238.
25. Hozdic, E. (2015). Smart factory for industry 4.0: A review. *Journal of Modern Manufacturing Systems and Technology*, *7*(1), 28–35.

CHAPTER 9

Analyzing Financial Efficiency of Indian NIFTY Oil Companies Through Fuzzy GTMA Method

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ABSTRACT

Oil companies are assuming a crucial role in driving socioeconomic development inside a nation. In India, the oil sector has experienced significant growth in recent times. Oil companies have demonstrated remarkable performance in terms of their services and availability. Undoubtedly, the financial performance of an oil company constitutes its primary component. In the current landscape of heightened market competition, the accurate and precise assessment of financial performance

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holds significant significance for an oil company that seeks to effectively sustain its market standing. This research aims to assess the financial performance and provides a ranking of the six NIFTY oil companies listed on August 16, 2023 in the National Stock Exchange (NSE), India, using their financial indicators. The valuations of these six oil companies are conducted based on nine financial indicators, which are then combined to derive a financial performance score utilizing a multicriteria decision-making (MCDM) methodology. In this study, triangular fuzzy number (TFN) and the fuzzy graph theory and matrix approach (F-GTMA) are utilized to rank the oil companies based on their financial performance. The findings indicate that Reliance exhibits the highest level of financial efficiency, with ONGC and IOC ranking second and third, respectively.

9.1 INTRODUCTION

9.1.1 OIL COMPANIES

India has a significant presence of oil companies that play a crucial role in the country's energy sector. The major players in the Indian oil industry include public-sector enterprises such as:

1. *Bharat Petroleum Corporation Limited (BPCL):* Another significant state-owned oil firm in India is called BPCL. It works on petroleum and petrochemical product exploration, production, refining, and marketing. The government has declared its intention to privatize BPCL, which could result in a substantial alteration to the company's ownership composition.
2. *Hindustan Petroleum Corporation Limited (HPCL):* A major participant in the Indian oil and gas sector is HPCL. It is engaged in several facets of the oil and gas value chain, including as exploration, refining, and marketing, just like Indian Oil Corporation (IOC) and BPCL.
3. *IOC:* IOC, being the biggest oil business in India, engages in the processes of refining, marketing, and distribution of petroleum products. It has a vast network of petrol stations and runs many refineries all over the nation.
4. *Oil India Limited (OIL):* It is one of the top public sector companies in India, working on natural gas and crude oil transportation, production, and exploration. The company, which was founded in 1959, is essential to supplying the nation's energy demands.

5. *Oil and Natural Gas Corporation (ONGC):* The main activities of ONGC are natural gas and oil production and exploration. Although it is not solely an oil firm, its operations provide a substantial contribution to India's energy security.
6. *Reliance Industries Limited:* Even though it is not a conventional state-owned oil business, Mukesh Ambani's Reliance Industries is a major player in the Indian oil and gas industry. It has significantly aided in the growth of India's petrochemical sector and runs one of the biggest refining complexes in the world, the Jamnagar Refinery in Gujarat.

These companies collectively contribute to meeting India's energy needs, ensuring the supply of petroleum products, and driving economic growth. The sector is dynamic, with ongoing developments such as the government's initiatives to promote renewable energy sources and the evolving landscape of private participation in the industry.

9.1.2 OIL COMPANIES SCENARIO IN INDIA

When oil was discovered close to Digboi, Assam, in 1889, the Indian oil industry was born. In Maharashtra and Assam, the natural gas industry got its start in the 1960s. India had reserves of 1339.57 billion cubic meters of natural gas and 594.49 million metric tonnes of crude oil as of March 2018. By 2022, India wants to cut its 82% reliance on oil imports to 67% by utilizing ethanol, renewable energy, and Indigenous exploration. With 205.3 Mt of crude oil imports in 2019, India ranked as the second-largest net importer. Nonetheless, in FY21, domestic output of natural gas decreased by 8.1% and crude oil plummeted by 5.2%. August 2021 saw a 2.3% decline in the production of crude oil and a 20.23% growth in domestic natural gas.

Oil businesses will contribute more to the socioeconomic structure of the Indian economy in 2023. In India, the potential for credit penetration is still very large. By collaborating with fin-techs and launching fresh business models with customized solutions, oil firms have the opportunity to redefine the standard.

In Figure 9.1, it has been shown that the upcoming demand of oil is increasing day by day.

9.1.3 CONTEXT

Conducting research on the financial performance of Indian oil companies is relevant for several reasons:

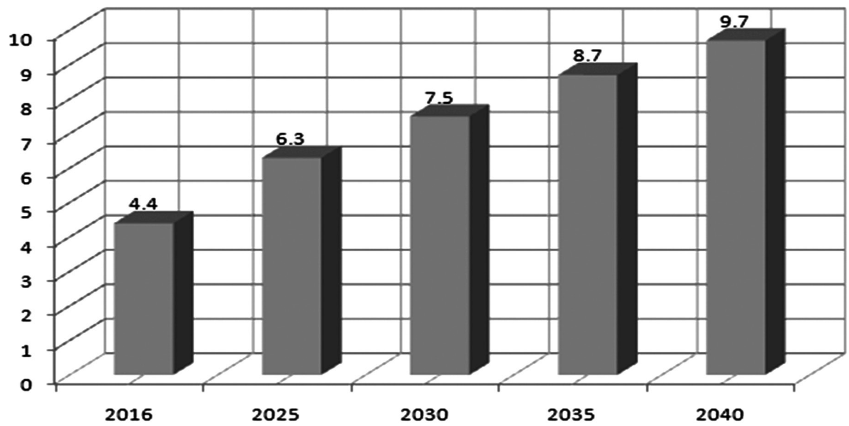

FIGURE 9.1 Demand of oil in India per day. ⏎

1. *Economic impact:* Oil companies play a crucial role in the Indian economy. Researching their financial performance provides insights into their contribution to the GDP, employment generation, and overall economic stability.
2. *Investor decision-making:* Investors, both domestic and international, rely on financial performance metrics to make informed investment decisions. Understanding the financial health of Indian oil companies helps investors assess risks and potential returns.
3. *Policy formulation:* Government policies often depend on the performance of key industries. Research on oil companies' financial metrics can inform policymakers about the industry's challenges and strengths, aiding in the formulation of effective regulations and incentives.
4. *Energy security:* Given the strategic importance of energy security, monitoring the financial performance of oil companies is crucial. It helps assess the country's ability to meet its energy needs and reduces dependency on external sources.
5. *Environmental impact:* The environmental sustainability of oil companies is a growing concern. Studying financial performance allows for an assessment of investments in eco-friendly practices, compliance with environmental regulations, and overall corporate responsibility.

So research on the financial performance of Indian oil companies is relevant for making informed decisions, shaping policies, ensuring energy security, addressing environmental concerns, and promoting overall economic development.

9.1.4 FINANCIAL INDICATORS

Because financial indicators offer important information about a company's overall performance, operational efficacy, and financial health, they are essential for assessing a company's financial efficiency. These indicators assist stakeholders in making defensible decisions by providing a quantitative means of evaluating several facets of a business's financial management. Because of performance evaluation, comparative analysis, identifying strengths and weaknesses, risk assessment, resource allocation, investor confidence, operational efficiency, decision-making, regulatory compliance, and continuous improvement, financial indicators are crucial for gauging a company's financial efficiency.

Therefore, financial indicators provide a systematic and quantifiable way to assess a company's financial efficiency, enabling stakeholders to make informed decisions, manage risks, allocate resources effectively, and drive continuous improvement in financial performance.

9.1.5 MULTICRITERIA DECISION-MAKING (MCDM)

A methodical process called MCDM is applied when several criteria or considerations must be taken into account at the same time. Making decisions in real-world scenarios sometimes requires weighing a number of criteria against one another rather than relying solely on one. A systematic framework for analyzing, assessing, and ranking various options according to how well they perform in light of these numerous criteria is offered by MCDM techniques. Numerous disciplines, including business, engineering, economics, environmental management, and public policy, frequently employ MCDM techniques. There exist multiple MCDM techniques, each possessing unique benefits and constraints. The Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution are two well-liked MCDM techniques.

9.1.6 JUSTIFICATION OF FUZZY GRAPH THEORY AND MATRIX APPROACH (F-GTMA)

F-GTMA are two decision-making methodologies that extend traditional GTMA techniques to handle uncertainty and imprecision in decision-making problems. Some justifications for using these techniques are uncertainty and fuzziness in decision-making, subjectivity and MCDM, inconsistent and incomplete data, trade-offs and ranking, flexible modeling, complex decision scenarios, project evaluation and selection, risk assessment, sensitivity analysis, and applicability in various fields. In shorts, the justification for using F-GTMA lies in their ability to handle uncertainty, subjective preferences, MCDM, and complex decision scenarios, making them valuable tools for making informed and robust decisions in real-world situations.

9.1.7 BENEFICIARIES

Research on the efficiency measurement of oil companies in India can have several beneficiaries: Regulators and Policymakers, Investors, Oil companies themselves, Academic Community, Financial Analysts and Consultants, Borrowers and Consumers, Economic Analysts and Forecasters, Industry Associations and Trade Groups, General Public, and many more.

9.1.8 NOVELTIES

Fuzzy numbers have been studied by numerous researchers using the MCDM methodologies AHP, TOPSIS, MARCOS, and COPRAS. Under the GTMA MCDM paradigm, hardly any study has been conducted with triangular fuzzy numbers (TFNs). The equations for TFN defuzzification have been created and applied. Additionally defined is the distance measured between two TFNs. To compute the triangular fuzzy weight of factors and sub-factors, formulas have been created. A method for combining the opinions of multiple decision-makers into a single complete value in terms of TFN has been created.

9.1.9 STRUCTURE OF THE STUDY

The rest portion of the paper is set for the following way as presented in Figure 9.2.

9.2 REVIEW OF LITERATURE

After conducting an extensive literature review, this study has noted that numerous research endeavors have been undertaken across diverse fields of finance and other industries, employing a range of MCDM techniques to address MCDM challenges. Various MCDM approaches are available for conducting comparative analyses and establishing rankings. Researchers have adopted different combinations of these methods based on their specific study's requirements to determine the most suitable alternative (Table 9.1).

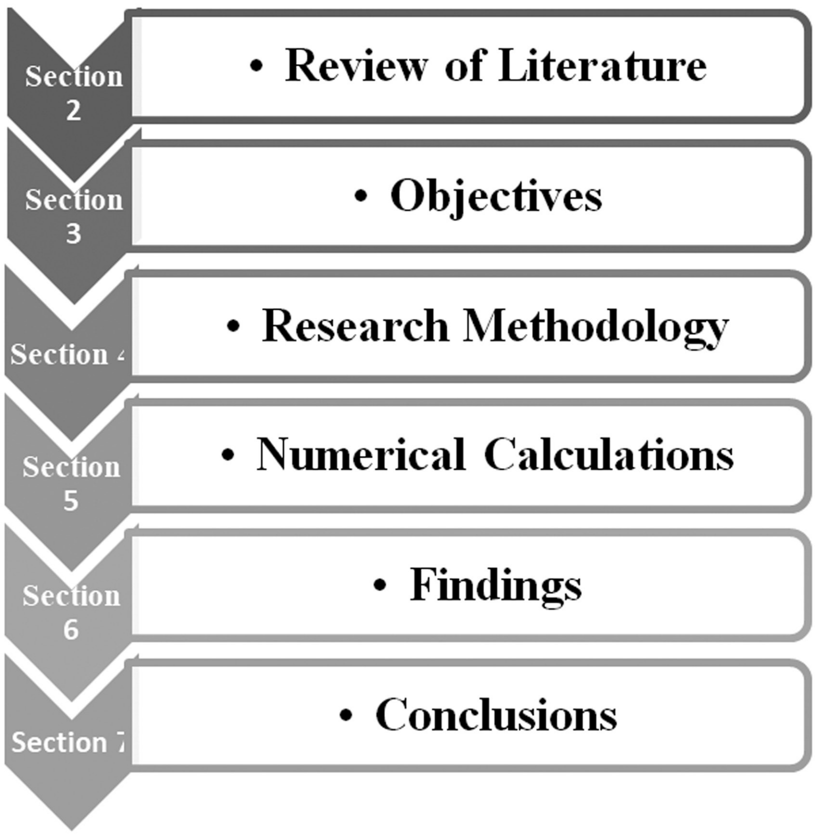

FIGURE 9.2 Structure of the study. ⏎

9.3 OBJECTIVES

The objectives of this study are:

1. To find the financial efficiency score of the NIFTY oil companies in India.
2. To find the ranking of the NIFTY oil companies in India.

TABLE 9.1 An Extensive Review of Literature ⏎

Reference	Authors	Application Area	Methodology Applied
[1]	Xidonas et al. (2009)	Equities selection	ELECTRE Tri
[2]	Gallizo et al. (2002)	Financial ratios analysis	A hierarchical Bayesian model derived from the partial adjustment model.
[3]	Laitinen (2006)	Evaluate Nokia's future potential during the years 1990–2000 using the financial statement approach.	Development procedure, income-generating method, financial progression.
[4]	Wang and Lee (2008)	To find the financial performance of a company	Clustering method
[5]	Ghosh et al. (2021)	Assessing the financial efficiency and effectiveness of life insurance firms operating in India.	DEA & SEM
[6]	Jana and Basu (2021)	To find rank the pharmaceutical companies according to their financial performance	TOPSIS
[7]	Saeed et al. (2018)	Selecting a PET scan device for individuals with cancer.	AHP with GTMA
[8]	Rao et al. (2018)	Examine the impact of various process parameters on the surface roughness (measured by Ra and Rq), tool wear, and cutter vibration during the micro-milling of AISI304 stainless steel.	GTMA Approach
[9]	Mohaghar et al. (2012)	To find the Strategy Ranking	Shannon's Entropy and GTMA
[10]	Geetha et al. (2016)	To find the optimal combination of operating parameters	Graph theory and matrix approach
[11]	Jain and Raj (2015)	To examine the strength or magnitude of factors influencing the flexible manufacturing system (FMS).	Exploratory factor analysis and graph theory and matrix approach
[12]	Andhare et al. (2012)	Examine the instances of malfunctions to pinpoint the essential subsystems in machine tools.	GTMA
[13]	Tuljak-Suban and Bajec (2020)	Selection of logistic provider (3PLP)	ANP & GTMA

TABLE 9.1 *(Continued)*

Reference	Authors	Application Area	Methodology Applied
[14]	Mohaghar et al. (2013)	Supplier selection	Logarithmic Fuzzy Preference Programming and Fuzzy GTMA methods
[15]	Yousufuddin et al. (2022)	Emission of diesel	GTMA
[16]	Baluch (2022)	Water resource	GTMA
[17]	Zhuang et al. (2018)	To select the best paper shredder	AHP–GTMA
[18]	Gul et al. (2021)	Total Knee Replacement (TKR)	GTMA
[19]	MiorAbd Halim et al. (2022)	Proper selection of solid waste	AHPGTMA

9.4 RESEARCH METHODOLOGY

9.4.1 SELECTION OF ALTERNATIVES

This chapter aims to present a proposal for a "MCDM" framework for assessing and comparing the financial performance of six oil companies listed on the National Stock Exchange (NSE) under the NIFTY index as of 16th August, 2023. The evaluation involves assigning a financial performance score and subsequent ranking to these oil companies. In Table 9.2, six oil companies scrip information is provided.

TABLE 9.2 Oil Companies (Alternatives) Scrip Info ⏎

SL. No	Oil Companies	NSE	BSE	ISIN Code[a]
*A*01	BPCL	BPCL	500547	*IN E*029*A*01011
*A*02	HPCL	HINDPETRO	5000104	*IN E*094*A*01015
*A*03	IOC	IOC	530965	*IN E*242*A*01010
*A*04	OIL	OIL	533106	*IN E*274*J*01014
*A*05	ONGC	ONGC	500312	*IN E*213*A*01029
*A*06	Reliance	RELIANCE	500325	*IN E*002*A*01018

[a]An ISIN Code, or International Securities Identification Number, serves as a unique identifier for a particular securities offering. It is assigned by the National Numbering Agency of a given country to distinguish it from other financial instruments within that jurisdiction.

9.4.2 SELECTION OF CRITERIA

The nine financial ratios of six oil companies which have enlisted at NIFTY on 16.08.2023 in NSE have been taken for six financial years, that is, FY 2017–2018, FY 2018–2019, FY 2019–2020, FY 2020–2021, FY 2021–2022, and FY 2022–2023.

1. Sources of data: NSE website.
2. Type of data: Secondary data.
3. Period of study: 6 years (FY 2017–2018 to FY 2022–2023).
4. Technique used: F-GTMA.

Nine financial ratios were analyzed in this study. Among these, seven were identified as Beneficiary criteria, including Quick Ratio, Current Ratio, Return on Capital Employed, Return on Net Worth, Return on Total Assets, Earnings per Share, and Dividend Yield. The remaining two, Debt–Equity Ratio and Price–Earnings Ratio, were considered as nonbeneficiary criteria. In Table 9.3, formulas for financial ratios are outlined and also beneficiary and nonbeneficiary criteria are defined.'

TABLE 9.3 Formula for Financial Ratios (Criteria) ⏎

SL. No.	Ratios	Formula	Criteria
*C*01	Quick Ratio	$\text{Quick Ratio} = \dfrac{\text{Current Assests} - \text{Inventories}}{\text{Current Liabilities}}$	Beneficiary
*C*02	Current Ratio	$\text{Cuurent Ratio} = \dfrac{\text{Current Assests}}{\text{Current Liabilities}}$	Beneficiary
*C*03	Debt-to-Equity Ratio	$\text{Debt to Equity Ratio} = \dfrac{\text{Total Debt}}{\text{Total Shareholders' Equity}}$	Nonbeneficiary
*C*04	Return on Capital Employed	$\text{Return on Capital Employed} = \dfrac{\text{Net Profit}}{\text{Total Capital Employed}}$	Beneficiary
*C*05	Return on Net Worth	$\text{Return on Net Worth} = \dfrac{\text{Net Profit}}{\text{Total Shareholders' Equity}}$	Beneficiary
*C*06	Return on Total Assests	$\text{Return on Total Assests} = \dfrac{\text{Net Profit}}{\text{Total Assets}}$	Beneficiary
*C*07	Earnings Per Share	$\text{Earnings Per Share} = \dfrac{\text{Net Profit}}{\text{Number of Equity Share}}$	Beneficiary
*C*08	Price Earnigs Ratio	$\text{Price Earnigs Ratio} = \dfrac{\text{Market Price Per Share}}{\text{Earnings Per Share}}$	Nonbeneficiary
*C*09	Dividend Yield	$\text{Dividend Yield} = \dfrac{\text{Dividend Per Share}}{\text{Market Price Per Share}}$	Beneficiary

9.4.3 FUZZY SET THEORY

Fuzzy set theory was introduced by Zadeh [20] and it is an extension of the classical crisp logic into a multivariate form.

Definition: *A set* $\check{A}$ *is defined as* $\check{A} = \{(¥, \mu_{\check{A}}(¥)\text{: } ¥ \in \check{A}, \mu_{\check{A}}(¥) \in (0,1)\}$ *where* $\mu_{\check{A}}(¥)$ *represents the membership function of* $\check{A}$

9.4.4 TFN

Definition: *Triangualar Fuzzy Number* $\check{A}_{TFN} = \{(a, b, c), \mu_{\check{A}}(x)\}$ *is defined as Triangualar Fuzzy Number if it satisfies the following properties:*

a. $\mu_{\check{A}}(x)$ *is zero when* $x \leq a$
b. $\mu_{\check{A}}(x)$ *is strictly increasing continous function when* $a < x \leq b$
c. $\mu_{\check{A}}(x)$ *has the maximum value, that is,* 1 *at* $x = b$
d. $\mu_{\check{A}}(x)$ *is strictly decreasing continous function in* $b < x \leq c$
e. $\mu_{\check{A}}(x)$ *is again zero when* $x \geq c$

9.4.5 THE MEMBERSHIP FUNCTION OF A SYMMETRIC AND LINEAR TFN

$$\mu_{\check{A}}(x) = \begin{cases} 0;\ x \leq a \\ \dfrac{x-a}{b-a};\ a < x \leq b \\ 1;\ x = b \\ \dfrac{c-x}{c-b};\ b < x \leq c \\ 0; x \geq c \end{cases} \tag{9.1}$$

9.4.6 GRAPH OF TFN

Figure 9.3 is the representation of the membership function of linear TFN.

In Figure 9.3, TFN diagrammed with $a \leq b \leq c$ where *a, b,* and *c* are all real numbers.

9.4.7 ARITHMETIC OPERATIONS OF TFN

Let E = (e_1, e_2, e_3) and $F = (f_1, f_2, f_3)$ be two different TFN.

1. Addition:

$$(E + F) = (e_1 + f_1, e_2 + f_2, e_3 + f_3) \tag{9.2}$$

2. Subtraction:

$$E - F = (e_1 + f_3, e_2 - f_2, e_3 + f_1) \tag{9.3}$$

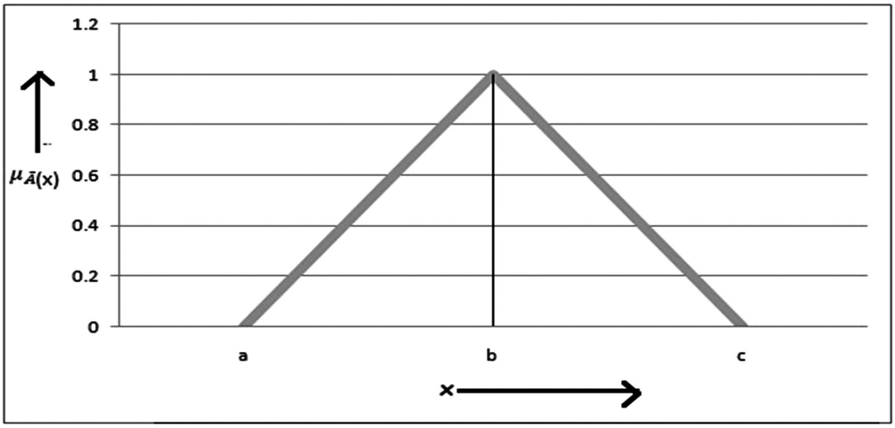

FIGURE 9.3 Membership function of linear TFN. ⏎

3. Multiplication:

$$(E \times F) = (e_1, f_1, e_2 f_2, e_3 f_3) \tag{9.4}$$

4. Scalar Multiplication:

$$\theta E = (\theta e_1, \theta e_2, \theta e_3) \tag{9.5}$$

5. Division:

$$(E/F) = (e_1/f_3, e_2/f_2, e_3/f_1) \tag{9.6}$$

6. Inverse:

$$E^{-1} = \left(\frac{1}{e_3}, \frac{1}{e_2}, \frac{1}{e_1}\right) \tag{9.7}$$

7. Distance measure:

$$d\left(\tilde{E}_d, \tilde{E}_d\right) = \sqrt{\frac{1}{3}\left[(e_1 - f_1)^2 + (e_2 - f_2)^2 + (e_3 - f_3)^2\right]} \tag{9.8}$$

9.4.8 F-GTMA

GTMA stands as a prominent method within the realm of MCDM, addressing decision problems in the presence of multiple criteria. This research introduces a F-GTMA model designed for the ranking of alternatives. Grounded in the broader context of operations research models, this approach employs a logical and systematic foundation.

Rao [21] extensively outlines GTMA in his book, highlighting its methodology and applications. The comprehensive nature of graph theory and its diverse applications is well-documented. Graph and digraph model representations have proven valuable for modeling and analyzing various systems across science and technology fields. The matrix approach emerges as a particularly effective tool for efficiently analyzing graph/digraph models, enabling the derivation of system functions and indices aligned with specific objectives.

The GTMA methodology comprises digraph representation, matrix representation, and permanent function representation. The digraph visually captures variables and their interdependencies, while the matrix transforms this visual representation into a mathematical form [22]. The permanent function, a mathematical representation, plays a crucial role in determining the numerical index associated with the model [23].

The step-by-step explanation of the methodology is as follows:

Step 1: Determining the factors influencing equipment selection involves identifying all the criteria that impact the decision. This can be achieved by referring to pertinent criteria outlined in existing literature or obtaining input from the decision maker.

Step 2: Identify all possible equipment alternatives and evaluate each option.

Step 3: A graphical depiction of criteria and their interdependencies is illustrated through an equipment selection criteria graph. Criteria are defined as factors that impact the choice of an alternative, and the equipment selection criteria digraph visually represents the relationships among these criteria. This digraph contains of a set of nodes $N = \{n_i\}$, with i – 1,2,3,…,M and a set of directed edges $E = \{e_{ij}\}$. A node n_i represents ith alternative selection criterion and edges denote the comparative importance among the criteria. The number of nodes M reflected is equal to the number of alternative selection criteria measured. If a node i has relative importance over another node j in the alternative selection, then a directed edge is drawn from node i to node j (i.e., e_{ij}). If j has relative importance over i directed edge is drawn from node j to node i (e_{ij}) [21].

Step 4: Create a matrix that represents the selection criteria for equipment in a one-to-one relationship, derived from the alternative selection criteria digraph. This matrix is referred to as the equipment selection criteria matrix. This is a M matrix and taking all of the criteria (i.e. A_i) and their relative importance (i.e., a_{ij}). Where A_i is the value of the ith criteria represented by node n_i and a_{ij} is the relative importance of the ith criteria over the jth denoted by the edge e_{ij}. The value of A_i should preferably be gotten from available data. When quantitative values of the criteria are available, normalized values of a criterion allocated to the alternatives are calculated by v_i/v_j, where v_i is the measure of the criterion for the *i*th alternative and v_j is the measure of the criterion for the *j*th alternative which has a higher measure of the criterion among the considered alternatives. This proportion holds true exclusively for beneficial criteria. A beneficial criterion is one in which greater measurements are preferable for the specified purpose. Conversely, a nonbeneficial criterion is one in which lower measurements are favored and the normalized values assigned to the alternatives are calculated by v_i/v_j.

$$\text{CS Matrix} = \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \cdots & \tilde{a}_{1m} \\ \tilde{a}_{21} & \tilde{a}_{22} & & \tilde{a}_{2m} \\ \vdots & & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & \tilde{a}_{mm} \end{bmatrix}$$

Step 5: Deriving an alternative selection criteria function for a matrix involves utilizing the permanent of the matrix as the defined measure. The concept of the permanent matrix, introduced by Cauchy in 1812 during the development of determinant theory, pertains to a specific subset of symmetric functions later coined as permanents by Muir [24]. The permanent matrix is a conventional matrix function utilized in combinatorial mathematics. It is derived similarly to the determinant, but with a distinctive feature—unlike the determinant where negative signs are involved, the permanent replaces these negatives with positive signs in its computation. Understanding the permanent concept enhances the comprehension of selection attributes. Furthermore, employing this approach ensures that no negative signs are present in the expression, preserving all information without loss [21]. The PER (CS) covers terms arranged in (M + 1) groups, and classification involves these groups corresponding to criteria measures and the significance of relative importance loops. The initial group signifies measures of M criteria, with the second group omitted due to the absence of self-loops in the digraph. The third group encompasses 2-criterion relative importance loops and measures of (M-2) criteria. Each term in the fourth group denotes a set of a 3-criterion relative importance loop, or its counterpart, and measures of (M-3) criteria. The fifth group is divided into two sub-groups. The first sub-group comprises sets of two 2-criterion relative importance loops and measures of (M-4) criteria. Meanwhile, each term in the second sub-group represents a set of a 4-attribute relative importance loop, or its pair, and measures of (M-4) criteria. The sixth group contains two sub-groups as well. The terms in the first sub-group are sets of a 3-criterion relative importance loop, or its pair, along with a 2-criterion importance loop and measures of (M-5) criteria. On the other hand, each term in the second sub-group represents a set of a 5-criterion relative importance loop, or its pair, and measures of (M-5) criteria. The remaining terms in the equation follow a similar pattern. Therefore, the comprehensive structure of the CS fully defines the alternative selection evaluation problem, encapsulating all conceivable structural components of criteria and their relative importance. It is worth noting that this equation is essentially the determinant of an M–M matrix, with all terms considered positive.

$$
\begin{aligned}
PER(CS) = {} & \sum_{i=1}^{M} A_i + \sum_{i=1}^{M-1}\sum_{j=i+1}^{M} \cdots\cdots \sum_{M=t+1}^{M} \left(a_{ij}a_{ji}\right) A_k A_l A_m A_n A_o \cdots\cdots A_t A_M \\
& + \sum_{i=1}^{M-2}\sum_{j=i+1}^{M-1}\sum_{k=i+1}^{M} \cdots\cdots \sum_{M=t+1}^{M} \left(a_{ij}a_{jk}a_{ki} + a_{ik}a_{kj}a_{ji}\right) A_l A_m A_n A_o \cdots\cdots A_t A_M \\
& + \sum_{i=1}^{M-3}\sum_{j=i+1}^{M}\sum_{k=i+1}^{M-1}\sum_{l=i+2}^{M} \cdots\cdots \sum_{M=t+1}^{M} \left(a_{ij}a_{jl} + a_{kl}a_{lk}\right) A_m A_n A_o \cdots\cdots A_t A_M \\
& + \sum_{i=1}^{M-3}\sum_{j=i+1}^{M}\sum_{k=i+1}^{M-1}\sum_{l=i+2}^{M} \cdots\cdots \sum_{M=t+1}^{M} \left(a_{ij}a_{jk}a_{kl}a_{li} + a_{il}a_{lk}a_{kj}a_{ji}\right) A_m A_n A_o \cdots\cdots A_t A_M \qquad (9.9)
\end{aligned}
$$

Step 6: Assessing and ranking the alternatives involves assigning positions based on the enduring values previously computed in the preceding stage (Tables 9.4–9.10).

9.5 NUMERICAL CALCULATIONS

TABLE 9.4 Inter Criteria Comparison Matrix ⏎

	C1			C2			C3			.	C9		
	l	**M**	**u**	**l**	**m**	**u**	**l**	**m**	**u**	.	**l**	**m**	**u**
C1	1.00	1.00	1.00	1.00	1.00	1.00	0.73	0.97	0.93	.	0.77	0.94	0.95
C2	0.73	0.97	0.93	1.00	1.00	1.00	0.77	0.94	0.95	.	1.00	1.00	1.00
C3	1.17	1.36	1.75	1.08	1.18	1.50	0.60	0.77	0.87	.	1.08	1.18	1.50
C4	0.60	0.77	0.87	0.77	0.94	0.95	1.00	1.00	1.00	.	0.50	0.65	0.80
C5	1.04	1.08	1.31	1.17	1.36	1.47	1.08	1.18	1.50	.	0.73	0.97	0.93
C6	1.08	1.18	1.50	1.06	1.18	1.45	1.00	1.00	1.00	.	1.17	1.36	1.75
C7	0.77	0.94	0.95	1.08	1.18	1.50	1.36	1.75	1.08	.	0.60	0.77	0.87
C8	0.60	0.77	0.87	0.50	0.65	0.80	0.77	0.87	0.77	.	1.04	1.08	1.31
C9	1.00	1.00	1.00	0.73	0.97	0.93	1.08	1.31	1.17	.	1.08	1.18	1.50

TABLE 9.5 Decision Matrix with Fuzzy GTMA ⏎

	C1			C2			C3			.	C9		
	l	M	u	l	m	u	l	m	u	.	l	m	u
A1	0.28	0.43	0.55	0.25	0.35	0.50	0.62	0.65	0.80	.	1.00	1.00	1.00
A2	0.14	0.25	0.35	0.50	0.50	0.60	0.71	0.81	0.88	.	0.25	0.35	0.50
A3	0.62	0.65	0.80	0.80	0.87	0.90	0.50	0.50	0.60	.	0.73	0.97	0.93
A4	1.00	1.00	1.00	0.62	0.65	0.80	0.14	0.25	0.35	.	0.80	0.87	0.90
A5	0.25	0.35	0.50	0.71	0.81	0.88	0.62	0.65	0.80	.	0.62	0.65	0.80
A6	0.14	0.25	0.35	0.50	0.50	0.60	1.00	1.00	1.00	.	0.71	0.81	0.88

TABLE 9.6 Pair-Wise Comparison Matrix ⏎

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1		0.27	0.11	0.08	0.08	0.06	0.22	0.18	0.19
C2	0.89		0.77	0.19	0.25	0.62	0.77	0.94	0.44
C3	0.93	0.78		0.35	0.74	0.27	0.43	0.67	0.67
C4	0.08	0.06	0.22		0.28	0.72	0.22	0.18	0.08
C5	0.25	0.22	0.18	0.08		0.37	0.77	0.94	0.26
C6	0.74	0.77	0.94	0.26	0.24		0.43	0.67	0.77
C7	0.77	0.43	0.67	0.77	0.78	0.46		0.12	0.38
C8	0.25	0.08	0.06	0.22	0.62	0.77	0.45		0.58
C9	0.74	0.25	0.62	0.77	0.27	0.43	0.11	0.49	

TABLE 9.7 Pair-Wise Comparison Matrix w.r.t. A1 (Lower Bound Fuzzy Decision Matrix) ⏎

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	0.92	0.81	0.59	0.87	0.11	0.08	0.42	0.28	0.38
C2	0.92	0.82	0.61	0.52	0.25	0.19	0.73	0.87	0.81
C3	0.93	0.85	0.66	0.58	0.28	0.42	0.88	0.33	0.54
C4	0.55	0.36	0.42	0.54	0.48	0.65	0.37	0.65	0.54
C5	0.38	0.38	0.73	0.98	0.36	0.28	0.42	0.80	0.11
C6	0.80	0.11	0.08	0.42	0.62	0.37	0.65	0.34	0.69
C7	0.48	0.69	0.27	0.87	0.87	0.25	0.19	0.73	0.76
C8	0.18	0.28	0.42	0.88	0.38	0.28	0.38	0.65	0.65
C9	0.58	0.39	0.54	0.88	0.11	0.87	0.81	0.28	0.42

TABLE 9.8 Pair-Wise Comparison Matrix w.r.t. A1 (Mean Bound Fuzzy Decision Matrix) ⏎

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	0.65	0.56	0.38	0.79	0.58	0.54	0.49	0.54	0.77
C2	0.38	0.76	0.86	0.55	0.36	0.42	0.67	0.11	0.55
C3	0.78	0.78	0.67	0.38	0.38	0.73	0.78	0.67	0.38
C4	0.67	0.81	0.57	0.80	0.11	0.08	0.81	0.54	0.67
C5	0.68	0.94	0.54	0.48	0.69	0.27	0.94	0.45	0.78
C6	0.25	0.74	087	0.36	0.28	0.42	0.33	0.36	0.87
C7	0.28	0.57	0.80	0.62	0.37	0.65	0.76	0.62	0.65
C8	0.48	0.54	0.48	0.87	0.25	0.19	0.54	0.87	0.38
C9	0.97	0.48	0.69	0.54	0.45	0.67	0.57	0.38	0.80

TABLE 9.9 Pair-Wise Comparison Matrix w.r.t. A1 (Upper Bound Fuzzy Decision Matrix) ⏎

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	0.67	0.38	0.69	0.27	0.65	0.48	0.08	0.81	0.46
C2	0.57	0.80	0.28	0.42	0.38	0.73	0.27	0.88	0.25
C3	0.54	0.38	0.73	0.80	0.11	0.08	0.39	0.37	0.65
C4	087	0.11	0.08	0.48	0.43	0.91	0.94	0.73	0.78
C5	0.80	0.77	0.80	0.76	0.28	0.42	0.27	0.08	0.81
C6	0.48	0.69	0.27	0.74	087	0.73	0.80	0.27	0.94
C7	0.36	0.28	0.42	0.57	0.80	0.47	0.57	0.27	0.48
C8	0.62	0.37	0.65	0.54	0.48	0.71	0.54	0.61	0.76
C9	0.57	0.80	0.11	0.08	0.57	0.77	0.61	0.28	0.74

TABLE 9.10 The Fuzzy and Crisp Permanent Matrix ⏎

Alternatives	Fuzzy Permanent Matrix	Crisp Permanent Matrix
A1	(7.8, 7.9, 8.3)	0.05
A2	(7.2, 7.5, 8.8)	0.11
A3	(5.5, 5.6, 7.7)	0.12
A4	(4.7, 5.1, 6.8)	0.04
A5	(6.1, 6.7, 7.9)	0.13
A6	(6.2, 8.2, 8.8)	0.34

9.6 FINDINGS

According the value of crisp permanent matrix, the ranking of the six oil companies is represented in Table 9.11. Greater crisp permanent value indicates more efficiency.

TABLE 9.11 Ranks ⏎

Alternatives	Crisp Permanent Matrix	Ranks
A1 (BPCL)	0.05	5
A2 (Hind Petro)	0.11	4
A3 (IOC)	0.12	3
A4 (Oil India)	0.04	6
A5 (ONGC)	0.13	2
A6 (Reliance)	0.34	1

Ranks are shown by line chart in Figure 9.4.

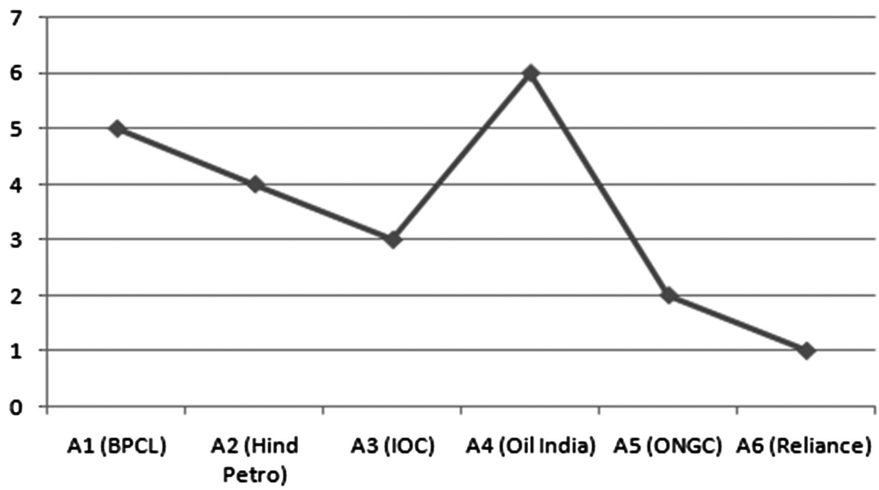

FIGURE 9.4 Ranks in line chart. ⏎

9.7 CONCLUSIONS

In this research, the financial ranking of prominent players in the Indian petroleum and energy sector—Reliance, BPCL, Hind Petro, IOC, Oil India, and ONGC—reveals interesting insights into their respective financial standings. Reliance emerges as the frontrunner, securing the top position with a financial ranking of 1, indicating robust fiscal health and strategic positioning. ONGC follows closely behind in second place, reinforcing its strength in the industry. IOC secures the third position, showcasing its stability and financial resilience. HPCL and Oil India occupy the fourth and fifth positions, respectively, indicating a solid but slightly lower financial standing compared with their counterparts. BPCL, positioned at sixth place, suggests room for improvement in its financial performance. Overall, these rankings provide valuable benchmarks for stakeholders and investors to assess and navigate the dynamic landscape of the Indian petroleum and energy sector, facilitating informed decision-making for future endeavors and investments.

KEYWORDS

- **Financial indicators**
- **NIFTY**
- **oil companies**
- **multicriteria decision-making**
- **triangular fuzzy number**
- **graph theory and matrix approach**

REFERENCES

1. Xidonas, P., Mavrotas, G., & Psarras, J. (2009). A multicriteria methodology for equity selection using financial analysis. *Computers & Operations Research*, *36*(12), 3187–3203.
2. Gallizo, J. L., Jiménez, F., & Salvador, M. (2002). Adjusting financial ratios: A Bayesian analysis of the Spanish manufacturing sector. *Omega*, *30*(3), 185–195.
3. Laitinen, E. K. (2006). Financial statement data in assessing the future potential of a technology firm: The case of Nokia. *International Review of Financial Analysis*, *15*(3), 256–286.
4. Wang, Y. J., & Lee, H. S. (2008). A clustering method to identify representative financial ratios. *Information Sciences*, *178*(4), 1087–1097.
5. Ghosh, A. (2021). Analyzing efficiency of Indian life insurance companies using DEA and SEM. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *12*(12), 3897–3919.
6. Jana, S., Basu, S (2021). Ranking of top 20 pharmaceutical companies in India using TOPSIS. *Empirical Economics Letters*, ISSN 1681 8997, Special Issue 3.
7. Saeed, M., Mahmood, S., & Taufeeq, H. (2018). A consistent hybrid of analytical hierarchy process (AHP) and graph theory matrix approach (GTMA) with application to selection of pet scan machine problem for cancer hospital. *International Journal of Computer Applications*, *181*(16), 42–48.
8. Rao, D. B., Rao, K. V., & Krishna, A. G. (2018). A hybrid approach to multi response optimization of micro milling process parameters using Taguchi method based graph theory and matrix approach (GTMA) and utility concept. *Measurement*, *120*, 43–51.

9. Mohaghar, A., Faghih, A., Fathi, M. R., & Keshavarzi, T. (2012). Applying GTMA method with Entropy weight for strategy ranking. In: *The 8th International Industrial Engineering Conference*.
10. Geetha, N. K., Siva Kumar, N., & Sekar, P. (2016). Assessment of optimal combination of operating parameters using graph theory matrix approach. *Indian Journal of Science and Technology*, *9*, 36.
11. Jain, V., & Raj, T. (2015). Evaluating the intensity of variables affecting flexibility in FMS by graph theory and matrix approach. *International Journal of Industrial and Systems Engineering*, *19*(2), 137–154.
12. Andhare, A. B., Tiger, C. K., & Ahmed, S. (2012). Failure analysis of machine tools using GTMA and MADM method. *International Journal of Engineering Research & Technology*, *1*, 1–11.
13. Tuljak-Suban, D., & Bajec, P. (2020). Integration of AHP and GTMA to make a reliable decision in complex decision-making problems: Application of the logistics provider selection problem as a case study. *Symmetry*, *12*(5), 766.
14. Mohaghar, A., Fagheyi, M. S., Moradi-Moghadam, M., & Ahangari, S. S. (2013). Integration of fuzzy GTMA and logarithmic fuzzy preference programming for supplier selection. *Report and Opinion*, *5*(5), 9–16.
15. Yousufuddin, S., Khan, N., & Saleem, M. (2022). Optimization of diesel engine performance and emission characteristics employing hybrid Taguchi-Gtma-utility technique. *Yanbu Journal of Engineering and Science*, *19*(1), 86–95.
16. Baluch, M. A. (2022). Parametric Graph Theory and Matrix Approach (GTMA) Model for assessing the surface water quality. *Technical Journal*, *27*(02), 10–19.
17. Zhuang, Z. Y., Lin, C. C., Chen, C. Y., & Su, C. R. (2018). Rank-based comparative research flow benchmarking the effectiveness of AHP–GTMA on aiding decisions of shredder selection by reference to AHP–TOPSIS. *Applied Sciences*, *8*(10), 1974.
18. Gul, A., Mehmood, M. N., & Mehmood, M. S. (2021). Graph Theory and Matrix Approach (GTMA) Model for the selection of the femoral-component of total knee joint replacement. *Non-Metallic Material Science*, *3*(1), 1–9.
19. MiorAbd Halim, W. N., Mohd Hanafi, I. F., Johari, N. I., & Mahad, N. F. (2022). The hybridization of analytic hierarchy process and graph theory matrix approach (ahp-gtma) to solve solid waste transshipment site selection problem. *Malaysian Journal of Computing (MJoC)*, *7*(2), 1120–1138.
20. Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*(3), 338–353.
21. Rao, R. V. (2007). Introduction to decision making in the manufacturing environment. In: *Decision Making in the Manufacturing Environment: Using Graph Theory and Fuzzy Multiple Attribute Decision Making Methods*. pp. 3–6.
22. Darvish, M., Yasaei, M., & Saeedi, A. (2009). Application of the graph theory and matrix methods to contractor ranking. *International Journal of Project Management*, *27*(6), 610–619.
23. Faisal, M. N., Banwet, D. K., & Shankar, R. (2007). Quantification of risk mitigation environment of supply chains using graph theory and matrix methods. *European Journal of Industrial Engineering*, *1*(1), 22–39.
24. Nourani, Y., & Andresen, B. (1999). Exploration of NP-hard enumeration problems by simulated annealing—the spectrum values of permanents. *Theoretical Computer Science*, *215*(1–2), 51–68.

CHAPTER 10

Fuzzy Applications in the Decision Models and Expert Systems for Control Capability Enhancement

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ABSTRACT

Fuzzy logic has emerged as a powerful paradigm with an approach to handling the inherent uncertainties and impressions of real-world data. In decision models, this property enables the incorporation of qualitative and quantitative data with varying degrees of certainty. Applications of fuzzy logic are manifold. In medical diagnosis, it aids in interpreting vague symptoms and assessing diagnostic probabilities, enhancing the accuracy of healthcare decision support systems. In financial modeling, empowers risk assessment by accommodating fluctuating market conditions and imprecise economic data. This concept has been used in shaping the environmental models by handling incomplete and uncertain ecological data. In control systems, fuzzy logic controllers excel at managing complex, nonlinear processes, and finding applications in robotics, manufacturing, and process control. Fuzzy logic concept in the pattern recognition systems can be concerned to the image recognition and natural language processing. The quality control and fault detection systems employ fuzzy logic to evaluate product quality using imprecise measurements. The optimization of traffic signal timing using fuzzy logic system is another control instance. The proposed chapter

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will provide detailed anecdote over the applicability of fuzzy system into various decision models and expert systems with consequent enhancement of efficiency and accuracy.

10.1 INTRODUCTION

Control capability enhancement is a crucial concept that finds applications in various domains, ranging from manufacturing and industrial processes to robotics, healthcare, finance, and beyond. It represents a pivotal aspect of improving efficiency, precision, and adaptability within complex systems. In this introductory section, we will explore the overarching importance of control capability enhancement in these diverse domains.

10.1.1 MANUFACTURING AND INDUSTRIAL PROCESSES

In manufacturing, precision and control are paramount. Control capability enhancement enables manufacturers to optimize processes, reduce defects, and ensure consistent product quality. Industries such as automotive, aerospace, and electronics heavily rely on control enhancements to achieve tighter tolerances and meet stringent regulatory requirements.

10.1.2 ROBOTICS AND AUTOMATION

In the realm of robotics, control capability enhancement translates into more agile and responsive robots. These robots can perform tasks with greater accuracy, improving productivity across industries [21]. Applications extend to fields like surgery, where robotic surgical systems offer surgeons enhanced control and precision during delicate procedures [1].

10.1.3 HEALTHCARE

Control capability enhancement in healthcare leads to advanced medical devices and equipment. This includes wearable health monitors, drug delivery systems, and diagnostic tools. Enhanced control ensures patient safety, precise drug administration, and real-time monitoring, improving healthcare outcomes [32].

10.1.4 FINANCE AND TRADING

In financial markets, control capabilities are essential for algorithmic trading systems. These systems make rapid decisions based on market conditions, optimizing trading strategies, and minimizing risk. Control enhancements enable financial institutions to respond to market fluctuations with unparalleled speed and accuracy.

10.1.5 AEROSPACE AND AVIATION

Aircraft and spacecraft demand precise control to ensure passenger safety and mission success. Control capability enhancements lead to better flight control systems and navigation. These enhancements also enable more efficient fuel consumption and contribute to environmental sustainability [31].

10.1.6 ENERGY AND ENVIRONMENTAL CONTROL

In the energy sector, control capability enhancement plays a role in smart grids, optimizing energy distribution, and consumption. Environmental control systems benefit from enhanced control to monitor and mitigate pollution, reduce energy waste, and conserve resources [18].

10.1.7 RESEARCH AND SCIENTIFIC EXPLORATION

Scientific experiments and explorations, whether in physics, chemistry, or space exploration, rely on precise control to collect accurate data. Control capability enhancement facilitates groundbreaking discoveries and innovations.

In conclusion, control capability enhancement is a cross-cutting imperative that drives advancements across various domains. It empowers industries, improves quality of life, and fosters innovation. As we delve deeper into this chapter, we will explore the tools and methodologies that enable control enhancement and examine their applications in detail.

10.2 THE ROLE OF DECISION MODELS AND EXPERT SYSTEMS

The role of decision models and expert systems in achieving control capability enhancement is pivotal across various domains. Decision models and expert systems leverage advanced algorithms, data analysis, and domain-specific knowledge to optimize control processes. Here is how these technologies contribute to enhancing control capabilities.

10.2.1 DECISION MODELS

Decision models are mathematical representations of systems, processes, or scenarios. They help in making informed choices by evaluating different options based on predefined criteria. In the context of control capability enhancement [7]:

- *Optimization:* Decision models can optimize control settings by considering multiple variables and constraints. For example, in manufacturing, decision models can optimize production schedules, resource allocation, and quality control parameters to enhance overall efficiency.
- *Predictive analytics:* Decision models can utilize historical data and predictive analytics to anticipate system behavior. This allows for proactive adjustments and fine-tuning of control parameters, reducing the likelihood of errors or disruptions [22].
- *Scenario analysis:* Decision models can simulate various scenarios and assess their impact on control processes. This capability helps in risk management and contingency planning, ensuring system stability even under adverse conditions.

10.2.2 EXPERT SYSTEMS

Expert systems are computer programs designed to mimic the decision-making capabilities of human experts in specific domains. They rely on knowledge bases, rules engines, and inference engines to provide expert-level advice. In control capability enhancement [28]:

- *Domain-specific knowledge:* Expert systems are built upon extensive domain-specific knowledge. They capture the expertise of experienced professionals, making it accessible to a broader audience. For instance, in healthcare, expert systems can assist medical practitioners in diagnosing complex conditions by providing recommendations based on a vast knowledge base.
- *Real-time decision support:* Expert systems can offer real-time decision support by continuously analyzing data and providing

recommendations. In manufacturing, these systems can monitor equipment performance and suggest maintenance actions to prevent breakdowns [15].

- *Consistency and accuracy:* Expert systems ensure consistent and accurate decision-making, eliminating human errors, and biases. In finance, they assist in portfolio management by adhering to predefined investment strategies consistently.

10.2.3 SYNERGY BETWEEN DECISION MODELS AND EXPERT SYSTEMS

Decision models and expert systems often work synergistically to achieve control capability enhancement. Decision models can incorporate expert system outputs as inputs for decision-making. For example, an expert system monitoring an industrial process can feed data and recommendations into a decision model that optimizes control settings [23].

The combination of decision models and expert systems enables adaptive control. Systems can learn from historical data and expert knowledge, continuously improving their control strategies to adapt to changing conditions and requirements.

The objectives of this chapter are to provide readers with a comprehensive understanding of the applications of fuzzy logic, decision models, and expert systems in enhancing control capabilities across diverse domains.

In summary, decision models and expert systems play a vital role in enhancing control capabilities across various domains. They enable optimization, predictive analytics, scenario analysis, domain-specific knowledge utilization, real-time decision support, and improved consistency and accuracy. By leveraging these technologies, industries and sectors can achieve greater control, efficiency, and reliability in their operations.

10.3 CONTROL CAPABILITY ENHANCEMENT

Control capability enhancement refers to the process of improving and strengthening the ability to regulate, manage, and optimize systems, processes, or operations within various domains. It involves the integration of advanced technologies, methodologies, and decision-making tools to achieve better control, accuracy, and adaptability in a given context [35]. Control capability enhancement is significant for several reasons.

1) *Improved efficiency:* Enhancing control capabilities leads to more efficient operations. It allows organizations to streamline processes, reduce waste, and achieve higher productivity levels.
2) *Enhanced decision-making:* With better control, decision-makers have access to more accurate and real-time data. This empowers them to make informed choices and respond quickly to changing circumstances.
3) *Error reduction:* Control capability enhancement minimizes errors and reduces the likelihood of costly mistakes. This is especially crucial in fields where precision is critical, such as manufacturing, healthcare, and finance.
4) *Adaptability:* Advanced control systems can adapt to changing conditions and requirements. They are flexible and can handle variations, making them suitable for dynamic environments [20].
5) *Cost savings:* By optimizing processes and reducing errors, control capability enhancement often leads to cost savings. It can result in lower operational expenses and increased profitability.
6) *Competitive advantage:* Organizations that excel in control capability are often more competitive in their respective industries. They can deliver higher quality products and services while maintaining cost-effectiveness.
7) *Risk mitigation:* Enhanced control capabilities can help identify and mitigate risks effectively. This is particularly important in industries like aviation, healthcare, and energy, where safety is paramount [5].
8) *Innovation:* The pursuit of control capability enhancement often drives innovation. It encourages the development of new technologies and approaches to achieve better control.
9) *Cross-domain applications:* Control capability enhancement is applicable across various domains, including manufacturing, healthcare, finance, transportation, and more. Its versatility makes it a valuable concept in many fields.
10) *Sustainability:* In sectors like energy and environmental management, control capability enhancement can contribute to sustainability efforts by optimizing resource usage and reducing waste.

In summary, control capability enhancement is a vital concept that plays a significant role in improving operational efficiency, reducing errors, and driving innovation across diverse domains. It empowers organizations to adapt to change, make informed decisions, and maintain a competitive edge in today's dynamic and complex world.

10.3.1 REAL-LIFE APPLICATION: CONTROL CAPABILITY ENHANCEMENT IN HEALTHCARE

One compelling real-life application of control capability enhancement is in the healthcare industry, particularly in the management of critical care units in hospitals. In these environments, precise control over patient care and medical equipment is essential to ensure patient safety and optimize treatment outcomes. Here is a case study illustrating the significance and impact of control capability enhancement in healthcare:

Case Study: Control Capability Enhancement in Intensive Care Units (ICUs)

Introduction:

ICUs are high-stress environments where critically ill patients receive specialized medical care. Timely and accurate decision-making, as well as precise control over medical devices, are paramount to patient survival and recovery. Control capability enhancement is vital to improving patient care and outcomes in ICUs.

Objectives:

The primary objectives of implementing control capability enhancement in ICUs are as follows:

1) *Real-time monitoring:* To enable real-time monitoring of patients' vital signs, such as heart rate, blood pressure, and oxygen levels.
2) *Precision medication delivery:* To ensure precise administration of medications, including dosage and timing.
3) *Ventilator control:* To optimize mechanical ventilation parameters based on patient needs.
4) *Alarm systems:* To develop advanced alarm systems that alert medical staff to critical changes in a patient's condition.
5) *Data analytics:* To collect and analyze patient data for early detection of complications and predictive analytics.

Implementation:

- *Advanced monitoring systems:* High-tech monitors are used to continuously track patients' vital signs and provide instant feedback to healthcare providers.
- *Smart infusion pumps:* These devices deliver medications at precise rates, reducing the risk of medication errors.

- *Closed-loop ventilation:* Advanced ventilators use closed-loop control systems to adapt ventilation settings in response to a patient's respiratory status.
- *Machine-learning algorithms:* Machine-learning algorithms analyze patient data to predict deteriorations in real-time, allowing for early intervention.

Results:

The implementation of control capability enhancement in ICUs has yielded significant results:

- *Improved patient outcomes:* Enhanced control over patient care has led to improved survival rates and reduced complications.
- *Reduced medication errors:* Precise medication delivery has minimized dosage errors, enhancing patient safety.
- *Early warning systems:* Advanced alarm systems provide timely alerts, enabling faster responses to critical situations.
- *Data-driven care:* Data analytics have facilitated evidence-based decision-making and better understanding of patient trends.

Conclusion:

Control capability enhancement in ICUs has revolutionized critical care by providing healthcare providers with the tools and systems needed to deliver more precise, timely, and effective care. This application demonstrates how control capability enhancement can significantly impact patient outcomes and safety in a real-world healthcare setting.

10.3.2 CHALLENGES AND COMPLEXITIES IN CONTROL SYSTEMS

Control systems play a pivotal role in various domains, including engineering, manufacturing, healthcare, and more. However, they are not without their challenges and complexities. Here, we discuss some of the key issues and difficulties associated with control systems:

1) *Nonlinearity:* Many real-world systems exhibit nonlinear behavior, making their control more complex. Traditional linear control techniques may not be effective in handling nonlinear systems. Nonlinearity can lead to unexpected behaviors and difficulties in designing control strategies [27].

2) *Uncertainty:* Uncertainty in system parameters, external disturbances, and noise can significantly impact control system performance. Robust control techniques are required to handle uncertainty and maintain stability and performance under varying conditions.
3) *Complexity of models:* Building accurate mathematical models of complex systems can be challenging. In some cases, models may be too complex to capture all relevant dynamics accurately. This can lead to difficulties in designing controllers that work effectively with the available models [33].
4) *Time delays:* Control systems often encounter time delays in measurements, actuations, or communication. Time delays can lead to instability or reduced performance, especially in systems requiring rapid responses.
5) *Multivariable systems:* Systems with multiple interacting variables can be challenging to control. The coupling between variables can lead to difficulties in designing controllers that provide optimal control while avoiding interactions [3].
6) *Sensor and actuator limitations:* Control systems rely on sensors to measure system variables and actuators to apply control actions. Sensor inaccuracies, limited measurement ranges, and actuator constraints can pose significant challenges in control system design [37].
7) *Human interaction:* In some applications, control systems need to interact with human operators. Designing user-friendly interfaces and control strategies that are intuitive for human users can be complex.
8) *Safety and reliability:* Control systems in critical applications, such as, automotive control or healthcare devices, must meet stringent safety and reliability requirements. Ensuring fail-safe mechanisms and redundancy can be complex and costly.
9) *Adaptation and learning:* Some control systems require adaptive or learning capabilities to adjust to changing operating conditions or improve performance over time. Designing adaptive control algorithms that are robust and stable is a complex task.
10) *Integration of control systems:* In modern industries, control systems often need to be integrated with other systems, such as data analytics, Internet of Things (IoT) devices, and communication networks. Ensuring seamless integration and interoperability can be challenging [24].
11) *Regulatory compliance:* Many control systems need to adhere to regulatory standards and certifications, which can introduce additional complexity in terms of documentation, testing, and validation.

12) *Energy efficiency:* With increasing emphasis on sustainability, control systems are expected to optimize energy usage. Achieving energy-efficient control without compromising performance can be complex.

In summary, control systems are essential for maintaining stability, improving performance, and ensuring the safe operation of various processes and devices. However, the challenges and complexities associated with control systems require continuous research and innovation to develop effective solutions that meet the demands of modern applications.

10.3.3 THE NEED FOR ADVANCED DECISION-MAKING TOOLS

Advanced decision-making tools are critical in today's complex and data-driven world. These tools provide organizations and individuals with the means to make informed, timely, and optimal decisions across various domains. Here are some key reasons highlighting the need for advanced decision-making tools:

1) *Complexity of decision environments:* In many fields, decision environments have become increasingly complex due to factors like globalization, technological advancements, and interconnectedness. Simple, rule-of-thumb decision-making is often inadequate to address the intricate interplay of variables and constraints in such environments [16].
2) *Big data and information overload:* The digital age has ushered in an era of massive data generation. Decision-makers are inundated with vast amounts of data from various sources. Advanced tools like data analytics, machine learning, and artificial intelligence (AI) are necessary to sift through this data, extract valuable insights, and support decision-making.
3) *Rapidly changing markets:* Business landscapes are highly dynamic, with markets evolving rapidly. Organizations must make quick decisions to stay competitive. Advanced tools provide real-time data analysis and predictive capabilities, enabling businesses to respond swiftly to market changes.
4) *Risk management:* Decision-making often involves assessing and mitigating risks. Advanced decision tools, including risk modeling and scenario analysis, help organizations identify potential risks, quantify their impact, and develop strategies to manage or mitigate them.
5) *Resource optimization:* Efficient resource allocation is essential for organizations to maximize their outcomes. Advanced optimization

algorithms can help allocate resources such as finances, personnel, and equipment optimally, reducing waste and improving overall efficiency.

6) *Strategic planning:* Organizations require sophisticated tools for strategic planning and goal setting. Decision support systems can assist in long-term strategic decision-making, aligning objectives with available resources and market conditions.
7) *Competitive advantage:* Those who harness advanced decision-making tools gain a competitive edge. These tools enable organizations to make data-driven decisions that can lead to cost savings, increased revenue, and improved customer satisfaction.
8) *Personalized experiences:* In fields like marketing and healthcare, personalization is key. Advanced tools analyze individual preferences and behaviors to tailor products, services, and recommendations, enhancing customer experiences.
9) *Scientific research and exploration:* In scientific research, advanced tools aid in data analysis, hypothesis testing, and simulations. They are instrumental in fields like genomics, climate modeling, and particle physics.
10) *Healthcare:* Clinical decision support systems assist healthcare providers in diagnosing diseases, choosing treatment options, and improving patient care. These tools integrate patient data, medical knowledge, and best practices.
11) *Government and public policy:* Government agencies use advanced decision-making tools to assess the impact of policies, allocate resources, and respond to crises efficiently.
12) *Environmental management:* Environmental decisions, such as climate change mitigation and natural resource conservation, require sophisticated modeling and analysis tools to understand complex ecosystems and predict outcomes.

In conclusion, the need for advanced decision-making tools arises from the increasingly complex, data-rich, and fast-paced nature of our world. These tools empower organizations and individuals to make informed, strategic, and effective decisions across a wide range of applications, ultimately driving success and innovation.

10.4 FUZZY LOGIC FUNDAMENTALS

Fuzzy logic is a mathematical framework that extends classical Boolean logic to handle uncertainty and imprecision in decision-making. It was introduced by Lotfi Zadeh in the 1960s and has since found applications in various fields, including control systems, AI, and decision support [4].

10.4.1 LINGUISTIC VARIABLES AND FUZZY SETS

1) *Linguistic variables:* Fuzzy logic introduces the concept of linguistic variables, which are variables whose values are expressed in linguistic terms rather than precise numerical values. For example, in the context of temperature control, a linguistic variable could be “temperature,” and linguistic terms associated with it might include “cold,” “warm,” and “hot.” Linguistic variables allow decision-makers to express their knowledge and preferences in a more human-like manner [2].
2) *Fuzzy sets:* Fuzzy sets are a fundamental concept in fuzzy logic. Unlike traditional sets where an element either belongs to a set (membership = 1) or does not belong (membership = 0), fuzzy sets allow for partial membership. Each element has a membership value between 0 and 1, indicating the degree to which it belongs to the set. This partial membership accommodates uncertainty and vagueness in real-world data.

10.4.2 MEMBERSHIP FUNCTIONS

Membership functions define how elements relate to a fuzzy set. They assign a membership value to each element based on its degree of membership in the set. Membership functions can take various shapes, such as triangular, trapezoidal, or sigmoidal, depending on the nature of the linguistic term and the context. For example, a membership function for the linguistic term “warm” might have a triangular shape, peaking at the point where something is considered moderately warm [6].

10.4.3 FUZZY INFERENCE SYSTEMS (FISS)

FISs are the core of fuzzy logic-based decision-making. They consist of three main components:

1) *Fuzzification:* In this step, crisp input values (numerical data) are converted into fuzzy values using appropriate membership functions. This process allows the model to handle imprecise input [30].

2) *Fuzzy rules:* FISs rely on a set of IF–THEN rules that relate the fuzzy input variables to fuzzy output variables. These rules encode expert knowledge or decision-making criteria. For example, a rule could be "IF temperature is cold AND humidity is high, THEN turn on the heater."
3) *Defuzzification:* After applying the fuzzy rules, the system produces fuzzy output values. Defuzzification is the process of converting these fuzzy outputs back into crisp values, making the final decision or control action. Various defuzzification methods, such as centroid or maximum membership, can be used [26].

Key Characteristics and Advantages of Fuzzy Logic:

- *Handling uncertainty:* Fuzzy logic excels in situations where data is imprecise or uncertain. It allows for a more nuanced representation of knowledge.
- *Human centric:* Fuzzy logic provides a framework that aligns well with human thinking and natural language expressions, making it suitable for expert systems and decision support.
- *Interpretability:* Fuzzy logic models are often more interpretable than complex mathematical models, making them valuable in situations where transparency is crucial.
- *Robustness:* Fuzzy logic systems can tolerate noisy data and variations, making them robust in real-world applications.

Fuzzy logic is particularly valuable in applications such as control systems (e.g., temperature control in heating, ventilation, and air conditioning (HVAC) systems), decision support systems (e.g., medical diagnosis), and expert systems (e.g., industrial automation), where decision-making is influenced by qualitative and uncertain information.

10.5 DECISION MODELS AND EXPERT SYSTEMS

Decision models and expert systems play a crucial role in control applications by facilitating intelligent and data-driven decision-making. These tools leverage advanced algorithms and domain expertise to enhance control capabilities in various industries and fields. Here is an exploration of their use:

1) *Process control:* In manufacturing and industrial processes, decision models and expert systems are employed to monitor and control variables such as temperature, pressure, and flow rates. They use real-time data to make decisions, optimize processes, and ensure product quality [10].

2) *Supply chain management:* Decision models are used to optimize supply chain operations, including inventory management, demand forecasting, and logistics. Expert systems assist in route planning, warehouse management, and order fulfillment to enhance control over the supply chain.
3) *Energy management:* In energy-intensive industries and smart grid systems, decision models are used to manage energy consumption efficiently. They can optimize energy generation, distribution, and consumption, leading to cost savings and reduced environmental impact [19].
4) *Financial control:* Financial institutions use decision models to assess risk, make investment decisions, and automate trading strategies. Expert systems assist in fraud detection and credit risk analysis, enhancing financial control.
5) *Healthcare:* Expert systems in healthcare assist in diagnosis and treatment planning. They incorporate medical knowledge and patient data to provide recommendations to healthcare professionals, enhancing the accuracy and effectiveness of medical decisions [13].
6) *Agriculture:* Decision models are used in precision agriculture to control irrigation, fertilization, and pest management. Expert systems help farmers make data-driven decisions to optimize crop yields and resource utilization [29].

Advantages of Using Decision Models and Expert Systems:

- *Data-driven decisions:* These tools leverage data analytics to make informed decisions, reducing reliance on intuition and guesswork.
- *Consistency:* Expert systems ensure consistent decision-making based on predefined rules and expert knowledge, reducing variability.
- *Automation:* They can automate routine tasks and decisions, freeing up human resources for more complex and strategic activities.
- *Scalability:* Decision models and expert systems can handle large datasets and complex scenarios, making them suitable for various industries and applications.
- *Continuous improvement:* They can adapt and improve over time as they learn from new data and experiences, enhancing control capabilities.

Examples of Industries and Fields

1) *Manufacturing:* Decision models and expert systems are used in manufacturing industries to control production processes, quality assurance, and predictive maintenance.

2) *Finance:* Financial institutions use these tools for risk management, fraud detection, and algorithmic trading.
3) *Healthcare:* Medical expert systems assist in disease diagnosis, treatment planning, and drug discovery.
4) *Transportation:* Airlines and logistics companies utilize decision models for route optimization and fleet management.
5) *Energy*: Smart grid systems use decision models to control energy distribution and consumption efficiently.
6) *Agriculture:* Precision agriculture relies on decision models to control irrigation, fertilization, and pest management.
7) *Retail:* Retailers use these tools for inventory management, demand forecasting, and pricing optimization.

In summary, decision models and expert systems are versatile tools that enhance control capabilities across a wide range of industries, providing data-driven, consistent, and automated decision-making processes. Their adaptability and scalability make them valuable assets for achieving control capability enhancement.

Example: Quality Control in Manufacturing

Imagine a manufacturing plant that produces electronic components such as microchips. The quality of these components is critical to ensuring they function correctly in various electronic devices. In this scenario, decision models and expert systems are employed for quality control.

Problem: The manufacturing process involves multiple parameters such as temperature, voltage, and production speed, which can affect the quality of the microchips. The challenge is to maintain consistent product quality and detect any deviations from the desired specifications.

Solution:

1) *Data collection*: Sensors are placed at various points along the production line to collect data on parameters like temperature (T), voltage (V), and speed (S). For each microchip produced, a set of measurements (T, V, S) is recorded.
2) *Decision model:* A decision model is created to evaluate the quality of each microchip based on the collected data. The model uses a mathematical formula to calculate a quality score (Q) for each chip. This formula could be as simple as

$$Q = 2T + 3V - 0.5S$$

   This is a simplified example; in practice, the formula would be more complex and based on domain expertise.

3) *Expert system:* An expert system is developed to set the acceptable quality threshold. It considers historical data, industry standards, and expert knowledge to determine the acceptable range of quality scores. If a chip's quality score falls outside this range, it is flagged as a potential issue.
4) *Automation:* The decision model and expert system work together in real-time. As each microchip is produced, its quality score is calculated and compared to the acceptable threshold. If a chip's quality score is within the acceptable range, it continues through the production process. If it falls outside the range, the system can automatically make adjustments to the production parameters to correct the issue or trigger an alert for manual inspection.

Mathematical example:

Suppose a microchip is produced with the following measurements:

- Temperature (T) = 100°C
- Voltage (V) = 5.2 V
- Speed (S) = 800 units

Using the quality formula:

$$Q = 2T + 3V - 0.5S$$
$$Q = 2(100) + 3(5.2) - 0.5(800) = 200 + 15.6 - 400 = -184.4$$

The quality score for this microchip is −184.4. The expert system compares this score to the acceptable range, and if it falls outside, corrective actions are taken.

In this way, decision models and expert systems enhance control capabilities by automating quality control processes, ensuring consistent product quality, and minimizing defects in manufacturing.

10.6 INTEGRATION OF FUZZY LOGIC

Fuzzy logic can be effectively integrated into decision models and expert systems to enhance their control capabilities in various domains. Here is how this integration can be achieved:

1) *Linguistic variables and fuzzy sets:* Fuzzy logic allows for the representation of linguistic variables and fuzzy sets, which capture the imprecise nature of real-world data. Instead of binary values

(true/false), fuzzy logic assigns degrees of membership to elements, allowing for a more nuanced representation of data [25].

2) *Membership functions:* Membership functions define the shape of fuzzy sets and determine the degree of membership of an element. They can be tailored to specific application domains, enabling decision models to capture expert knowledge and imprecise information effectively.
3) *FISs:* FISs are used to model the decision-making process based on fuzzy logic rules. These systems involve fuzzy logic operators (AND, OR, NOT) and fuzzy if–then rules that mimic human expert reasoning. FIS combines linguistic variables and membership functions to derive meaningful conclusions [34].
4) *Control systems:* Fuzzy logic-based control systems, such as fuzzy controllers, are employed to manage complex and nonlinear processes. These controllers can adapt to changing conditions and make decisions based on linguistic rules, making them suitable for control applications.

Benefits of Integrating Fuzzy Logic:

The integration of fuzzy logic into decision models and expert systems offers several advantages for control capability enhancement:

1) *Handling uncertainty:* Fuzzy logic can effectively handle uncertainty and imprecision in real-world data, making it suitable for decision-making in domains where precise numerical values are challenging to obtain.
2) *Expert knowledge incorporation:* Fuzzy logic allows for the incorporation of expert knowledge through linguistic rules and membership functions. This enables systems to make decisions that align with human expertise.
3) *Adaptability:* Fuzzy logic-based systems can adapt to changing conditions and adjust their decisions accordingly. This adaptability is valuable in control systems where conditions may vary.
4) *Complex systems:* Fuzzy logic is well-suited for controlling complex and nonlinear systems, making it applicable in various industries such as automotive, robotics, and manufacturing.

Real-World Examples of Integration:

1) *Automotive cruise control:* Fuzzy logic is used in adaptive cruise control systems, which adjust a vehicle's speed based on distance

and relative speed to the vehicle ahead. Fuzzy controllers make smooth decisions in varying traffic conditions.

2) *Air conditioning systems:* Fuzzy logic-based controllers are used in HVAC systems to optimize temperature and humidity control in buildings. These systems adapt to changing environmental conditions.
3) *Washing machines:* Fuzzy logic is employed in washing machines to determine the optimal washing cycle based on factors like load size, fabric type, and dirt level.
4) *Traffic signal control:* Fuzzy logic-based traffic signal controllers adjust signal timings based on traffic flow, reducing congestion and improving traffic management.

Incorporating fuzzy logic into decision models and expert systems enhances their control capabilities by addressing uncertainty, leveraging expert knowledge, and enabling adaptability, making it a valuable tool across various industries and applications.

Let us consider a real-world case study of how fuzzy logic can be applied to enhance control capabilities in an HVAC system. In this case, we will focus on optimizing temperature control in a building using a fuzzy logic-based controller.

Case study: Fuzzy logic HVAC temperature control

Background:

Imagine a large office building with varying occupancy and external weather conditions. The goal is to maintain a comfortable indoor temperature (IT) while minimizing energy consumption. Traditional HVAC systems often struggle to adapt to changing conditions efficiently.

Problem:

Design a fuzzy logic-based HVAC temperature control system that can adjust the heating and cooling output based on occupancy, temperature setpoints, and external weather conditions.

Solution:

A fuzzy logic controller (FLC) can effectively handle this complex problem by incorporating linguistic rules and membership functions.

Variables:

1) *IT:* Represented as a linguistic variable with membership functions for “Cold,” “Comfortable,” and “Warm.”

2) *Occupancy (O):* Represented as a linguistic variable with membership functions for "Low," "Medium," and "High."
3) *Outdoor temperature (OT):* Represented as a linguistic variable with membership functions for "Cold," "Mild," and "Hot."
4) *HVAC output:* Represented as a linguistic variable with membership functions for "Cooling," "No Action," and "Heating."

Fuzzy Rules:

The FLC incorporates rules such as:

1. IF IT is "Cold" AND O is "High" THEN HVAC is "Heating"
2. IF IT is "Warm" AND O is "Low" THEN HVAC is "Cooling"
3. IF IT is "Comfortable" AND O is "Medium" THEN HVAC is "No Action"

Membership Functions:

Membership functions are defined for each linguistic variable. For example, "Cold" for IT might have a triangular membership function centered around 65°F, while "High" for O might have a trapezoidal membership function centered around 80 occupants.

Fuzzy Inference:

The controller evaluates the fuzzy rules using the current values of IT, O, and OT to determine the appropriate HVAC output. This process considers the linguistic variables and their membership values.

Defuzzification:

The final fuzzy output is defuzzified to obtain a crisp value representing the HVAC output. This crisp value determines whether the HVAC system should cool, heat, or remain idle.

Calculations:

Suppose the current conditions are as follows:

- IT = 72°F (membership values: Cold = 0.2, Comfortable = 0.8, Warm = 0.3)
- O = 60 occupants (membership values: Low = 0.3, Medium = 0.7, High = 0.2)
- OT = 80°F (membership values: Cold = 0.1, Mild = 0.9, Hot = 0.3)

Using fuzzy logic, the controller evaluates the fuzzy rules and membership functions to determine the HVAC output. Let us assume the output is "Cooling" with a membership value of 0.6.

Conclusion:

The fuzzy-logic-based HVAC controller efficiently adjusts the HVAC output based on the complex interactions between IT, O, and OT. By considering linguistic variables and membership functions, it provides adaptive and energy-efficient temperature control in real-time.

This case study demonstrates the practical application of fuzzy logic in enhancing control capabilities, especially in scenarios where traditional control systems may struggle to adapt effectively.

10.7 CHALLENGES AND FUTURE DIRECTIONS

1) *Computational complexity:* Fuzzy logic systems can become computationally intensive, especially in large-scale applications. Efficient algorithms and hardware acceleration methods need to be developed to handle complex FISs.
2) *Data uncertainty:* Fuzzy logic is effective at handling uncertainty, but it can be challenging to model and quantify uncertainty accurately. Improvements in uncertainty modeling and propagation are essential.
3) *Interoperability:* Integrating fuzzy logic-based controllers with existing control systems or IoT platforms can be complex. Standards and protocols for seamless integration are needed.
4) *Tuning and optimization:* Fuzzy systems often require manual tuning of membership functions and rules, which can be time-consuming. Automated tuning methods, such as machine learning-based approaches, are an ongoing research area.
5) *Explainability:* Fuzzy logic systems can be seen as "black boxes," making it difficult to explain their decisions. Developing methods to enhance the transparency and interpretability of fuzzy models is crucial, especially in critical applications.

Future Directions:

1) *Hybrid systems:* The integration of fuzzy logic with other AI techniques like neural networks and reinforcement learning is a promising direction. Hybrid systems can leverage the strengths of each approach for improved control and decision-making [36].
2) *Edge computing:* Fuzzy logic is well-suited for edge computing environments, where decisions need to be made locally and in real-time. Future research should focus on optimizing fuzzy systems for edge devices with limited resources [17].

3) *Explainable AI (XAI):* Advancements in XAI will benefit fuzzy logic by making its decision-making processes more transparent and understandable to users and stakeholders [14].
4) *Human–machine collaboration:* Fuzzy logic can play a vital role in collaborative decision-making between humans and autonomous systems. Research in this area can enhance the effectiveness and acceptance of autonomous systems in various domains [9].
5) *Energy efficiency:* Developing energy-efficient fuzzy controllers is crucial, especially for applications in renewable energy, smart buildings, and green technologies. Fuzzy systems can help optimize energy usage in real-time.
6) *Healthcare and biotechnology:* Fuzzy logic-based expert systems have substantial potential in healthcare for diagnostics, treatment recommendation, and monitoring of chronic diseases. Further research can improve the accuracy and reliability of such systems [12].

Emerging Trends:

1) *XAI:* As AI ethics and transparency gain importance, XAI techniques that work in conjunction with fuzzy logic will be a significant trend.
2) *AI in autonomous systems:* Fuzzy logic will continue to play a role in autonomous vehicles, drones, and robotics, where real-time decision-making under uncertainty is critical [8].
3) *Industry 4.0:* Fuzzy logic will be a key technology in the realization of smart factories and industrial automation, enabling flexible and adaptive manufacturing processes.
4) *Health tech:* Fuzzy logic will be applied in wearable devices and healthcare apps for personalized health monitoring and decision support [11].
5) *Environmental control:* Fuzzy logic will contribute to smart city initiatives and environmental monitoring by optimizing energy consumption and resource allocation.

In summary, fuzzy logic remains a valuable tool for control capability enhancement, and ongoing research will address challenges, drive innovations, and expand its applications across diverse domains in the future.

10.8 CONCLUSION

In this chapter, we explored the fascinating world of control capability enhancement through the lens of decision models, expert systems, and the integration of fuzzy logic. Here are the key takeaways:

1) *Control capability enhancement:* Control capability enhancement is a vital aspect of various domains, including industrial automation, healthcare, environmental management, and more. It involves improving the ability to make decisions, control processes, and respond to dynamic situations effectively.
2) *Role of decision models:* Decision models provide structured frameworks for making informed choices. They help in identifying optimal decisions, considering various factors, and enhancing overall control in complex systems.
3) *Expert systems:* Expert systems leverage human knowledge and expertise to make decisions in specific domains. They excel in capturing and replicating the decision-making processes of human experts, thus enhancing control capabilities.
4) *Significance of fuzzy logic:* Fuzzy logic, with its ability to handle uncertainty and imprecision, plays a crucial role in control capability enhancement. It offers a powerful framework for decision-making, particularly when dealing with vague or incomplete information.
5) *Fuzzy logic integration:* Integrating fuzzy logic into decision models and expert systems enhances their adaptability and resilience. Fuzzy logic enables systems to make decisions based on linguistic variables, which align well with human-like decision processes.
6) *Real-life applications:* We explored real-life applications across various domains where these technologies have made a significant impact. From industrial process control to healthcare diagnostics, decision models, expert systems, and fuzzy logic have demonstrated their effectiveness.
7) *Challenges and future directions:* We discussed the challenges associated with these technologies, such as computational complexity and explainability. Moreover, we highlighted future directions, including hybrid systems, edge computing, and advancements in XAI.
8) *Emerging trends:* The emerging trends in control systems point to a future where decision models, expert systems, and fuzzy logic continue to evolve and contribute to intelligent decision-making, autonomous systems, and sustainability.

In conclusion, control capability enhancement is essential for addressing the complexities of modern systems and industries. Decision models, expert systems, and fuzzy logic are powerful tools that, when applied judiciously, empower organizations and individuals to navigate uncertainty, optimize processes, and make informed decisions. As technology advances and new challenges arise, these tools will remain at the forefront of intelligent decision-making, shaping a more efficient, adaptive, and sustainable future.

KEYWORDS

- **fuzzy rules**
- **uncertainty**
- **inferences**
- **knowledgebase**
- **expert system**
- **control system**
- **aggregation**

REFERENCES

1. Ahmadzadeh, H., & Masehian, E. (2015). Modular robotic systems: Methods and algorithms for abstraction, planning, control, and synchronization. *Artificial Intelligence*, *223*, 27–64. https://doi.org/10.1016/j.artint.2015.02.004
2. Alkouri, A. U., & Salleh, A. R. (2014). Linguistic variable, hedges and several distances on complex fuzzy sets. *Journal of Intelligent & Fuzzy Systems*, *26*(5), 2527–2535. https://doi.org/10.3233/ifs-130923
3. Benra, F.-K., Dohmen, H. J., Pei, J., Schuster, S., & Wan, B. (2011). A comparison of one-way and two-way coupling methods for numerical analysis of fluid-structure interactions. *Journal of Applied Mathematics*, *2011*, 1–16. https://doi.org/10.1155/2011/853560
4. Bouchon-Meunier, B., Ramdani, M., & Valverde, L. (1994). Fuzzy logic, inductive and analogical reasoning. *Fuzzy Logic in Artificial Intelligence*, *847*, 38–50. https://doi.org/10.1007/3-540-58409-9_4
5. Božić, V. (2023). Fuzzy approach to risk management: Enhancing decision-making under uncertainty. *Drought, Risk Management, and Policy*. *14*, 319–341. https://doi.org/10.13140/RG.2.2.13517.82405.
6. Cheng, C.-H. (1997). Evaluating naval tactical missile systems by Fuzzy AHP based on the grade value of membership function. *European Journal of Operational Research*, *96*(2), 343–350. https://doi.org/10.1016/s0377-2217(96)00026-4
7. Cinelli, M., Kadziński, M., Gonzalez, M., & Słowiński, R. (2020). How to support the application of multiple criteria decision analysis? Let us start with a comprehensive taxonomy. *Omega*, *96*, 102261. https://doi.org/10.1016/j.omega.2020.102261
8. Dong, N., Wu, Z., Zhang, W., Chen, G., & Gao, Z. (2024). Intention-prioritized fuzzy fusion control for BCI-based Autonomous Vehicles. *Biomedical Signal Processing and Control*, *87*, 105486. https://doi.org/10.1016/j.bspc.2023.105486

9. D'Aniello, G. (2023). Fuzzy logic for situation awareness: A systematic review. *Journal of Ambient Intelligence and Humanized Computing*, *14*(4), 4419–4438. https://doi.org/10.1007/s12652-023-04560-6
10. Gupta, Y. P., & Chin, D. C. W. (1989). Expert systems and their applications in production and operations management. *Computers & Operations Research*, *16*(6), 567–582. https://doi.org/10.1016/0305-0548(89)90042-7
11. Hameed, K., Bajwa, I. S., Ramzan, S., Anwar, W., & Khan, A. (2020). *An Intelligent IOT Based Healthcare System Using Fuzzy Neural Networks*. Scientific Programming. https://doi.org/10.1155/2020/8836927
12. Hassanzad, M., Orooji, A., Valinejadi, A., & Velayati, A. (2017). A fuzzy rule-based expert system for diagnosing cystic fibrosis. *Electronic Physician*, *9*(12), 5974–5984. https://doi.org/10.19082/5974
13. Holman, J. G., & Cookson, M. J. (1987). Expert systems for medical applications. *Journal of Medical Engineering & Technology*, *11*(4), 151–159. https://doi.org/10.3109/03091908709008986
14. Kamruzzaman, M. M., Alanazi, S., Alruwaili, M., Alrashdi, I., Alhwaiti, Y., & Alshammari, N. (2022). Fuzzy-assisted machine learning framework for the FOG-computing system in remote healthcare monitoring. *Measurement*, *195*, 111085. https://doi.org/10.1016/j.measurement.2022.111085
15. Kocsi, B., Matonya, M. M., Pusztai, L. P., & Budai, I. (2020). Real-time decision-support system for high-mix low-volume production scheduling in industry 4.0. *Processes*, *8*(8), 912. https://doi.org/10.3390/pr8080912
16. Le Bris, S. (2019). Decision-making in complex environments under time pressure and risk of critical irreversibility: The role of meta rules. *M@n@gement*, *22*(1), 1. https://doi.org/10.3917/mana.221.0001
17. Li, D. C., Huang, C.-T., Tseng, C.-W., & Chou, L.-D. (2021). Fuzzy-based Microservice resource management platform for edge computing in the internet of things. *Sensors*, *21*(11), 3800. https://doi.org/10.3390/s21113800
18. Meliani, M., Barkany, A. E., Abbassi, I. E., Darcherif, A. M., & Mahmoudi, M. (2021a). Energy Management in the smart grid: State-of-the-art and future trends. *International Journal of Engineering Business Management*, *13*, 184797902110329. https://doi.org/10.1177/18479790211032920
19. Meliani, M., Barkany, A. E., Abbassi, I. E., Darcherif, A. M., & Mahmoudi, M. (2021b). Energy Management in the smart grid: State-of-the-art and future trends. *International Journal of Engineering Business Management*, *13*. https://doi.org/10.1177/18479790211032920
20. Mo, F., Monetti, F. M., Torayev, A., Rehman, H. U., Mulet Alberola, J. A., Rea Minango, N., Nguyen, H. N., Maffei, A., & Chaplin, J. C. (2023). A maturity model for the autonomy of manufacturing systems. *The International Journal of Advanced Manufacturing Technology*, *126*(1–2), 405–428. https://doi.org/10.1007/s00170-023-10910-7
21. Morris, B. (2005). Robotic surgery: Applications, limitations, and impact on surgical education. *MedGenMed*, *7*(3), 72. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC 1681689/
22. Parra, X., Tort-Martorell, X., Alvarez-Gomez, F., & Ruiz-Viñals, C. (2022). Chronological evolution of the information-driven decision-making process (1950–2020). *Journal of the Knowledge Economy*. *14*, 2363–2394. https://doi.org/10.1007/s13132-022-00917-y
23. Pfeifer, R., & Lüthi, H.-J. (1987). Decision support systems and expert systems: A complementary relationship? In: *Expert Systems and Artificial Intelligence in Decision Support Systems*. Springer: Dordrecht, pp. 41–51. https://doi.org/10.1007/ 978-94-009-3805-2_4

24. Rajendran, N., Singh, R., Moudgil, M. R., Turukmane, A. V., Umadevi, M., & Glory, K. B. (2022). Secured control systems through integrated IOT devices and control systems. *Measurement: Sensors*, *24*, 100487. https://doi.org/10.1016/j.measen.2022.100487
25. Reyes-García, C. A., & Torres-García, A. A. (2022). Fuzzy logic and fuzzy systems. In: *Biosignal Processing and Classification Using Computational Learning and Intelligence*. Academic Press, pp. 153–176. https://doi.org/10.1016/b978-0-12-820125-1.00020-8
26. Rondeau, L., Ruelas, R., Levrat, L., & Lamotte, M. (1997). A defuzzification method respecting the fuzzification. *Fuzzy Sets and Systems*, *86*(3), 311–320. https://doi.org/10.1016/s0165-0114(95)00399-1
27. Schoukens, J., & Ljung, L. (2019). Nonlinear system identification: A user-oriented road map. *IEEE Control Systems*, *39*(6), 28–99. https://doi.org/10.1109/mcs.2019.2938121
28. Shang, Y. (2005). Expert systems. In: *The Electrical Engineering Handbook*. Academic Press, pp. 367–377. https://doi.org/10.1016/b978-012170960-0/50031-1
29. Singh, P., Pandey, P. C., Petropoulos, G. P., Pavlides, A., Srivastava, P. K., Koutsias, N., Deng, K. A., & Bao, Y. (2020). Hyperspectral remote sensing in precision agriculture: Present status, challenges, and future trends. In: *Hyperspectral Remote Sensing*. Elsevier, pp. 121–146. https://doi.org/10.1016/b978-0-08-102894-0.00009-7
30. Sinha, D., & Dougherty, E. R. (1993). Fuzzification of set inclusion: Theory and applications. *Fuzzy Sets and Systems*, *55*(1), 15–42. https://doi.org/10.1016/0165-0114(93)90299-w
31. Sridhar, B., & Bell, D. (2022). Sustainable aviation operations and the role of information technology and data science: Background, current status and future directions. *AIAA AVIATION 2022 Forum*. https://doi.org/10.2514/6.2022-3705
32. Story, M. F. (n.d.). Medical Devices in home health care. In: *The Role of Human Factors in Home Health Care*. National Academies Press: Washington (DC).. https://www.ncbi.nlm.nih.gov/books/NBK210047/
33. Tedeschi, L. O. (2023). Review: The prevailing mathematical modeling classifications and paradigms to support the advancement of sustainable animal production. *Animal*, *17*, 100813. https://doi.org/10.1016/j.animal.2023.100813
34. Wang, K. (2001). Computational intelligence in agile manufacturing engineering. In: *Agile Manufacturing: The 21st Century Competitive Strategy*. Elsevier Science Ltd, pp. 297–315. https://doi.org/10.1016/b978-008043567-1/50016-4
35. Ying Xiao, Song, Y. H., Chen-Ching Liu, & Sun, Y. Z. (2003). Available transfer capability enhancement using facts devices. *IEEE Transactions on Power Systems*, *18*(1), 305–312. https://doi.org/10.1109/tpwrs.2002.807073
36. Zhang, G., Band, S. S., Ardabili, S., Chau, K.-W., & Mosavi, A. (2022). Integration of neural network and fuzzy logic decision making compared with bilayered neural network in the simulation of Daily Dew Point temperature. *Engineering Applications of Computational Fluid Mechanics*, *16*(1), 713–723. https://doi.org/10.1080/19942060.2022.2043187
37. Zook, D., & Samad, T. (n.d.). Sensors in control systems. In: Bonne, U. (Ed.), *Control Systems, Robotics, and Automation. Essay, Encyclopedia of Life Support Systems*. Vol. XXI.

CHAPTER 11

Tourist Attractiveness Assessment Using Fuzzy Set Interface (fsQCA) in Kolkata, West Bengal, India

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ABSTRACT

The research's objective is pertaining toward fuzzy-set qualitative comparative analysis (fsQCA) research on tourist attractiveness assessments in Kolkata is to thoroughly assess and comprehend the complex aspects that contribute toward the enticement and growth of tourism in this thriving and culturally diverse city. Kolkata, additionally known as the "City of Joy," is a culturally important urban area with an established tourist sector. Through the creative vision of fsQCA, this study seeks to highlight the numerous factors that influence Kolkata's attraction as a travel destination. The research being conducted aims to pinpoint the main factors that influence Kolkata's tourist appeal. We may account for the inherent contradictions and complexity involved with tourism assessment by using fsQCA, which blends fuzzy-set logic and qualitative analysis. Through this research, we determine the complex causal connections between the variables. Through fsQCA, we may identify factors that are both essential and adequate to make Kolkata a desirable travel destination. To conclude, the tourism attractiveness

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assessment utilizing fsQCA in Kolkata is a useful technique for separating the myriad variables that affect the city's tourism industry. It advances academic understanding while also providing stakeholders with practical information they can use to make educated choices, thereby promoting sustainable tourist growth in Kolkata. Both the regional tourism industry as a whole and the local economy are anticipated to gain from this study.

11.1 INTRODUCTION

A robust and virtually limitless reservoir of data, the Internet as a whole and particularly one of its amenities, the World Wide Web [2]. The widespread availability of Internet access has transformed the way people engage in activities related to travel and tourism [20]. The ability to reserve transport tickets, reserve lodging, arrange transfers to attractions, and other services was previously only available through a mediator; but today, anyone can do so on their own [39]. Everyone can work as their own travel agency by using services like vehicle rental, hotel reservations, ticket counters at museums and theme parks, and websites for airlines and railroads [43]. This has become possible through a trend known as electronic tourism, or e-tourism [33].

The recent boom and expansion of the tourism industry has become a key factor in the development and growth of economies around the world, boosting job opportunities, foreign exchange profits, and infrastructural growth [27]. The Indian government recognizes the value of the tourist sector and its contribution to the country's economic and cultural development of the many wonderful locations in India [3]. E-tourism, or the use of technological advances in the tourist sector, has fundamentally changed how visitors discover and interact with their travel destinations [11]. Kolkata, the vivacious "City of Joy," remains no exemption to this widespread trend. E-tourism has numerous advantages in Kolkata. It provides an exciting framework for highlighting its unique heritage of culture, historical sites, and variety of pleasures while allowing visitors to plan, schedule, and navigate their journeys with unmatched simplicity. E-tourism also improves connectivity because it reaches a worldwide audience, promotes local companies, and helps the economy by drawing more tourists [6].

The need for stable facilities and safety precautions, a possible overdependence on technological advances, plus the necessity of preserving the true essence of the travel experience are a few of the difficulties that come with this digital revolution [18]. Nonetheless, there are certain difficulties that the Indian tourist industry must overcome, such as the requirement of greater advertising and promotional efforts, an absence of standardization as well as quality regulation in certain regions, and limited facilities and services in other locations [25]. Additionally, disputes have been raised regarding the absence of customization and the decline of real human contacts in travel experiences due to a heavy dependence on Internet booking services [7].

Besides these technological challenges, the creation and upkeep of the infrastructure pose an important concern. Even though Kolkata is home to many famous attractions, the city's infrastructure, including its roadways, transportation system, and lodging options, frequently needs to be upgraded to keep up with the demands of visitors. The assessment and improvement of the town's travel experience appeal is one of the issues that this thriving tourism business has brought about [15]. Therefore, to draw in a wide variety of visitors, efficient tourism analysis is essential, both locally and globally [31].

Despite the value of using classic methods to evaluate tourist attractions, modern study increasingly depends on cutting-edge and novel methodologies to comprehend the sophisticated dynamics of traveler choices along with decision-making processes [1]. The use of fuzzy-set qualitative comparative analysis (fsQCA), a technically advanced method for determining and analyzing tourist appeal, constitutes a similar inventive approach [5].

With the use of a combination approach known as fsQCA, which integrates fuzzy set theory and qualitative comparative analysis, complicated and diverse factors can be understood in more detail [22]. It subsequently presents an in-depth study that highlights the elusive and complex character of individual desires and gives a more comprehensive viewpoint on the elements shaping tourist attractions [46].

RQ1: What are the factors that influence tourist satisfaction in tourism attractiveness assessment?

This approach takes into account how numerous factors interact, including "perceived enjoyment," "cultural heritage," "trustworthiness," "historical significance," "accommodation and hospitality," and overall "tourist satisfaction" by giving a thorough picture of how these factors influence tourists' decision to visit a particular location. Through the analysis, we can obtain the factors that account for a necessary condition for providing tourist satisfaction and hence [44], these findings can then be used to influence strategic choices, policy creation, and marketing initiatives, ultimately resulting in the sustained development and growth of Kolkata's tourist industry. It serves as a potent instrument that can direct the tourism sector in Kolkata in favor of an improved and analytical approach to comprehend and improve its visitor appeal [29]. This study aims to thoroughly evaluate

Kolkata's tourism appeal using the cutting-edge fsQCA approach. By developing the approach for evaluating tourism attractions in a wider context, this study provides a crucial step toward maximizing Kolkata's prospective as an attraction for travelers.

11.2 LITERATURE REVIEW

Analysis of many aspects that affect tourists' decisions and experiences is necessary to gauge Kolkata's tourist appeal, a city renowned for its dynamic culture and historic importance.

11.2.1 PERCEIVED ENJOYMENT

A key consideration for evaluating Kolkata's tourism appeal is perceived enjoyment. The research draws attention to the ways that local food, cultural events, and leisure pursuits affect how much visitors think they are having fun [41]. The delicious eateries as well as authentic Bengali cuisine of the city of Kolkata, along with its dynamic culinary scene, greatly contribute to the culinary pleasure of visitors. Traveler contentment, return business, and favorable word-of-mouth are all influenced by perceived enjoyment, which is strongly linked to the whole experience [30]. In addition to influencing visitors' happiness, perceived enjoyment also affects their propensity to return and refer other people to Kolkata [17]. Kolkata's distinct fusion of innovative and traditional elements, exemplified by its rich historic and creative legacy, cultivates an atmosphere conducive to subjective pleasure [4]. The vibrant dancing, literary, cultural, and artistic cultures of the city are widely recognized. Such aspects of culture enhance every aspect of the experience for tourists while also reflecting the cultural and intellectual significance associated with the city [35].

Although tourists find great pleasure in Kolkata's cultural and gastronomic attractions, maintaining and expanding these facets presents constant difficulties [47]. Likewise, overcommercialization of artistic performances may compromise their true meaning and lessen tourists' enjoyment of them [12]. This method can uncover complicated combinations of factors that contribute to significant or lower reported satisfaction in the city by taking into account the inaccurate and convoluted character of tourists' opinions and inclinations [10]. Moreover, it facilitates the identification of certain blends of situations and characteristics that are necessary to improve perceived satisfaction by policymakers allowing them to adapt their objectives and efforts accordingly [21].

11.2.2 CULTURAL HERITAGE

The rich history and creative diversity of Kolkata are closely linked to its cultural legacy [9]. An important factor in drawing tourists to the city is its diverse array of cultural attractions, art, and literary works [13]. The town's intellectual and cultural past is exhibited by significant sites including the Victoria Memorial, Tagore's family house, the Marble Palace, and other traditional temples and cathedrals [14]. It is a complex responsibility for city officials and tourism organizations to maintain the equilibrium between conserving the authenticity of history and responding to the changing demands and desires of visitors [32]. This element, which is deeply integrated into the historical foundation of the city, has a significant impact on visitors' experiences and level of enjoyment [8].

Although there are sustainability and authenticity issues that need to be resolved, the use of fsQCA as a study methodology offers a more thorough and nuanced knowledge of the interactions between the various elements that affect how much cultural heritage is valued [24]. In conclusion, Kolkata's cultural legacy should be preserved and effectively promoted in order to increase visitor pleasure and support the city's sustained stability in tourism.

11.2.3 TRUSTWORTHINESS

From tourism's framework, "trustworthiness" includes security, accuracy, reliability, and integrity. It is a critical component that influences travelers' decision-making and general level of satisfaction [37]. This aspect affects a lot of people because travelers are looking for more reliable and safe travel experiences, which greatly increases their trust in a place [19]. In Kolkata's tourism industry, perceptions of safety and reliability are strongly correlated [42]. The degree to which a city can guarantee visitors' individual hygiene and security affects how confident travelers are in the location [23]. The dependability of services and public transit networks are important factors in establishing the city's overall credibility [36]. When travelers believe Kolkata to be a reliable location, they are more inclined to relax and have fun while there.

fsQCA offers a potential way to completely examine the significance of trustworthiness in Kolkata's popular tourist sites [26]. Because these impressions are ambiguous and multifaceted, fsQCA can identify complex patterns of factors that contribute to varying degrees of trustworthiness throughout the city [24]. This approach can be employed by policymakers to ascertain specific pairings of characteristics and circumstances that are imperative for augmenting trustworthiness, so serving as a roadmap for their policies and initiatives. This factor—which includes trustworthiness, security, honesty, and reliability—has an enormous effect on visitors' overall impressions of the city and their level of satisfaction [38].

11.2.4 HISTORICAL SIGNIFICANCE

Travelers are drawn to Kolkata by its historical significance, which is intricately entwined with the story of India's freedom movement and its status as a hub for creative and artistic pursuits [45]. The town is dedicated to several destinations that not merely represent historic importance but additionally provide a comprehensive experience to visitors. This chapter highlights the value of cultural excursions as ways for visitors to completely engage themselves in the rich history of the city. This historical account considerably boosts the city's touristic attraction and generates a strong sense of community [40]. Kolkata's cultural importance attracts many tourists, but maintaining and highlighting these historical features is a constant struggle [34]. It is a challenging effort for city officials and tourism stakeholders to strike a balance between maintaining the genuineness of the legacy and adjusting to the changing demands and standards of tourists [16].

This element, which is intertwined with the city's historical significance as well as its societal and artistic remarks, has a significant impact on visitors' perceptions of the city as well as their overall pleasure with it [28]. The inclusion of fsQCA as an investigation method has the possibility of delivering a more complex and thorough understanding of the interaction of elements impacting the appraisal of historical value, even though challenges connected to conservation and integrity must be addressed [26].

11.2.5 HOSPITALITY AND ACCOMMODATION

The warmth and high standard of service that the locals and the tourism sector provide to guests is referred to as hospitality [48]. It includes the warmth, politeness, and welcoming disposition of the locals in a place. Restaurants, bars, cafes, and other businesses that provide food and beverage services are included in the hospitality sector [49]. Travelers' experiences can be greatly improved by hospitable and friendly locals, who make them feel at ease and appreciated [50]. Travelers' experiences can be greatly improved by hospitable and friendly locals, who make them feel at ease and appreciated [51]. The availability of housing and rental options for travelers is referred to as accommodation. These can include motels and resorts as well as cabins, hostels, and other lodging options [52]. By providing a location for travelers to relax and recharge, accommodations are essential in drawing in tourists [53]. Because they accommodate a range of tastes, spending limits, and vacation styles, the caliber and variety of lodging alternatives at a destination play a big role in determining a tourist's decision to come [54].

Together, lodging and hospitality contribute a vital part in the attraction of a place for tourists. They enhance visitors' overall enjoyment and experience, increasing the likelihood that they will return or refer others to the location [55]. Superior amenities and an extensive selection of lodging choices can increase a place's allure and competitiveness within the travel sector.

11.3 RESEARCH METHODOLGY

An organized strategy is used in the research technique for data collection in the context of tourism attractiveness using fsQCA. To start, this study has been directed by well-defined research objectives. Important elements influencing the allure of tourism are determined, and travel locations or areas are chosen as Kolkata.

Online reviews and statistical records were collected from TripAdvisior and MakemyTrip. A thorough framework for gathering data is created, outlining the characteristics of every component and the techniques for gathering data. To ensure accuracy, data is cleansed, checked, and calibrated as needed. Using the fsQCA software, an fsQCA is carried out, and the findings are evaluated to determine the configurations of conditions impacting the attractiveness of tourists. Results are presented with consideration for limitations to provide clarity on the elements influencing tourism attraction in the chosen locations.

11.4 FINDINGS AND ANALYSIS

The associations between two or more category variables can be better understood by using cross-tabulation analysis using a Likert scale with a range of 1–5 (strongly disagree to strongly agree) Likert scales are frequently used to evaluate thoughts, opinions, and views. Understanding how various groups or categories of respondents interpret or react to various factors is essentially what we are attempting to ascertain when we cross-tabulate data from a Likert scale.

A cross-data tabulation analysis is carried out to comprehend the association between different variables: "perceived enjoyment," "trustworthiness," "cultural heritage," "historical significance," "hospitality and "accommodation," and the independent construct "tourist satisfaction." From Table 11.1, the total count for each quantile in each row shows how ratings of visitor satisfaction are distributed along the Likert scale can be observed. By comparing the collected ratings, we can see that "perceived enjoyment" and "historical significance" show comparatively homogeneous distributions, whereas "cultural heritage" and "trustworthiness" possess a larger percentage of effective ratings (4 and 5), and, finally, "accommodation and hospitality" have moderate ratings.

TABLE 11.1 Brief Description of Factors Affecting Tourism Attractiveness Assessment ⏎

Constructs	Definition
Perceived Enjoyment	The extent to which using an arrangement is regarded as pleasurable unto itself, regardless of how it may affect efficiency.
Trustworthiness	The level of trust in the information, analysis, and procedures utilized to guarantee a study's quality.
Cultural Heritage	An artistic representation of a community's ideals, rituals,practises, locations, artefacts, and ways of life that have been passed down through the generations.
Historical Significance	An essential concept in historiography that looks into and attempts to articulate how particular historic instances are selected for memory by cultures worldwide.
Hospitality & Accommodation	The availability of lodging for those departing from home for the night as well as alternatives for eating out.

fsQCA is a research technique that examines and studies intricate connections between several elements that may result in a certain result. The conditions and result data must be calibrated prior to running the QCA. To calibrate a fuzzy set, a target set must be identified. This establishes the calibration of the set and creates a clear link between theoretical discourse and empirical research. The fsQCA was used in this study, and the associated factors and results were calibrated as fuzzy set membership scores through the use of the direct calibration approach. The objective of fsQCA is to calibrate set membership in a way that the membership levels reflect meaningful groups.

The fsQCA 3 software was used to understand complex relationships between factors affecting tourist attractiveness assessment. The collected original data is calibrated into fuzzy membership score ranging from 0.00 to 1.00: where the nonmembership score represents 5%, cross-over anchors are 50%, and the full-membership score represents 95% of the value our measures and used the values obtained as the three thresholds while calibrating the variables in fsQCA 3 software. Next, the truth table was then constructed. The truth table was then sorted by frequency using the column “number“ sorting method (Figure 11.1).

ENJOYMENT	HISTORICAL	HERITAGE	HOSPITALITY	RUSTWORTHINES	number	SATISFACTION	cases	raw consist.	PRI consist.	SYM consist
1	0	1	1	1	3	1	cases	1	1	1
0	0	0	0	0	1	1	cases	1	1	1
0	1	0	0	0	1	1	cases	1	1	1
0	1	1	0	0	1	1	cases	1	1	1
0	0	1	1	0	1	1	cases	1	1	1
0	0	0	0	1	1	1	cases	1	1	1
0	0	1	0	1	1	1	cases	1	1	1
1	0	1	0	1	1	1	cases	1	1	1
1	1	1	0	1	1	1	cases	1	1	1
1	1	1	1	1	14	1	cases	0.997893	0.997871	1

FIGURE 11.1 Solution scores distribution to the truth table (fsQCA). ⏎

The truth table was ordered by “raw consistency” after being sorted by frequency, with a frequency threshold of 0.8 applied. Three distinct outcomes are obtained from standard analysis: complex, parsimonious, and intermediate solutions. Further, we will discuss these solutions broadly.

A thorough examination of data patterns yields a sophisticated answer through fsQCA , which reveals a number of complex solutions and conditions within a particular dataset. The solution has the ability to extract valuable insights from the data, as seen by its remarkable metrics, which include raw coverage, unique coverage, and consistency. Table 11.2 gives the complex solutions generated through fsQCA analysis.

The three main focuses of the study in this instance are “perceived enjoyment,” “cultural heritage,” and “trustworthiness.” Initially, the word “perceived enjoyment” pertains regarding the pleasant and contented sensation that is essential in a tourist attractiveness. “Trustworthiness” indicates the presence of dependability and confidence, whilst “Cultural Heritage” indicates the presence of cultural and historical components. The intricate answer is based on the interactions between these elements.

TABLE 11.2 Cross-Data Tabulation Analysis ⏎

CONSTRUCT/QUINTILE		**TOURIST SATISFACTION**					
		1	**2**	**3**	**4**	**5**	**Total Count**
Percieved enjoyment	1	0	12	0	3	0	15
	2	15	27	9	0	9	60
	3	6	42	75	90	12	225
	4	0	18	12	78	9	117
	5	0	0	9	48	60	117
Total count		21	99	105	219	90	534
		1	2	3	4	5	
Historical significance	1	3	0	6	0	0	9
	2	18	33	15	21	3	90
	3	0	60	69	93	27	249
	4	0	3	12	36	0	51
	5	0	3	3	69	60	135
Total count		21	99	105	219	90	534
		1	2	3	4	5	
Cultural heritage	1	0	6	3	6	6	21
	2	15	18	9	12	3	57
	3	6	51	42	63	24	186
	4	0	21	45	117	30	213
	5	0	3	6	21	27	57
Total count		21	99	105	219	90	534

TABLE 11.2 *(Continued)*

CONSTRUCT/QUINTILE		TOURIST SATISFACTION					
		1	**2**	**3**	**4**	**5**	**Total Count**
		1	2	3	4	5	
Accommodation and hospitality	1	0	6	3	0	0	9
	2	15	15	9	3	3	45
	3	6	66	75	48	21	216
	4	0	12	18	129	6	165
	5	0	0	0	39	60	99
Total count		21	99	105	219	90	534
		1	2	3	4	5	
Trustworthiness	1	0	6	0	3	3	12
	2	6	12	15	18	15	66
	3	12	54	21	78	21	186
	4	3	27	66	114	45	255
	5	0	0	3	6	6	15
Total count		21	99	105	219	90	534

The complex solution's (Table 11.3) high coverage scores of **0.992757** indicates that it captures nearly all relevant occurrences in the dataset, as it shows its capacity to catch a major fraction of the data patterns. This broad coverage demonstrates how well fsQCA finds and captures important relationships and conditions within the data. Furthermore, the strong and consistent links within the complicated solution are shown by the high consistency value of **0.997574**. It implies that the links discovered are backed by substantial evidence found in the data and are not just random events. This degree of regularity makes it more probable that there are real relationships between the three dominant factors than merely coincidental ones.

TABLE 11.3 Complex Solutions ⏎

Enjoyment*heritage*trust	0.765795	0.757344	0.996857
~Enjoyment*~historical*~heritage*~hospitality	0.0804829	0.0804829	1
~Enjoyment*historical*~hospitality*~trust	0.0828974	0.075654	1
~Enjoyment*~historical*~hospitality*trust	0.0828974	0.0378269	1
~Enjoyment*~historical*heritage*hospitality*~trust	0.0462777	0.037827	1
Solution coverage: 0.992757			
Solution consistency: 0.997574			

A theoretical examination of this intricate solution provides numerous insightful discoveries. It shows that in the dataset, "Enjoyment" is strongly associated with "cultural heritage" and "trustworthiness" with a consistency level of **0.996857**. This implies that, given the evidence, heritage-related experiences and the trust they generate have a substantial impact on tourist satisfaction. This conclusion, which emphasizes the value of trust and heritage in raising tourists' overall experience, is especially pertinent to the tourism sector.

Some components, such as "historical significance," have negations (~) in them, which suggests that comprehending the relationships within the dataset also requires knowing the lack of certain aspects. For example, the lack of historical components may significantly affect heritage, trust, and enjoyment. A more thorough knowledge of the variables affecting these qualities is provided by this nuanced understanding.

The intermediate solution (Table 11.4) produced by the fsQCA analysis provides insightful information about determining tourist appeal. The analysis looks at how "perceived enjoyment," "cultural heritage," and "trustworthiness" relate to each other in the context of travel locations. The solution is an effective tool for determining and improving tourist attraction because of its high coverage, originality, and consistency criteria.

TABLE 11.4 Intermediate Solutions ⏎

	Raw Coverage	Unique Coverage	Consistency
Enjoyment*heritage*trust	0.765795	0.757344	0.996857
~Enjoyment*~historical*~heritage*~hospitality	0.0804829	0.037827	1
~Enjoyment*historical*~hospitality*~trust	0.0828974	0.075654	1
~Enjoyment*~historical*~hospitality*trust	0.0828974	0.0378269	1
~Enjoyment*~historical*heritage*hospitality*~trust	0.0462777	0.037827	1
Solution coverage: 0.992757			
Solution consistency: 0.997574			

"Perceived Enjoyment" is a very important part of traveling. When traveling, tourists look for contentment, happiness, and special moments. This component of the approach highlights how important it is to offer pleasurable experiences in order to draw tourists. "Cultural heritage" refers to a place's historical and cultural features. In an effort to learn more about and appreciate a region's history, customs, and cultural diversity, many travelers are drawn to locations with a rich cultural legacy. For travelers, "trustworthiness" is crucial while selecting a location. Trust is correlated with an establishment's dependability, security, and good standing. Travelers need to have faith in the place they have chosen and feel safe.

With a solution coverage value of **0.992757**, the solution appears to fully account for a number of elements influencing visitor attraction, as it catches a significant amount of the data patterns. It highlights how crucial it is to look at all pertinent factors in order to develop a comprehensive picture of tourism locations. The dependability and strength of the detected relationships are reinforced by the consistency value of **0.997574**. The research strongly suggests that the correlations between the necessary factors are not coincidental, but rather that these factors are critical to the attractiveness of tourism.

The analysis reveals that the factors perceived enjoyment, cultural heritage, and trustworthiness have a significant contribution in enhancing Tourist Satisfaction with a consistency level of **0.996857**. This implies that in order to achieve the intended result, a blend of tradition, enjoyment, and trust is necessary. There is a significant and constant association between these three qualities and the maximum level of satisfaction associated with heritage when they are present.

To sum up, the fsQCA study offers insightful information about the variables influencing “enjoyment heritage trust” results. It makes clear the crucial elements, how they work together, and what happens when these elements are missing. Considering the intricate and varied nature of the interactions involved, this analysis can help guide decision-making and methods for reaching the intended result. In-depth case studies and additional investigation may be necessary to fully investigate these results in particular situations and offer more thorough insights.

The configurations of sufficient conditions for determining the outcome (Table 11.5) above signifies the solution coverage of various factors affecting tourist attractiveness assessment. Blank domains imply an insignificant domain in which the result is independent of the existence or absence of the causative factors, whereas When a circumstance is present, black circles (●) show it, and when it is absent, white circles (○) show it. The findings demonstrate if different configuration paths of conditions that are equally effective lead to the same result, answering three significant characteristics of causative intricacy: conjunction, asymmetry, and equality.

TABLE 11.5 Configurations of Sufficient Conditions for Determining the Outcome ⏎

Perceived Enjoyment	Trustworthiness	Cultural Heritage	Historical Significance	Hospitality and Accommodation
●	●		●	
●	○	○	○	○
○	●	●	○	●
○		○	●	○
●	○	○	●	●

11.5 CONCLUSION

The tourism sector has expanded significantly in recent years, and places like Kolkata are becoming more and more popular travel destinations. This research’s aim is to evaluate Kolkata’s tourism appeal using the fsQCA approach. This research was intended to identify the complex interrelationships between many factors that contribute to Kolkata’s appeal as a vacation destination. It provides insightful information regarding the various features of the city’s tourism attractiveness through careful data gathering and fsQCA analysis.

The results of our study showed that Kolkata’s tourism attractiveness is influenced by a number of interconnected elements instead of just one dominant factor. Numerous significant factors were considered during the inquiry, including the vicinity's environment, security, amenities as well as culture. The importance of these components when assessing the town's general tourist attractiveness varied. To develop policies that successfully boost Kolkata's appeal to tourists, legislators, tourism developers, as well as other partners must recognize this diversity.

Kolkata's tourism appeal is largely attributed to its rich ancestral legacy. The city's fascinating past and multitude of cultures, which are demonstrated in its historical sites, museums, and celebrations, are major attractions for tourists. The way other things interact is also very important. In summary, this study shows that Kolkata's visitor appeal is the result of a complex interaction between a number of variables, each of which adds to the city's overall allure. The city's natural attractions, infrastructure, safety, warmth, and historical and cultural legacy all have important roles to play. Improving the allure of Kolkata for tourists necessitates a comprehensive strategy that takes into account and makes use of these diverse circumstances. In order to effectively increase tourism appeal, local governments, tourism boards, and enterprises can use the foundation provided by this study to customize their strategies and investments. By identifying and using these many yet interrelated elements, Kolkata's potential as a flourishing travel destination may be further realized, eventually resulting in increased economic and cultural advantages for the city and its citizens.

KEYWORDS

- **fuzzy-set qualitative comparative analysis**
- **attractiveness**
- **qualitative approach**
- **tourism**
- **tourism industry**

REFERENCES

1. Kutsenko, A., Megel, Y., Kovalenko, S., Kovalenko, S., et al. (2019). An approach to quality evaluation of embryos based on their geometrical parameters. In: *Photonics Applications in Astronomy, Communications, Industry, and High-Energy Physics Experiments*. SPIE, p. 11176.

2. Adebayo, W. J. (2014). The economic impact of tourism development. *Journal of Tourism, Hospitality and Sports*.
3. Aerts, J. C., Botzen, W. J., Clarke, K. C., Cutter, S. L., Hall, J. W., Merz, B., et al. (2018). Integrating human behaviour dynamics into flood disaster risk assessment. *Nature Climate Change*, *8*(3), 193–199.
4. Andereck, K. L., & Nyaupane, G. P. (2011). Exploring the nature of tourism and quality of life perceptions among residents. *Journal of Travel Research, 50*(3), 248–260.
5. Chang, B., & Chang, J. R. Using fuzzy theory to analyze tourism preference. In: *Future Information Technology*. Springer: Berlin, Heidelberg, 2014, pp. 705–711.
6. Boletsis, C., & Chasanid, D. Smart tourism in cities: Exploring urban destinations with audio augmented reality. In: *Proceedings of the 11th Pervasive Technologies Related to Assistive Environments Conference*. PETRA, 2018, Corfu, Greece.
7. Brauckmann, S. (2017). City tourism and the sharing economy–potential effects of online peerto-peer marketplaces on urban property markets. *Journal of Tourism Futures, 3*(2), 114–126.
8. Buonincontri, P., & Marasco, A. (2017). Enhancing cultural heritage experiences with smart technologies: An integrated experiential framework. *European Journal of Tourism Research, 17*, 83–101.
9. Camarero, C., Garrido, M. J., & Vicente, E. (2015). Achieving effective visitor orientation in European museums. Innovation versus custodial. *Journal of Cultural Heritage, 16*(2), 228–235.
10. Casady, C. B. (2021). Examining the institutional drivers of public-private partnership (PPP) market performance: A fuzzy set qualitative comparative analysis (fsQCA). *Public Management Review, 23*(3) 981–1005. https://doi.org/10.1080/14719037.2019.1708439
11. Chen, X., Cheng, Z. F., & Kim, G. B. (2020). Make it memorable: Tourism experience, fun, recommendation and revisit intentions of Chinese outbound tourists. *Sustainability*, *12*(5), 1904. https://doi.org/10.3390/su12051904
12. Chiu, Y. T. H., Lee, W. I., & Chen, T. H. (2014a). Environmentally responsible behaviour in ecotourism: Antecedents and implications. *Tourism Management*, *40*, 321–329.
13. Davis, P., Huang, H.-Y., & Liu, W.-C. (2010). Heritage, local communities and the safeguarding of “Spirit of Place” in Taiwan. *Museum and Society*, *8*(2), 80–89. http://openarchive.icomos.org/84/1/77-LtNt-2012_.pdf
14. du Cros, H., & McKercher, B. (2015). *Cultural Tourism*, 2nd edn. Routledge.
15. Fathima, K. M., Sowdesh, R. M., Mugilanandam, R., Anend, S. N., & Raj, D. K. (2023). Trip Backer: A fuzzy logic based approach to E-tourist attractiveness assessment. *International Journal of Research in Engineering, Science and Management*, *6*(6), 74–77.
16. Go, H., & Kang, M. (2023). Metaverse tourism for sustainable tourism development: Tourism agenda 2030. *Tourism Review*, *78*, 381–394..
17. Gössling, S., Scott, D., Hall, C. M., Ceron, J. P., & Dubois, G. (2012). Consumer behaviour and demand response of tourists to climate change. *Annals of Tourism Research*, *39*(1), 36–58.
18. Hadinejad, A., Moyle, B. D., Scott, N., Kralj, A., & Nunkoo, R. (2019). Residents’ attitudes to tourism: A review. *Tourism Review*, *74*(2), 150–165. https://doi.org/10.1108/TR-01-2018-0003
19. Han, H., & Hyun, S. S. (2017). Drivers of customer decision to visit an environmentally responsible museum: Merging the theory of planned behavior and norm activation theory. *Journal of Travel & Tourism Marketing*, *34*(9), 1155–1168.

20. Henry, A. D. (2018). Learning sustainability innovations. *Nature Sustainability*, *1*(4), 164–165. https://doi.org/10.1038/s41893-018-0053-9
21. Hultman, M., Kazeminia, A., & Ghasemi, V. (2015). Intention to visit and willingness to pay a premium for ecotourism: The impact of attitude, materialism, and motivation. *Journal of Business Research*, 68(9), 1854–1861.
22. Merigó, J. M., Gil-Lafuente, A. M., & Yager, R. R. (2015).An overview of fuzzy research with bibliometric indicators. *Applied Soft Computing*, 27, 420–433.
23. Jansson, J., Marell, A., & Nordlund, A. (2011). Exploring consumer adoption of a high involvement eco-innovation using value-belief-norm theory. *Journal of Consumer Behaviour*, *10*(1), 51–60.
24. Kraus, S., Ribeiro-Soriano, D., Schüssler, M. (2018). Fuzzy-set qualitative comparative analysis (fsQCA) in entrepreneurship and innovation research—the rise of a method. *International Entrepreneurship and Management Journal 14*(1), 15–33. https://doi.org/10.1007/S11365-017-0461-8.
25. Kuhzady, S., Seyfi, S., & Béal, L. (2022). Peer-to-peer (P2P) accommodation in the sharing economy: A review. *Current Issues in Tourism*, *25*(19), 3115–3130.
26. Kumar, S., Sahoo, S., Lim, W.M., Kraus, S., Bamel, U.K. (2022). Fuzzy-set qualitative comparative analysis (fsQCA) in business and management research: A contemporary overview. *Technological Forecasting and Social Change*, *178*, 121599. https://doi.org/10.1016/j. techfore.2022.121599.
27. Lawton, L. J., & Weaver, D. B. (2015). Using residents' perceptions research to inform planning and management for sustainable tourism: A study of the Gold Coast Schoolies Week, a contentious tourism event. *Journal of Sustainable Tourism, 23*(5), 660–682. https://doi.org/10.1080/09669582.2014.991398
28. Lopez-Cabarcos, M.A., Pineiro-Chousa, J., Quiñoá-Piñeiro, L. (2020). An approach to a country's innovation considering cultural, economic, and social conditions. *Economic Research-Ekonomska Istraživanja, 34*, 2747–2766. https://doi.org/10.1080/1331677X.2020.1838314.
29. Chen, M. Y., & Linkens, D. A. (2004). Rule-base self-generation and simplification for data-driven fuzzy models. *Fuzzy Sets and Systems*, *142*(2), 243–265.
30. Nunkoo, R., & Gursoy, D. (2012). Residents' support for tourism: An identity perspective. *Annals of Tourism Research*, *39*(1), 243–268.
31. Nunkoo, R., Ramkissoon, H., & Gursoy, D. (2012). Public trust in tourism institutions. *Annals of Tourism Research*, *39*(3), 1538–1564. https://doi.org/10.1016/j.annals.2012.04.004
32. Nunkoo, R., Ribeiro, M. A., Sunnassee, V., & Gursoy, D. (2018). Public trust in mega event planning institutions: The role of knowledge, transparency and corruption. *Tourism Management*, 66, 155–166.
33. Bing, P. (2015). E-Tourism. In: *Entry in Encyclopedia of Tourism*. Springer: New York.
34. Pratt, M. (2022). Metaverse pros and cons: Top benefits and challenges. Retrieved from https://www.techtarget.com/searchcio/tip/Metaverse-pros-and-cons-Top-benefits-and challenges.
35. Prayag, G., & Ryan, C. (2012). Antecedents of tourists' loyalty to Mauritius: The role and influence of destination image, place attachment, personal involvement, and satisfaction. *Journal of Travel research, 51*(3), 342–356.
36. Ramkissoon, H., Mavondo, F., & Uysal, M. (2018). Social involvement and park citizenship as moderators for quality-of-life in a national park. *Journal of Sustainable Tourism*, *26*(3), 341–361.

37. Rasoolimanesh, S. M., & Jaafar, M. (2017). Sustainable tourism development and residents' perceptions in World Heritage Site destinations. *Asia Pacific Journal of Tourism Research*, *22*(1), 34–48.
38. Raymond, C. M., Brown, G., & Robinson, G. M. (2011). The influence of place attachment, and moral and normative concerns on the conservation of native vegetation: A test of two behavioural models. *Journal of Environmental Psychology*, *31*(4), 323–335.
39. Ribeiro, M. A., Pinto, P., Silva, J. A., & Woosnam, K. M. (2017). Residents' attitudes and the adoption of pro-tourism behaviours: The case of developing island countries. *Tourism Management*, *61*, 523–537. https://doi.org/10.1016/j. tourman.2017.03.004
40. Rubio-Escuderos, L., García-Andreu, H., & Michopoulou Buhalis, D. (2021). Perspectives on experiences of tourists with disabilities: Implications for their daily lives and the tourist industry. *Tourism Recreation Research*, *49*, https://doi.org/10.1080/02508281. 2021.1981071
41. Sharpley, R., & Telfer, D. J. (Eds.). (2014). *Tourism and Development: Concepts and Issues*.
42. Singh, S. S. (2015). The bankers of Bengal. *The Hindu*. India.
43. Song, M., Noone, B. M., & Han, R. J. (2019). An examination of the role of booking lead time in consumers' reactions to online scarcity messages. *International Journal of Hospitality Management*, *77*, 483–491. DOI: 10.1016/j.ijhm.2018.08.012.
44. Terano, T., Asai, K., & Sugeno, M. (2014). *Applied Fuzzy Systems*. Academic Press.
45. Tsai, S. (2022). Investigating metaverse marketing for travel and tourism. *Journal of Vacation Marketing*, *30*(3), 479–488. https://doi.org/10.1177/13567667221145715
46. Megel, Y., Kovalenko, S., Kovalenko, S., & Mikhnova, O. An approach to quantitative assessment of inbound tourism impact on the country's economy.
47. Zhang, H., Wu, Y., & Buhalis, D. (2018). A model of perceived image, memorable tourism experiences and revisit intention. *Journal of Destination Marketing & Management*, *8*, 326–336. https://doi.org/10.1016/j.jdmm.2017.06.004
48. Venkatesh, M., & Raj, D. J. (2016). Impact of tourism in India. *International Journal of Scientific Engineering and Applied Science*, *2*(1), 167–184.
49. Gössling, S., & Higham, J. (2021). The low-carbon imperative: Destination management under urgent climate change. *Journal of Travel research, 60*(6), 1167–1179.
50. Jaswal, S. S. (2014). Role of tourism industry in India's development. *Journal of Tourism and Hospitality*, 3(2), 1–6.
51. Chakrabarty, N. (2020). A regression approach to distribution and trend analysis of quarterly foreign tourist arrivals in India. *Journal of Soft Computing Paradigm (JSCP)*, *2*(01), 57–82.
52. Han, J. S., Lee, T. J., & Ryu, K. (2018). The promotion of health tourism products for domestic tourists. *International Journal of Tourism Research*, *20*(2), 137–146.
53. Jørgensen, H. (2019). Postcolonial perspectives on colonial heritage tourism: The domestic tourist consumption of French heritage in Puducherry, India. *Annals of Tourism Research*, *77*, 117–127.
54. Bosangit, C., Hibbert, S., & McCabe, S. (2015). "If I was going to die, I should at least be having fun": travel blogs, meaning, and tourist experience. *Annals of Tourism Research*, *55*, 1–14.
55. Vernekar, S. (2015). The growth of travel and tourism: An overview. *Journal of Commerce and Management Thought*, *6*(3), 547–557.

CHAPTER 12

Intelligent Fuzzy Logic Controller-Based Greenhouse Automation Using Sensor Networks

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ABSTRACT

The application of advanced control systems and sensor networks in greenhouse automation has drawn an immense amount of attention recently due to the pressing need for sustainable and efficient agricultural practices. This ok chapter explores the integration of intelligent fuzzy logic controllers (FLCs) with sensor networks to enhance the automation and management of greenhouse environments. Sensor networks play a pivotal role, providing real-time data on environmental variables including temperature, humidity, light intensity, soil moisture, irrigation, and carbon dioxide levels. These sensors feed data to the intelligent FLC, which serves as the decision-making hub of the automation system. It uses fuzzy logic rules and membership functions to adjust parameters, create an optimal microclimate for plant growth. It also presents case studies and experimental results that demonstrate the system's effectiveness in maintaining a conducive environment for various plant species. The environmental and economic benefits of the proposed system are explored in-depth, emphasizing its potential to reduce energy consumption, water usage, and the need for chemical inputs, thereby contributing

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to sustainable and eco-friendly agriculture practices; thereby ultimately contributing to food security and environmental sustainability.

12.1 INTRODUCTION

Due to the rapid increase in population in India, plant-based food production also needs to be significantly increased. As the climate changes, conventional agricultural practices are currently facing difficulties. By utilizing cutting-edge technology, agriculture has seen a tremendous transition recently. Greenhouse farming offers controlled conditions for the best plant growth and is one of the most promising technologies. Crops can be cultivated in greenhouses under controlled conditions, increasing yields and better-quality produce. Implementing sophisticated automation systems that can adapt to changing climatic conditions and optimize resource utilization is crucial for maximizing the potential of greenhouse farming. Greenhouse farming offers a climate-controlled environment that reduces the influence of outside variables on crop growth. Although the idea of automation in greenhouse farming is not new, incorporating intelligent systems, such as fuzzy logic controllers (FLCs), can potentially transform the sector entirely. The automation of greenhouses, where climatic conditions are dynamic and frequently unpredictable, is a good application for FLCs that are excellent at managing uncertainties and imprecise data.

Designing an intelligent FLC-based greenhouse automation system is the primary goal of this research work. In real time, the system incorporates a variety of sensors to collect data on environmental parameters, including temperature, humidity, and soil moisture. The acquired data is processed using fuzzy logic algorithms to make wise decisions regarding regulating greenhouse components, including ventilation, irrigation, heating, and cooling systems. The technology promises to achieve precision control, energy efficiency, and resource optimization, improving agricultural yields and saving operating costs. The proposed strategy has the ideals of sustainable agriculture because it optimizes energy use, consumes less water, and depends less on chemical inputs. The study also investigates the usefulness of FLCs in real-time agricultural automation, which contributes essential knowledge to intelligent control systems.

The remaining parts are structured as follows: Section 12.2 thoroughly analyzes related literature, highlighting earlier studies in fuzzy logic control and greenhouse automation. The design and execution of the intelligent FLC-based greenhouse automation system are covered in detail in Section 12.3.

Section 12.4 describes the experimental design and highlights the results. Section 12.5 summarizes the results, discusses their implications, and makes suggestions for further research to bring the paper to a conclusion.

12.2 LITERATURE REVIEW

The rapid growth of the human population worldwide has impacted the environment, resulting in reduced greenery. This is necessitated for new technologies and innovation in agriculture and plant cultivation [1]. Greenhouses are utilized to cultivate plants to enhance crop productivity and guarantee optimal product quality. Greenhouse management and control are a complex undertaking due to the interdependence of numerous variables. The implementation of real-time monitoring and the utilization of intelligent approaches for control play crucial roles in optimizing the environmental conditions for plant growth [2]. The early consideration of subsystem interactions, such as heating systems, and component interactions, such as actuators and sensors, in the design phase of an autonomous greenhouse can facilitate the product development process due to its mechatronic nature. Taking this factor into account can undoubtedly expedite the design process, minimize the need for iterative revisions, and enhance the overall performance of the mechatronic system.

In recent years, there has been a growing interest in applying sophisticated control techniques and associated tactics, including predictive control and adaptive control [3]. The concepts of optimum and compatible control have been proposed as potential approaches for controlling greenhouse environments. These studies are essential in using engineering principles in greenhouse production [4, 5]. Nevertheless, most of these methodologies are characterized by either intricate theoretical frameworks or practical challenges regarding their implementation in real-world greenhouse cultivation. Greenhouse environmental control systems commonly employ standard proportional, integral, and derivative (PID) controllers due to their straightforward design, implementation, and exceptional performance [6]. The majority, approximately 95%, of the regulatory controllers utilized in various industries, such as process control motor drives, automotive, flight control, and instrumentation, are structured according to the PID control mechanism. Despite the prevalence of their usage, the efficacy of PID controllers is frequently constrained due to inadequate tuning.

Consequently, the efficient tuning of PID controllers remains an area of current investigation [7, 8]. The extant literature has introduced several tuning strategies, including "guess-and-check" approaches such as trial and error, as well as methods rooted in linear control theory, such as Ziegler–Nichols and Cohen–Coon methods. However, attaining the desired performance of a controlled greenhouse via standard tuning methods poses challenges because of the need for appropriate analytical approaches for determining the ideal set of gain parameters [9–11].

Recently metaheuristic techniques and nonlinear control systems for climate control in greenhouses have been implemented by engineers and researchers [12]. These approaches utilize FLCs to regulate the environmental parameters in greenhouses, such as temperature, humidity, and light intensity. This makes it easy for ordinary greenhouse workers to interact with the system because it could be more user-friendly, and it is simple to implement an FLC system. The work done by [13] focuses on using a fuzzy logic-based controller combined with a wireless communication system to control the climate of a greenhouse [14]. The authors integrate temperature, humidity, carbon dioxide levels, and illumination data into a fuzzy set, external meteorological variables, and user-defined set points.

It is evident from the literature that wireless communication adds complexity to the design of autonomous greenhouses. Integrating fuzzy logic-based controllers with wireless communication systems based on platforms like ZigBee presents both opportunities and challenges in climate control. Implementing an FLC system can be complex and not user-friendly, as highlighted by the proposed intelligent variable control system for greenhouses, utilizing fuzzy logic and wireless information monitoring and providing real-time data access [15]. The proposed control system was experimentally validated and proved efficient in conserving water and power.

The literature review also highlights the use of fuzzy logic in analyzing data gathered from sensors for decision-making in irrigation systems [16]. Moreover, fuzzy logic in greenhouses is not limited to climate control. Fuzzy logic has also been applied in various other aspects of greenhouse management, including crop yield prediction, pest and disease detection, and optimization of resource allocation. The literature review suggests that fuzzy logic-based controllers and wireless communication systems have been successfully implemented in greenhouse automation [17]. With the continuous advancements in technology, the integration of fuzzy logic-based controllers with wireless communication systems has significantly improved the automation and efficiency of greenhouses. Not only has it facilitated climate control, but it has also extended to various other aspects of greenhouse management, such as crop yield prediction, pest and disease detection, and resource allocation optimization.

Wireless communication, mainly through implementing platforms like ZigBee, enables real-time monitoring and control of environmental factors, thus enhancing greenhouse operations' overall productivity and sustainability [18, 19].

12.3 PROPOSED METHOD

12.3.1 PID-BASED CONTROLLER FOR GREENHOUSE CONTROL

Figure 12.1 shows the greenhouse control system's schematic diagram.

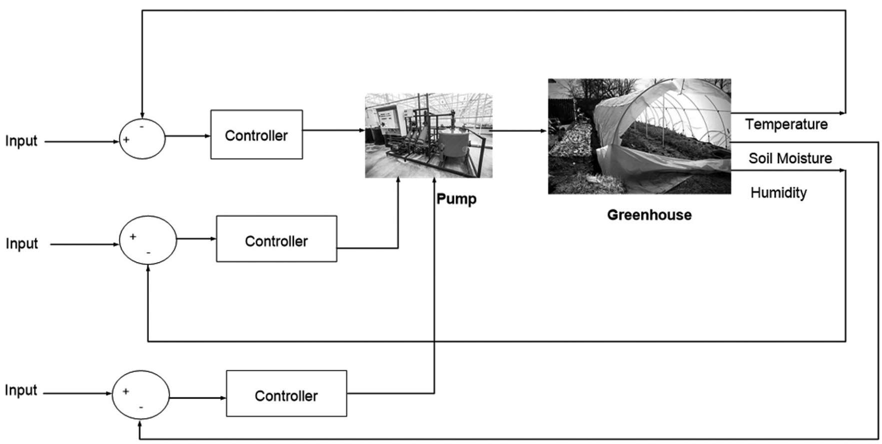

FIGURE 12.1 Block diagram of PID-based greenhouse control system. ⏎

The proposed scheme considers three factors, that is, temperature, humidity, and soil moisture. The design of greenhouse control necessitates a precise system model from the perspective of classical control theory. Nevertheless, acquiring such a model is a considerable challenge. One of the primary difficulties in greenhouse modeling lies in accurately representing the internal dynamics. This is due to the complex nature of these dynamics, which typically encompass many physical, chemical, and biological processes. Examples of such techniques include heat transfer between different components and the various physiological activities of crops, such as photosynthesis, transpiration, and respiration. The complexity inherent in these processes has resulted in a need for more understanding regarding many of their mechanisms.

Consequently, researchers often employ empirical or fitting formulas derived from measured data from a specific greenhouse. However, this approach needs to be revised in order to maintain the general applicability of the resulting greenhouse climate model. On the other hand, determining the controller gain is typically straightforward due to the prevalent linear characteristics of most actuators. For instance, the heat flux generated by the direct air heater exhibits a proportional relationship with the control signal. Consequently, the input–output dynamics of the actuator can be effectively captured by a linear model. Hence, in this particular scenario, ensuring the control performance and universality of the control methods emerges as a critical practical challenge. PID control has been identified as an effective approach to attain the desired outcome.

To generate control signals for temperature, humidity, and soil moisture in the considered greenhouse, it is necessary to introduce three PID controllers. Each PID controller drives one output and generates one control signal. It is evident that the typical PID control technique cannot be simply applied to a system characterized by three inputs and three outputs. Hence, it is necessary to convert the system under consideration into an equivalent system with three outcomes.

Tuning of PID controllers is another challenge to obtain optimum outputs. Traditional methods, such as the Ziegler–Nichols method, are widely employed, but it suffers from certain limitations and fails to deliver optimum outcomes. This work applies a meta-heuristic technique to obtain optimum controller gains. Particle swarm optimization is employed to tune the controller, and optimum gain parameters are obtained for temperature, soil moisture, and relative humidity control. The results are presented in Section 12.4.

12.3.2 FUZZY LOGIC-BASED CONTROLLING MODEL

Sensor networks are the backbone of greenhouse automation, providing real-time data on crucial parameters. Temperature, humidity, and soil moisture are monitored using advanced sensors. These sensors facilitate data-driven decision-making, enabling farmers to create ideal conditions for plant growth. Challenges, such as sensor calibration, data integration, and network reliability are addressed through robust sensor network architectures.

Fuzzy logic control systems offer a unique methodology for handling imprecise and uncertain information. Fuzzy logic allows the representation of human knowledge and reasoning, making it well-suited for agricultural applications where precise mathematical models are often elusive. The components of an FLC, including fuzzification, rule base, inference engine, and defuzzification, are explained in detail. Fuzzy rules are derived from expert knowledge and sensor inputs, enabling the controller to make intelligent decisions. The block diagram of the proposed system is given in Figure 12.2.

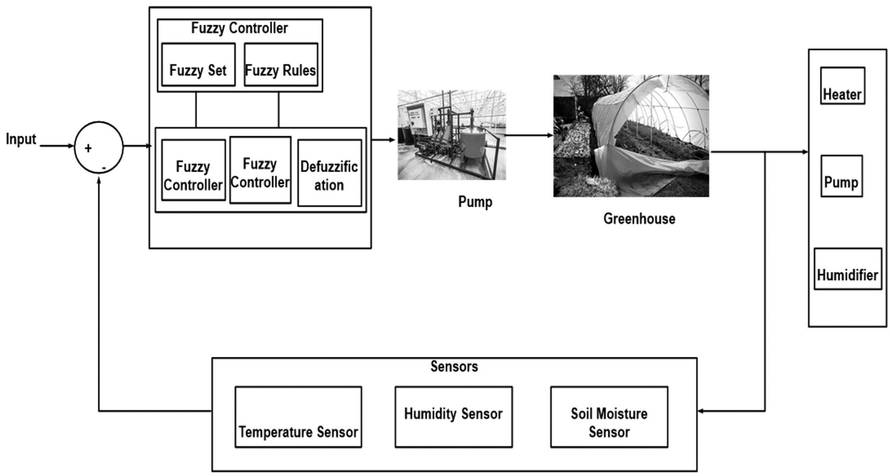

FIGURE 12.2 Block diagram of FLC-based greenhouse control system. ⏎

Fuzzy membership functions are used in fuzzy logic systems to represent the degree of membership of a particular element in a fuzzy set. In greenhouse measurement, fuzzy membership functions can be employed to handle uncertainty and imprecision in sensor data. Greenhouse measurements often involve temperature, humidity, and soil moisture levels. Fuzzy logic can be applied to model these parameters and make decisions based on vague or incomplete information.

To use the fuzzy Tsukamoto technique, a fuzzy set with a monotonous membership function must be provided for each outcome of an IF–THEN rule. Fuzzy logic by Tsukamoto was selected because it produces well-defined individual rules. Consequently, each rule's inference output is provided crisply based on the α-predicate, and a weighted average is used to get the conclusion. Phases of fuzzy operation are as follows.

1. Fuzzification: Membership functions recorded in the knowledge base translate explicit values from the system into linguistic variables.
2. Formation of a fuzzy rule in the form of IF–THEN.
3. Fuzzy Interference System: Process of using the IF–THEN rules on fuzzy knowledge to transform fuzzy input into fuzzy output.

4. Aggregation: There are frequently situations where many rules apply. This indicates that the implications have more than one value. As a result, we must create a single fuzzy set from all of these findings. The MIN method is the aggregating technique applied here.
5. Defuzzification: The procedure for turning the fuzzy output from an inference engine into an explicit value by applying the membership function matching the time the fuzzification was completed.

12.3.2.1 TEMPERATURE CONTROLLER

Fuzzy logic is used to regulate the temperature of the greenhouse parameter (Table 12.1). The temperature range for this design system is −10–50°C. This temperature is classified as a membership function and is separated into five sections (Figure 12.3).

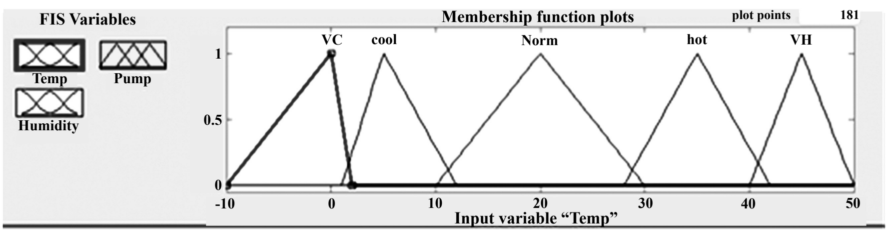

FIGURE 12.3 Temperature as an input of fuzzy logic system. ⏎

TABLE 12.1 Membership Function of Current Temperature ⏎

Fuzzy Membership Function	Temperature Range (°C)
VC	−10 to 2
Cool	1–12
Norm	10–30
Hot	28–42
VH	40–50

12.3.2.2 MOISTURE CONTROLLER

The proportion of moisture in the soil and its relationship to holding at a specific temperature is used to maintain the greenhouse system (Figure 12.4).

Temperatures affect humidity, which creates a comfortable environment; these are shown below. Table 12.2 demonstrates the five designed membership functions, spanning from 0% to 100% relative humidity.

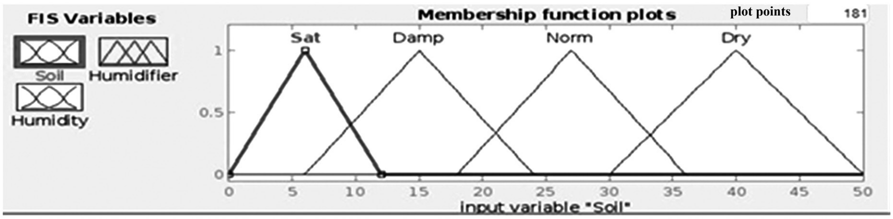

FIGURE 12.4 Soil as an input of fuzzy logic system. ⏎

TABLE 12.2 Membership Function of Current Soil Moisture ⏎

Fuzzy Membership Function	Range (Moisture Value)
Sat	0–12
Damp	6–24
Norm	18–30
Dry	30–50

12.3.2.3 HUMIDITY CONTROLLER

The soil's moisture proportion and its relationship to holding at a specific temperature are used to determine humidity (Figure 12.5). Temperatures affect humidity, which creates a comfortable environment; these are shown below. Table 12.3 illustrates the five membership functions that were designed, spanning from 0% to 100% relative humidity.

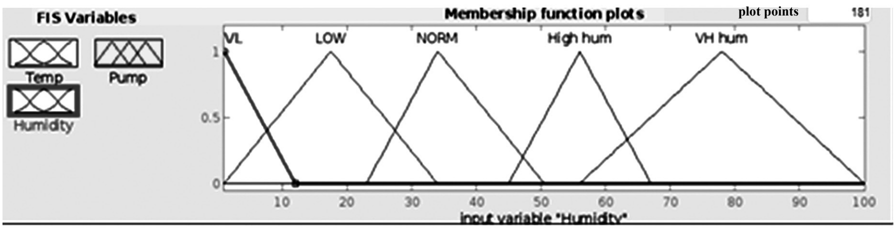

FIGURE 12.5 Humidity as an input of fuzzy logic system. ⏎

TABLE 12.3 Membership Function of Current Humidity ⏎

Fuzzy Membership Function	Range (%)
VL	0–20
LOW	10–40
NORM	30–55
High hum	50–70
VH hum	60–100

12.3.2.4 WATER PUMP CONTROLLER

The water pump motor is used to regulate the temperature and humidity content (Figure 12.6). The motor has three settings: off, medium, and large. The motor determines whether to turn on (large or medium amount) or off this water pump. Table 12.4 focuses on the pump motor's output membership function.

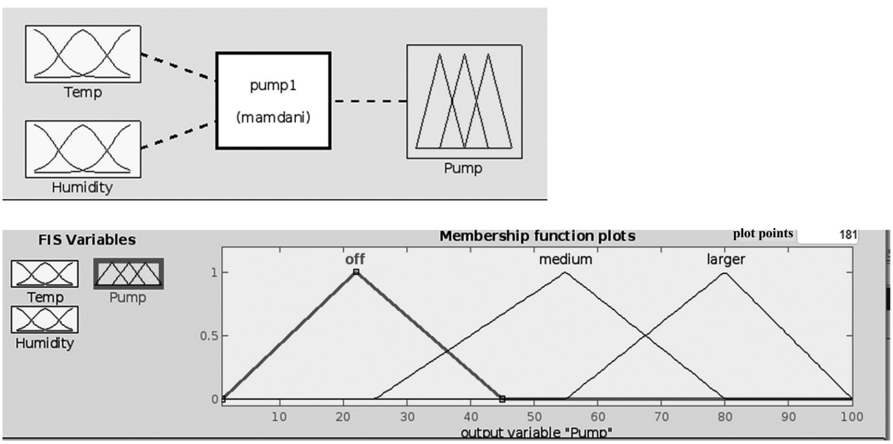

FIGURE 12.6 The output of watering through pump duration of fuzzy logic method. ⏎

TABLE 12.4 Membership Function of Water Pump ⏎

Fuzzy Membership Function Water Pump	Range (Value)
Off	0–45
Med	25–80
Large	55–100

12.3.2.5 HUMIDIFIER CONTROLLER

The humidifier will turn on and speed up when the humidity rises above the predetermined humidity. There are three membership functions for humidifiers: off, medium, and large. The fuzzy controller decides what action to take to regulate the moisture (Table 12.5).

TABLE 12.5 Membership Function of Humidifier ⏎

Fuzzy Membership Function Humidifier	Range (Value)
Off	0–45
Med	25–60
Large	55–100

12.3.2.6 HEATER CONTROLLER

The heater primarily regulates temperature. Fuzzy controllers aid in speeding up the heating supply when the heater is in either an ON or OFF state based on the room's current temperature, whereas standard logic consists of just two forms: ON and OFF. The output variable heater has three membership functions: large, medium, and off.

Designing a rule-based fuzzy system for controlling temperature and humidity in a greenhouse involves defining fuzzy membership functions, fuzzy rules, and an inference mechanism.

12.3.2.6 FUZZY RULES

1. The rules stored in the database are the basis for the decisions made by the fuzzy controller during operation. These choices are kept in the form of a fixed rule. The rule, merely a linguistic assertion, is an if–then statement that is intuitive and simple to comprehend.
2. The water pump's duration is adjusted based on 27 rules at this greenhouse. Figure 12.7 shows these rules are entered into the "rule editor."
3. The same happens in humidifiers and heaters. The humidifier and heater are adjusted based on 27 rules.

The rule option viewer, as depicted in Figure 12.8, allows users to view rules included in the rule editor. The rule viewer determines how long the water pump is likely to run; the length of the condition can be set to off, medium, or large, depending on the output temperature. The center red line for each membership function can be moved to establish the trends.

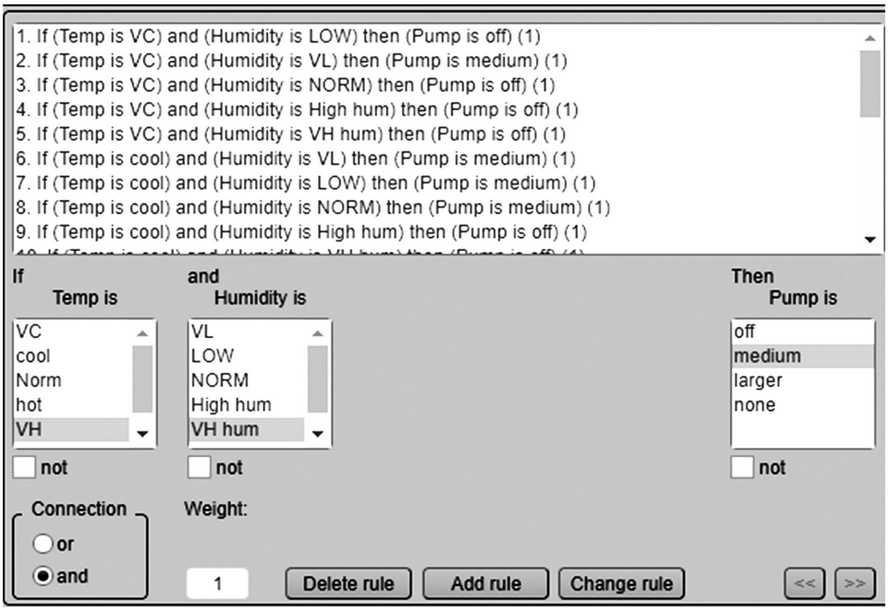

FIGURE 12.7 Setting of fuzzy rule at fuzzy editor. ⏎

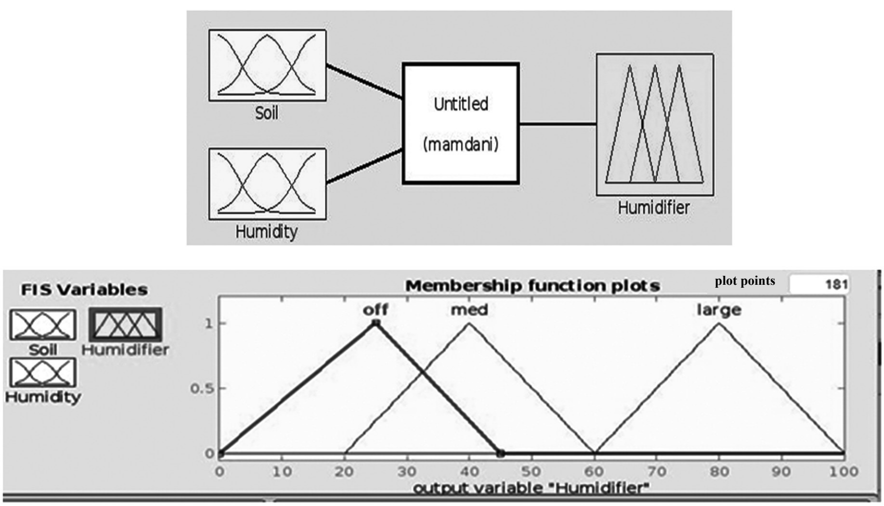

FIGURE 12.8 The output of humidifier of fuzzy logic method. ⏎

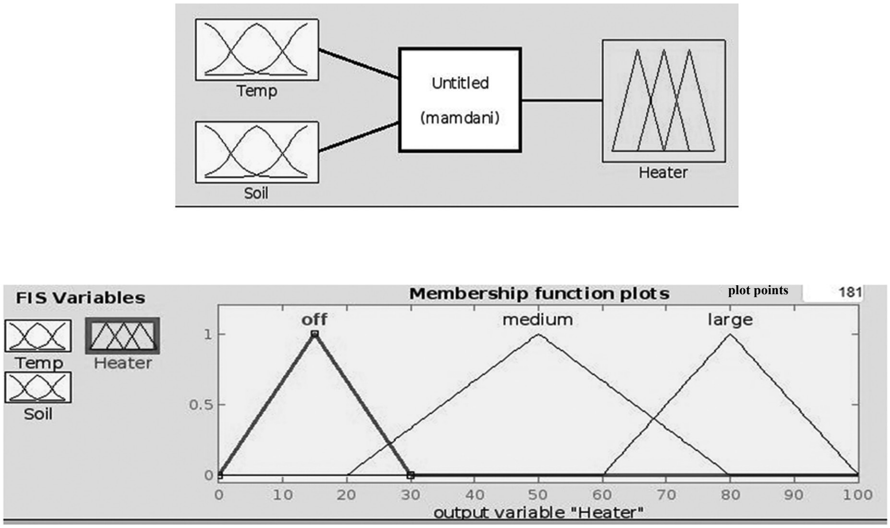

FIGURE 12.9 The output of controlling the heater of fuzzy logic method. ⏎

The outcomes of the rule viewer are displayed in Figure 12.9 as a three-dimensional surface viewer. Plotting a graph of the data released during the defuzzification process is called surface viewer (Figure 12.10).

12.4 RESULTS AND DISCUSSION

The fuzzy logic embedded in the Arduino microcontroller enhances system accuracy and performance (Figure 12.11). The output of fuzzy inference controls the Arduino microcontroller are as follows.

1. Fuzzy rule 1: The microcontroller automatically switches the pump on, heater off, and humidifier off.
2. Fuzzy rule 2: The microcontroller automatically switches the pump on, heater off, and humidifier off.
3. Fuzzy rule 3: The microcontroller automatically switches the pump on, heater on, and humidifier off.
4. Fuzzy rule 4: The microcontroller automatically switches the pump on, heater off, and humidifier off.
5. Fuzzy rule 5: The microcontroller automatically switches the pump off, heater off, and humidifier off.
6. Fuzzy rule 6: The microcontroller automatically switches the pump off, heater on, and humidifier off.

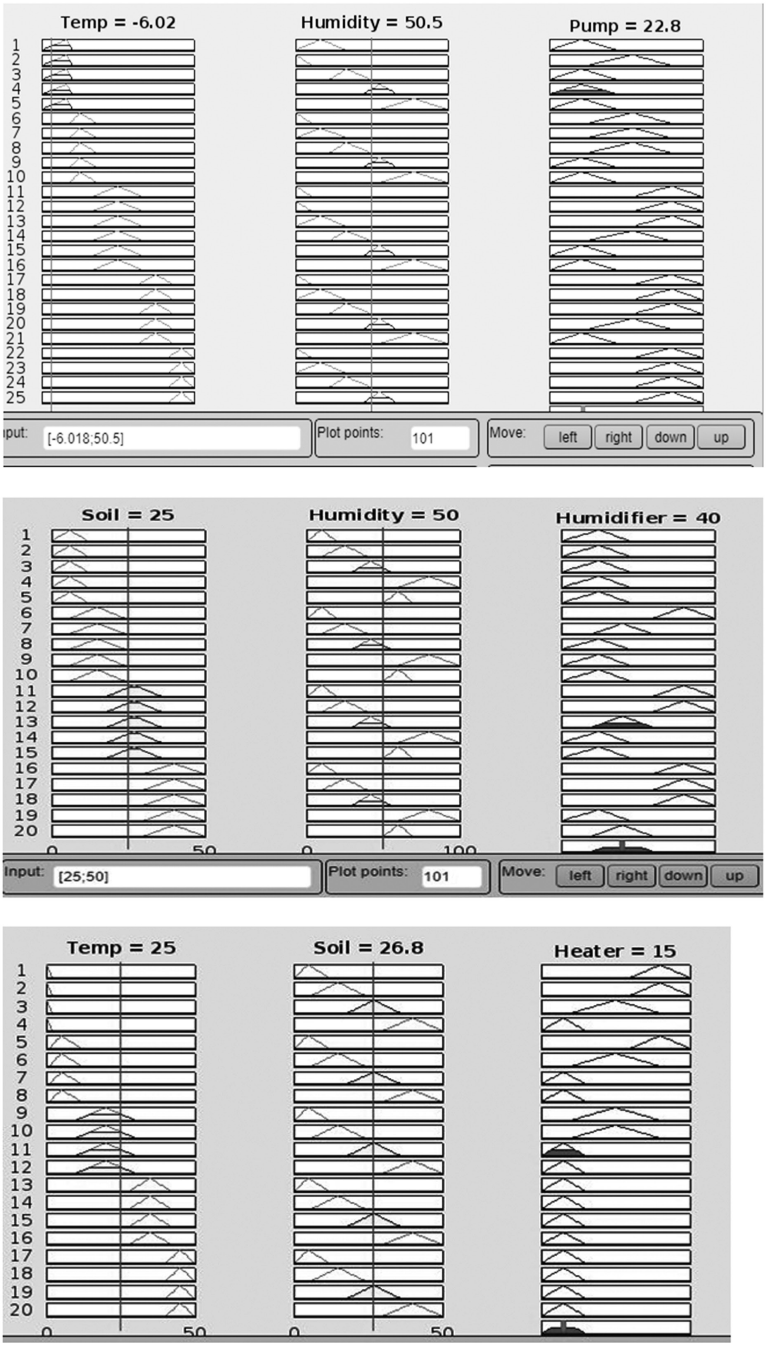

FIGURE 12.10 Fuzzy rule viewer at fuzzy editor. ⏎

7. Fuzzy rule 7: The microcontroller automatically switches the pump on, heater off, and humidifier on.
8. Fuzzy rule 8: The microcontroller automatically switches the pump off, heater off, and humidifier on.
9. Fuzzy rule 9: The microcontroller automatically switches the pump off, heater on, and humidifier on.

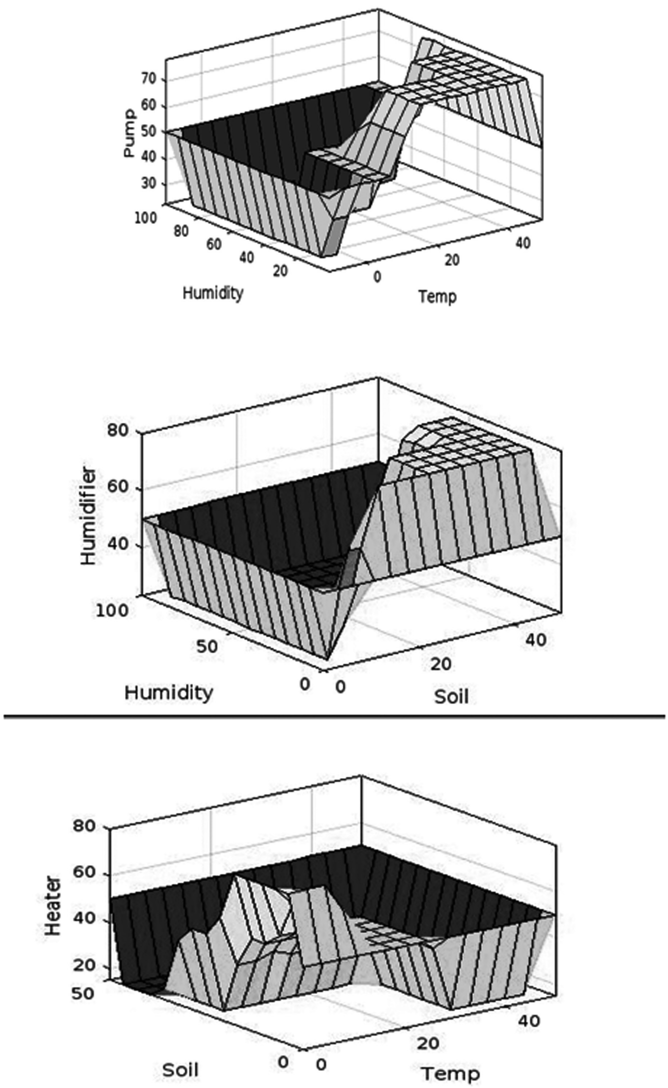

FIGURE 12.11 Surace view of the rules base. ⏎

At first, the system is tested with traditional PI controllers, then the PID and FLC controllers are applied. In Figure 12.12, the performance variation with different controllers is shown. A sample set temperature of 25°C is chosen to evaluate the performance parameters. It is observed that the system exhibits the least overshoot with the application of FLC, and the maximum overshoot is obtained for the PI controller. Correspondingly, FLC has given better settling time as compared to other controllers.

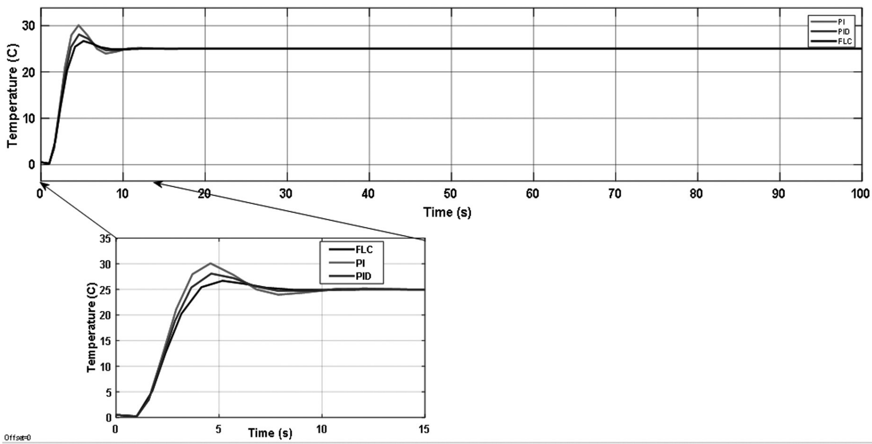

FIGURE 12.12 Temperature control with PI, PID, and FLC controllers. ⏎

In Figure 12.13, the comparison of different controllers for relative humidity control is presented. A sample humidity value of 60% is set to evaluate the performance of the controllers. Like temperature control, it is observed that FLC has the best performance in terms of less overshoot and settling time over PI and PID controllers.

Similarly, in Figure 12.14, soil moisture content is depicted under the three proposed controllers. Here, a sample preset value of 30% is set to check the performance parameters of the three different controllers. Usually, moisture content varies from time to time based on the type of crop, soil, and weather conditions. It can be observed in previous cases. FLC has exhibited the best performance over PI and PID controllers.

12.5 CONCLUSION

This design technique makes the system more efficient and has better control. This analytical value explains in detail how fuzzy logic operates to

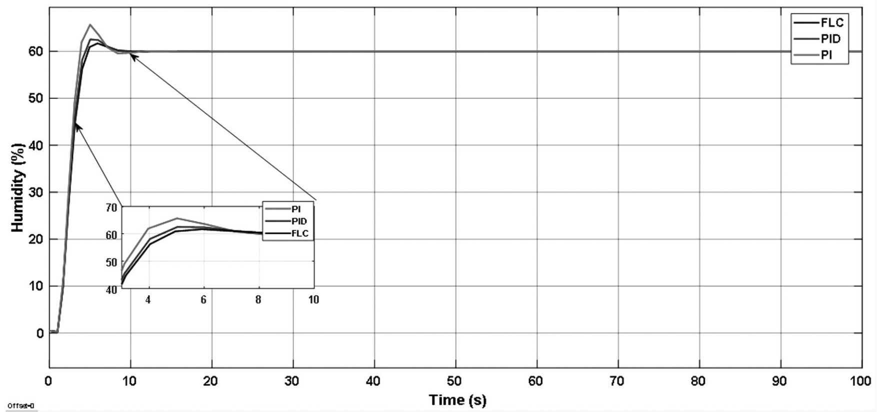

FIGURE 12.13 Humidity control using PI, PID, and FLC ⏎

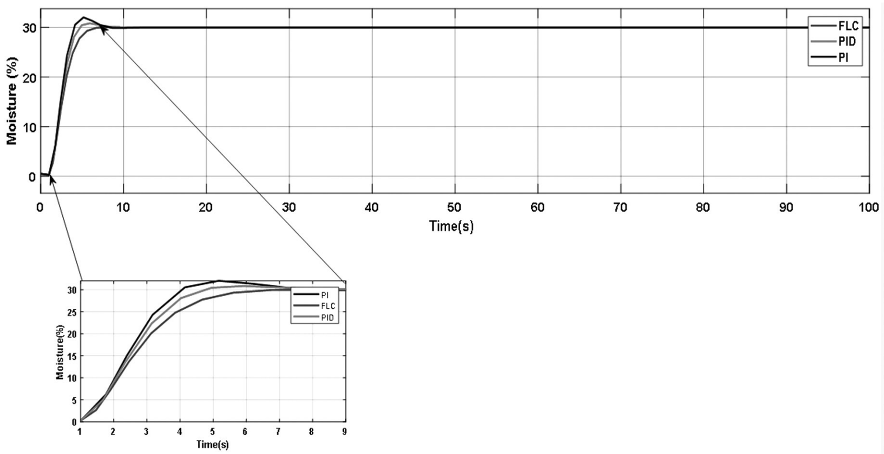

FIGURE 12.14 Soil moisture control using PI, PID, and FLC. ⏎

address the issue of various smooth controls in challenging circumstances. Fuzzy logic assisted the greenhouse system in resolving the problematic issue without requiring physical variable interaction. It was sufficient to intuitively understand input and output parameters to build the system for maximum performance. This suggested system is being implemented in the processing facility. It will assist with the construction of cutting-edge controlling systems for various environmental monitoring and management applications in the future. This system primarily monitors and maintains the greenhouse's environment, creating a sustainable plant growing space. The results corroborated that the proposed FLC has exhibited better PI and

PID performance parameters in terms of overshoot and settling time. This approach can also be extended for other parameter evaluations of the greenhouse to make a more holistic and elaborate scheme for the future.

KEYWORDS

- **proportional integral (PI)controller**
- **proportional, integral, and derivative**
- **fuzzy logic**
- **greenhouse**
- **temperature**
- **soil moisture**
- **humidity**
- **humidifier**

REFERENCES

1. Choab, N., Allouhi, A., El Maakoul, A., Kousksou, T., Saadeddine, S., & Jamil, A. (2019). Review on greenhouse microclimate and application: Design parameters, thermal modeling and simulation, climate controlling technologies. *Solar Energy*, *191*, 109–137, https://doi.org/10.1016/j.solener.2019.08.042.
2. Ahamed. M. S., Guo, H., & Tanino, K. (2018). A quasi-steady state model for predicting the heating requirements of conventional greenhouses in cold regions. *Information Processing in Agriculture*, *5*(1), 33–46, https://doi.org/10.1016/j.inpa.2017.12.003.
3. Shen, M., Huang, W., Chen, M., Song, B., Zeng, G., & Zhang, Y. (2020). (Micro) plastic crisis: Un-ignorable contribution to global greenhouse gas emissions and climate change. *Journal of Cleaner Production*, *254*, 120138, https://doi.org/10.1016/j.jclepro.2020.120138.
4. Liu, Y., Li, D., Wan, S., et al. (2022). A long short-term memory-based model for greenhouse climate prediction. *International Journal of Intelligent Systems*, *37*, 135–151. https://doi.org/10.1002/int.22620.
5. Rayhana, R., Xiao, G., & Liu, Z. (2020). Internet of things empowered smart greenhouse farming. *IEEE Journal of Radio Frequency Identification*, *4*(3), 195–211, https://doi.org/10.1109/JRFID.2020.2984391.
6. Sigrimis, N., Arvanitis, K. G., Kookos, I. K., & Paraskevopoulos, P. N. (1999). H∞-PI controller tuning for greenhouse temperature control. *IFAC Proceedings Volumes*, *32*(2), 5644–5649, https://doi.org/10.1016/S1474-6670(17)56963-3.

7. Zeng, S., Hu, H., Xu, L., & Li, G. (2012). Nonlinear adaptive PID control for greenhouse environment based on RBF Network. *Sensors*, *12*(5), 5328–5348. https://doi.org/10.3390/s120505328.
8. Giraldo, S. A. C., Flesch, R. C. C., & Normey-Rico, J. E. (2016). Multivariable greenhouse control using the filtered smith predictor. *Journal of Control, Automation and Electrical Systems*, *27*(4), 349–358.
9. Su, Y., Yu, Q., & Zeng, L. (2020). Parameter self-tuning PID control for greenhouse climate control problem. *IEEE Access*, *8*, 186157–186171, https://doi.org/10.1109/ACCESS.2020.3030416.
10. Joseph, S. B., Dada, E. G., Abidemi, A., Oyewola, D. O., & Khammas, B. M. (2022). Metaheuristic algorithms for PID controller parameters tuning: Review, approaches and open problems. *Heliyon*, *8*(5), e09399, https://doi.org/10.1016/j.heliyon.2022.e09399.
11. Latha, K., Rajinikanth, V., & Surekha, P. M. (2013). PSO-based PID controller design for a class of stable and unstable systems. In: *International Scholarly Research Notices*. Wiley.
12. Thangavel, K. D., Seerengasamy, U., Palaniappan, S., & Sekar, R. (2023). Prediction of factors for controlling of green house farming with fuzzy based multiclass support vector machine. *Alexandria Engineering Journal*, *62*, 279–289, https://doi.org/10.1016/j.aej.2022.07.016.
13. Kia, P. J., et al. (2009). Intelligent control based fuzzy logic for automation of greenhouse irrigation system and evaluation in relation to conventional systems. *World Applied Sciences Journal*, *6*(1), 16–23.
14. Sriraman, A., & Mayorga, R. V. (2007). Climate control inside a greenhouse: An intelligence system approach using fuzzy logic programming. *Journal of Environmental Informatics*, *10*(2), 68–74.
15. Pacco, H. C. (2022). Simulation of temperature control and irrigation time in the production of tulips using Fuzzy logic. *Procedia Computer Science*, *200*, 1–12, https://doi.org/10.1016/j.procs.2022.01.199.
16. Atia, D. M., & El-madany, H. T. (2017). Analysis and design of greenhouse temperature control using adaptive neuro-fuzzy inference system. *Journal of Electrical Systems and Information Technology*, *4*(1), 34–48.
17. Riahi, J., Vergura, S., Mezghani, D., & Mami, A. (2020). Intelligent control of the microclimate of an agricultural greenhouse powered by a supporting PV system. *Applied Sciences*, *10*, 1350. https://doi.org/10.3390/app10041350.
18. Wang, Z. (2021). Greenhouse data acquisition system based on ZigBee wireless sensor network to promote the development of agricultural economy. *Environmental Technology & Innovation*, *24*, 101689, https://doi.org/10.1016/j.eti.2021.101689.
19. Ding, F., & Song, A. (2016). Development and coverage evaluation of ZigBee-based wireless network applications. *Journal of Sensors*, *2016*, 1–9. 10.1155/2016/2943974.

CHAPTER 13

Fuzzy Logic in the Automotive Industry: A Review

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ABSTRACT

This chapter explores the transformative role of fuzzy logic in the evolving automotive industry, emphasizing its technical significance in intelligent system design. Fuzzy logic, with its ability to handle imprecision and uncertainty, has become integral to key advancements in automotive technologies, including control systems, autonomous vehicles, fuel optimization, and safety applications. By processing ambiguous inputs, fuzzy logic enables real-time decisions in adaptive cruise control, collision avoidance, and other dynamic scenarios, enhancing vehicle reliability and performance. The chapter highlights its role in optimizing engine management, reducing emissions, and promoting sustainable driving practices. Autonomous systems utilize fuzzy logic to navigate complex urban environments with precision and safety. Advanced driver-assistance technologies, such as blind-spot detection and lane departure warnings, leverage fuzzy logic for context-aware responses, while predictive maintenance systems improve operational efficiency by minimizing unplanned downtimes. Furthermore, fuzzy logic enhances user-centric design through personalized interfaces and adaptive infotainment

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systems. The chapter also examines the integration of fuzzy logic with emerging technologies like artificial intelligence and IoT, addressing ethical considerations and technical challenges. By illustrating the potential of fuzzy logic in reshaping the automotive landscape, this chapter positions it as a critical enabler of innovation, sustainability, and intelligent mobility solutions.

13.1 FUNDAMENTALS OF FUZZY LOGIC

In the 1960s, Lotfi Zadeh created fuzzy logic, a computing paradigm that leverages real-world uncertainty instead of binary reasoning. It has several uses, especially in the automotive sector [1]. The mathematical framework of fuzzy logic handles decision-making ambiguity and imprecision. It uses fuzzy sets to represent confusing data. Fuzzy sets are generalizations of classical sets having membership values between 0 and 1 [2, 3]. Membership functions convert input values to membership degrees. Union, intersection, and complement use fuzzy sets to make judgments. Fuzzy rules, if–then statements, establish input-output relationships utilizing language and fuzzy logic. Fuzzy inference uses fuzzy rules to predict output from input variables [4, 5]. Fuzzy logic handles partial or ambiguous data and makes qualitative conclusions. It simulates uncertain and imprecise human thinking and decision-making. Managing complicated and unpredictable systems using fuzzy logic is flexible and intuitive.

Fuzzy logic is essential in automotive computers for imprecision and unpredictability. The complexity of automotive systems has increased the need for adaptive decision-making in dynamic contexts. Fuzzy logic processes unclear inputs and makes real-time judgments with subtlety [6–8]. This chapter discusses fuzzy logic's role in the automobile industry, its capacity to manage uncertainties, optimize fuel economy, improve safety, and promote sustainability as presented/briefed in Table 13.1.

The chapter explores how fuzzy logic affects control systems, autonomous automobiles, fuel efficiency, safety, and other automotive technologies. Fundamentals, applications, problems, and opportunities are covered. Fuzzy logic enhances fuel efficiency, safety, and sustainability in car technology, according to key findings [9, 10]. We finish with an overview of key findings and the need for further research and innovation in this dynamic field.

TABLE 13.1 Applications of Fuzzy Logic in Automotive Control Systems ⏎

Category	Role	Description
Safety	Adaptive cruise control and collision avoidance	Fuzzy logic is used to improve adaptive cruise control (ACC) systems by considering speed, distance, and traffic. This lets the system adapt to traffic flow in real-time, making driving safe and enjoyable. Fuzzy logic also helps to prevent collisions by generating sophisticated reactions based on vehicle speed, distance, and collision likelihood.
	Lane departure warning and correction	Fuzzy logic is used to improve lane-keeping accuracy and reliability by analyzing vehicle trajectory and warning of inadvertent lane departure in real time. Fuzzy logic is also used to detect lane departures and guide the car back into its lane based on departure risk, road conditions, and speed.
	Blind-spot detection and intervention	Fuzzy logic is used to notify drivers of cars in their blind spots using sensors, cameras, and radar. Fuzzy logic is also used to proactively avoid collisions by evaluating neighboring vehicle speed and trajectory and driver reaction.
	Fuzzy-based safety systems for occupant protection	Fuzzy logic is used to evaluate airbag deployment during crashes. This is done by making real-time judgments based on impact intensity, occupant placements, and accident type. Fuzzy logic is also used to optimize seatbelt tension based on acceleration, deceleration, and posture. Additionally, fuzzy logic is used to build occupant safety profiles based on size, age, and health.
Performance and efficiency	Engine management and optimization	Fuzzy logic is used to optimize fuel consumption by considering throttle position, engine load, and environmental conditions. This ensures efficient engine operation under varying driving conditions and improves fuel economy. Fuzzy logic is also used to regulate fuel injection and exhaust recirculation to reduce emissions.
	Transmission control and gear shifting	In order to dynamically adjust gear ratios in response to vehicle speed, loads, and driver behavior, fuzzy logic is implemented. This adaptive methodology enhances the performance and maneuvrability of the vehicle by efficiently navigating various driving conditions. Additionally, fuzzy logic aids gear shifting by simultaneously evaluating multiple factors, such as driver error and road conditions.

TABLE 13.1 *(Continued)*

Category	Role	Description
Navigation and decision-making	Navigation and obstacle detection	The utilization of fuzzy logic in conjunction with real-time traffic, route architecture, and vehicle capabilities serves to augment autonomous car navigation. This enhances the safety and effectiveness of navigation in complex environments, such as urban areas characterized by diverse traffic conditions. Fuzzy logic is also utilized by autonomous vehicles to identify obstacles and make decisions based on sensors by applying rules and fuzzy sets to interpret uncertain data.
	Decision-making in complex traffic scenarios	Autonomous vehicles utilize fuzzy logic to assist them in making real-time traffic decisions. In order to arrive at context-aware judgments, factors such as pedestrian activity, traffic flow, and road indicators are taken into account. Also aiding in the management of uncertain conditions, fuzzy logic represents the confidence or uncertainty associated with decision-making. This proves to be advantageous in ambiguous circumstances, such as divergent traffic signals or sudden road conditions.
Comfort and environment	Fuzzy logic in climate control and cabin temperature regulation	In order to enhance interior comfort, adaptive temperature management is governed by fuzzy logic. This is accomplished by considering factors such as climate, sunlight, and occupant preferences. Additionally, occupant comfort is modeled using fuzzy logic, and temperature profiles are personalized based on climate and seat occupancy.
	Eco-driving principles	Fuzzy logic is implemented in order to reduce environmental impact and enhance fuel economy through the provision of real-time recommendations for fuel-efficient driving, which are determined by factors such as vehicle speed, acceleration, and traffic conditions. Also optimized using fuzzy logic are the acceleration and deceleration patterns of a vehicle.
	Emission control and reduction using fuzzy logic	By dynamically adjusting parameters in response to engine temperature, load, and exhaust gas composition, fuzzy logic reduces hazardous emissions and optimizes combustion efficiency. In order to reduce nitrogen oxide emissions, fuzzy logic is also utilized to optimize urea administration in selective catalytic reduction (SCR) systems.

TABLE 13.1 *(Continued)*

Category	Role	Description
Vehicle diagnostics and maintenance	Fuzzy logic for predictive maintenance and condition monitoring	Fuzzy logic helps in predictive maintenance and condition monitoring of vehicles.
	Predictive maintenance strategies	Predictive maintenance systems use fuzzy logic to anticipate problems based on engine performance, sensor data, and maintenance history. This proactive strategy predicts component failures or performance deterioration to decrease unexpected breakdowns and maintenance expenses.
	Condition monitoring	Fuzzy logic analyses sensor and diagnostic data to monitor vehicle components continuously. It checks the engine, gearbox, and brake system health. Fuzzy sets provide nuanced assessment and early anomaly identification, allowing timely maintenance for optimum vehicle performance.
	Fuzzy reasoning in diagnostics	Fuzzy logic helps in diagnostic systems to identify and localize faults accurately, as well as evaluate the severity of problems, enabling effective maintenance actions. This adaptive reasoning analyses symptom membership to predetermined fault patterns to identify and localize defects even with ambiguous or variable symptoms.

13.2 APPLICATIONS OF FUZZY LOGIC IN AUTOMOTIVE CONTROL SYSTEMS

Automotive control systems including adaptive cruise control (ACC), collision avoidance, engine management, and gearbox control use fuzzy logic to improve safety and economy [11, 12].

13.2.1 ACC AND COLLISION AVOIDANCE

1. *ACC*: Fuzzy logic analyses sensor data to improve ACC systems by considering speed, distance, and traffic [13–15]. This lets the system adapt to traffic flow in real time, making driving safe and enjoyable.
2. *Collision avoidance systems*: By affecting decision-making, fuzzy logic helps prevent collisions. It generates sophisticated reactions based on vehicle speed, distance, and collision likelihood [16–18]. This lets collision avoidance systems stop or steer to avoid crashes.

13.2.2 ENGINE MANAGEMENT AND OPTIMIZATION

1. *Optimizing fuel consumption*: Engine management systems use fuzzy logic to optimize fuel consumption by considering throttle position, engine load, and environmental conditions, ensuring efficient engine operation under varying driving conditions and improving fuel economy and reduced environmental impact.
2. *Emission control and reduction*: Fuzzy logic regulates fuel injection and exhaust recirculation using real-time data to improve fuel economy and emissions. This fine-tuning reduces emissions, encourages eco-friendly driving, and meets emission regulations.

13.2.3 TRANSMISSION CONTROL AND GEAR SHIFTING

1. *Optimizing transmission control*: Fuzzy logic dynamically adjusts gear ratios depending on vehicle speed, load, and driver behavior to enhance gearbox control systems [19]. This adaptive technique improves vehicle performance and drivability by effectively handling different driving circumstances.

2. *Smooth gear shifting*: Fuzzy logic improves gear changing by assessing numerous factors at once, including driver error and road circumstances [20]. This improves driving and extends the gearbox system's life.

13.3 FUZZY LOGIC IN AUTONOMOUS VEHICLES

The utilization of fuzzy logic in autonomous vehicles to facilitate obstacle detection, navigation, and decision-making in intricate traffic situations showcases its capacity to manage ambiguity [21] and adjust to practical driving obstacles; this guarantees secure navigation and well-informed choices that emulate the intuitiveness and responsiveness of human drivers [22, 23].

13.3.1 NAVIGATION AND OBSTACLE DETECTION

1. *Navigation in dynamic environments*: Fuzzy logic methods use real-time traffic, route layout, and vehicle capabilities to enhance autonomous car navigation [24, 25]. In complicated situations, such as metropolitan locations with varied traffic conditions, adaptive route planning improves navigation safety and efficiency.
2. *Obstacle detection and avoidance*: Fuzzy logic helps autonomous cars recognize obstacles and makes sensor-based decisions [26, 27]. It interprets data uncertainty using fuzzy sets and rules to alter the vehicle's course or speed to prevent crashes, taking into account various obstacles' degrees of confidence [28].

13.3.2 DECISION-MAKING IN COMPLEX TRAFFIC SCENARIOS

1. *Real-time decision-making*: Autonomous automobiles perform real-time traffic choices using fuzzy logic [29, 30]. Considers traffic flow, pedestrian activity, and road signs to make context-aware judgments. This flexibility lets cars manage traffic situations intuitively, improving safety and efficiency like human drivers [31, 32].
2. *Handling uncertain conditions*: Fuzzy logic in autonomous cars represents decision-making confidence or uncertainty to meet real-world

imprecision [33]. This helps in unclear situations like conflicting traffic lights or abrupt road conditions. Fuzzy sets and rules allow educated judgments, improving autonomous driving system dependability and vehicle reliability [34, 35].

13.4 OPTIMIZING FUEL EFFICIENCY AND EMISSIONS

Eco-driving systems employ fuzzy logic to optimize fuel economy and minimize pollutants, showing its flexibility to dynamic driving situations. This supports worldwide automobile transportation environmental initiatives.

13.4.1 FUZZY LOGIC-BASED STRATEGIES FOR ECO-DRIVING

1. *Eco-driving principles*: Eco driving uses fuzzy logic to improve fuel economy and reduce environmental impact. Fuzzy logic algorithms provide real-time fuel-efficient driving suggestions based on vehicle speed, acceleration, and traffic circumstances [36, 37].
2. *Adaptive speed control*: Adaptive speed control systems optimize vehicle speed using fuzzy logic and real-time inputs including traffic density and road grade. This strategy optimizes speed for fuel economy, reducing fuel consumption and improving driving [38, 39].
3. *Optimizing acceleration and deceleration*: Fuzzy logic optimizes acceleration and deceleration patterns for eco-driving, according to driver behavior, traffic flow, and road topography. Smoother transitions improve eco-driving by minimizing fuel usage and environmental effect [40].

13.4.2 EMISSION CONTROL AND REDUCTION USING FUZZY LOGIC

1. *Adaptive engine control*: Emission control systems use fuzzy logic to dynamically adjust parameters based on engine temperature, load, and exhaust gas composition to optimize combustion efficiency and reduce harmful emissions, ensuring environmental compliance [41, 42].
2. *Selective catalytic reduction (SCR) systems*: Nitrogen oxide emissions are reduced using SCR systems in diesel automobiles. These systems

optimize urea injection using fuzzy logic and real-time sensor data. Maximum NOx reduction without wasteful use guarantees optimum urea injection [43, 44].

3. *Continuous emission monitoring*: Processing sensor data and adapting control systems using fuzzy logic ensures consistent emission optimization under different situations. Responding to sensor data imprecision reduces emissions effectively and reliably [45, 46].

13.5 ENHANCING INTERIOR COMFORT AND SAFETY

Fuzzy logic in car temperature control and safety systems improves interior comfort and occupant protection by intuitively adjusting to dynamic situations, keeping passengers safe and comfortable [47–50].

13.5.1 FUZZY LOGIC IN CLIMATE CONTROL AND CABIN TEMPERATURE REGULATION

1. *Adaptive climate control*: Fuzzy logic controls adaptive temperature management to improve interior comfort. These systems take weather, sunshine, and tenant preferences into account. The vehicle's climate management system intelligently adjusts airflow, temperature, and fan speed using fuzzy logic algorithms to maximize passenger comfort.
2. *Occupant comfort modeling*: Fuzzy logic is used in occupant comfort modeling to determine passenger preferences and comfort. It customizes temperature profiles depending on climate and seat occupancy to make driving comfortable.

13.5.2 FUZZY-BASED SAFETY SYSTEMS FOR OCCUPANT PROTECTION

1. *Adaptive airbag deployment*: Safety systems evaluate airbag deployment during crashes using fuzzy logic. It makes real-time judgments based on impact intensity, occupant placements, and accident type to safeguard occupants and reduce injury risk.
2. *Dynamic seatbelt tensioning*: Dynamic seatbelt tensioning systems respond to driving circumstances and occupant behavior using fuzzy

logic. It optimizes seatbelt tension based on acceleration, deceleration, and posture for safety.

3. *Personalized safety profiles*: Fuzzy logic considers size, age, and health to build occupant safety profiles. This method maximizes passenger protection and reduces hazards by optimizing airbag deployment and seatbelt tensioning.

13.6 FUZZY LOGIC APPLICATIONS IN ADVANCED DRIVER ASSISTANCE SYSTEMS (ADAS)

Fuzzy logic in ADAS like lane departure warning (LDW) and correction and blind-spot detection (BSD) and intervention improves driver safety and experience [51]. Fuzzy logic's versatility and ability to accept imprecise inputs make it useful in intelligent, context-aware accident prevention and road safety systems [52].

13.6.1 LDW AND LANE DEPARTURE CORRECTION (LDC)

1. *LDW*: LDW systems use fuzzy logic to improve lane-keeping accuracy and reliability. Cameras and sensors analyze vehicle trajectory and warn of inadvertent lane departure in real time, allowing for complex decision-making based on road circumstances and driver behavior.
2. *LDC*: LDC systems detect lane departures using fuzzy logic. Based on departure risk, road conditions, and speed, algorithms guide the car back into its lane. Safety and smooth driving are improved by this adaptive adjustment.

13.6.2 BSD AND BLIND-SPOT INTERVENTION (BSI)

1. *BSD*: BSD devices notify drivers to cars in their blind spots using fuzzy logic [53]. It detects vehicle proximity and speed using sensors, cameras, and radar. Alerts are timely and context-aware using this adaptive technique.
2. *BSI*: BSI systems proactively avoid collisions using fuzzy logic. It evaluates neighboring vehicle speed and trajectory and driver reaction

to guide steering adjustments or targeted braking. The versatility of fuzzy logic provides appropriate and contextual interventions.

13.7 VEHICLE DIAGNOSTICS AND MAINTENANCE

Vehicle diagnostics and maintenance employ fuzzy logic to manage complexity and ambiguity in monitoring vehicle status and forecasting maintenance requirements [54]. Adaptive reasoning in intelligent diagnostic systems ensures vehicle dependability, safety, and durability via proactive maintenance [55].

13.7.1 FUZZY LOGIC FOR PREDICTIVE MAINTENANCE AND CONDITION MONITORING

1. *Predictive maintenance strategies*: Predictive maintenance systems use fuzzy logic to anticipate difficulties based on engine performance, sensor data, and maintenance history. This proactive strategy predicts component failures or performance deterioration to decrease unexpected breakdowns and maintenance expenses.
2. *Condition monitoring*: Fuzzy logic analyses sensor and diagnostic data to monitor vehicle components continuously. It checks engine, gearbox, and brake system health. Fuzzy sets provide nuanced assessment and early anomaly identification, allowing timely maintenance for optimum vehicle performance.

13.7.2 DIAGNOSTIC SYSTEMS BASED ON FUZZY REASONING

1. *Fuzzy reasoning in diagnostics*: Diagnostic systems employ fuzzy logic to discover and diagnose faults, particularly with imprecise or confusing sensor data [56]. This adaptive reasoning analyses symptom membership to predetermined fault patterns to identify and localize defects even with ambiguous or variable symptoms [57].
2. *Fault localization and severity assessment*: Fuzzy logic employs sensor readings, historical data, and contextual knowledge to locate and diagnose errors [58]. This adaptive technique locates faults accurately and reveals problem severity, allowing effective maintenance actions [59].

13.8 HUMAN-CENTRIC DESIGN: FUZZY LOGIC AND USER EXPERIENCE

Fuzzy logic is being used in human-centric infotainment and user interface design to make driver-vehicle interactions more intuitive, adaptable, and pleasurable. Its versatility helps create user-centric systems that meet current car user expectations for safety and happiness.

13.8.1 FUZZY LOGIC IN INFOTAINMENT AND USER INTERFACE DESIGN

1. *Adaptive infotainment systems*: Infotainment systems employ fuzzy logic to automatically alter material and layout depending on user preferences, driving circumstances, and contextual information to make the experience more pleasant [60]. Presenting context-appropriate information, entertainment, and controls boosts user engagement [61].
2. *Intuitive user interfaces*: Fuzzy logic analyses user interactions, driving behavior, and feedback to provide intuitive user interfaces. This versatility reduces distractions, making driving safer and more pleasurable.

13.8.2 PERSONALIZED DRIVING EXPERIENCE THROUGH FUZZY-BASED SYSTEMS

1. *Adaptive driving profiles*: Adjustable driving profiles using fuzzy logic are tailored to individual tastes and behaviors. It automatically adjusts vehicle characteristics based on driving style, seating position, and temperature control settings to customize each driver's experience.
2. *Intelligent assistance and recommendations*: Intelligent assistance systems use fuzzy logic to provide context-aware suggestions based on driver behavior, traffic, and history. This adaptive intelligence makes the car a proactive aide, improving driving.

13.9 CHALLENGES AND FUTURE PROSPECTS

Fuzzy logic implementation in the automobile sector is complicated by ethics, safety, integration with new technology, and electric and autonomous vehicle adaptation. These problems must be overcome to maximize fuzzy logic's potential and ensure appropriate use in automobile technologies.

13.9.1 ETHICAL CONSIDERATIONS AND SAFETY CONCERNS

1. *Ethical implications*: In autonomous vehicle interventions, fuzzy logic in the automobile sector creates ethical difficulties [62]. System decisions raise questions of duty, accountability, and morality. Public trust and acceptance need fuzzy logic systems to follow ethical and social norms.
2. *Safety challenges*: Collision avoidance and ACC increase safety using fuzzy logic, however, robustness and failure modes are issues [63]. Fuzzy logic algorithms must be rigorously tested, validated, and improved to avoid accidents and mistakes.

13.9.2 INTEGRATION OF FUZZY LOGIC WITH OTHER EMERGING TECHNOLOGIES

1. *Synergy with artificial intelligence (AI)*: Integration of fuzzy logic with AI approaches may increase adaptability and learning, although balancing interpretability with AI model complexity and opacity is difficult and may not completely solve certain models [64].
2. *Integration with connectivity and Internet of Things (IoT)*: IoT-connected automobiles with fuzzy logic pose data security and privacy problems. To retain user confidence and comply with data protection laws, sensitive data must be handled properly [65].

The above can be explained with an example of an air conditioner which is a device for producing human comfort and is also employed in modern automobiles and vehicles [66–71]. Air conditioners may employ fuzzy logic for adaptive temperature management. Fixed rules make typical air conditioners inefficient in varied situations. Air conditioners use fuzzy logic to adjust to individual comfort and environmental factors. Key characteristics include adjustable control, energy efficiency, user-centric comfort, fault tolerance, and IoT integration. Traditional air conditioners save energy and money by following restrictions. Fuzzy logic strengthens systems against sensor and equipment failures. Smart, sustainable living environments result from this mix [72, 73].

13.9.3 THE ROLE OF FUZZY LOGIC IN THE TRANSITION TO ELECTRIC AND AUTONOMOUS VEHICLES

1. *Electric vehicle (EV) optimization*: Fuzzy logic enhancing energy usage, battery management, and charging procedures improves EV fuel economy and emissions, extending their lifespan [74].
2. *Autonomous vehicle challenges*: Fuzzy logic is being used in autonomous cars, but it must make complicated decisions and withstand unexpected events [75]. Adaptability and safety need ongoing study.

13.10 CONCLUSIONS AND FUTURE SCOPE

The automobile industry uses fuzzy logic to improve control systems, autonomous cars, environmental impact reduction, interior comfort and safety, human-centric design, and predictive maintenance. Its ability to handle imprecision, adapt to dynamic surroundings, and provide context-aware solutions matches automotive complexity. Fuzzy logic connects rule-based systems to intelligent, adaptive, and autonomous vehicle technology. From safety and economy to environmental sustainability, fuzzy logic improves vehicle technology. As the automobile sector evolves rapidly, research and innovation are needed. The following areas need further study.

1. *Ethical frameworks*: Create ethical frameworks for fuzzy logic in important decision-making to ensure morality.
2. *AI integration*: Use fuzzy logic with AI to create synergy and handle interpretability and transparency issues.
3. *Cybersecurity and connectivity*: Improve fuzzy logic system cyber-security, particularly for connected automobiles and the IoTs.
4. *Adaptability in autonomous driving*: Improve fuzzy logic's adapt-ability and decision-making in complicated traffic conditions.
5. *Human–machine interaction*: Keep fuzzy logic at the forefront of intuitive and user-friendly automobile interfaces by innovating in human-centric design, infotainment systems, and personalized driving experiences. Fuzzy logic may drive innovation in the automobile sector, making mobility solutions safer, more efficient, and more pleasant.

KEYWORDS

- **fuzzy logic**
- **automotive industry**
- **advanced technologies**
- **control systems**
- **autonomous vehicles**
- **safety enhancements**
- **environmental awareness**

REFERENCES

1. Upadhyay, E. (2022). A critical evaluation of handling uncertainty in Big Data processing. *Advances in Engineering Software*, *173*, 103246.
2. Gadaras, I. (2009). *The Proposal and Development of a General, Accurate Comprehensible Fuzzy Classification Framework and its Application to Medical Diagnosis*. The University of Manchester: United Kingdom.
3. Baloi, D., & Price, A. D. (2003). Modelling global risk factors affecting construction cost performance. *International Journal of Project Management*, *21*(4), 261–269.
4. Celikyilmaz, A., & Turksen, I. B. (2009). Modeling uncertainty with fuzzy logic. *Studies in Fuzziness and Soft Computing*, *240*(1), 149–215.
5. Yogeesh, N. (2023). Fuzzy logic modelling of nonlinear metamaterials. In *Metamaterial Technology and Intelligent Metasurfaces for Wireless Communication Systems*. IGI Global, pp. 230–269.
6. Stecyk, A., & Miciuła, I. (2023). Empowering sustainable energy solutions through real-time data, visualization, and fuzzy logic. *Energies*, *16*(21), 7451.
7. Mizrak, F. (2023). Analyzing criteria affecting decision-making processes of human resource management in the aviation sector—A fuzzy logic approach. *Journal of Aviation*, *7*(3), 376–387.
8. Chauhan, V., Chang, C. M., Javanmardi, E., Nakazato, J., Lin, P., Igarashi, T., & Tsukada, M. (2023). Fostering fuzzy logic in enhancing pedestrian safety: Harnessing smart pole interaction unit for autonomous vehicle-to-pedestrian communication and decision optimization. *Electronics*, *12*(20), 4207.
9. Rajak, S., Parthiban, P., & Dhanalakshmi, R. (2016). Sustainable transportation systems performance evaluation using fuzzy logic. *Ecological Indicators*, *71*, 503–513.
10. Hezam, I. M., Mishra, A. R., Rani, P., Cavallaro, F., Saha, A., Ali, J., ... & Štreimikienė, D. (2022). A hybrid intuitionistic fuzzy-MEREC-RS-DNMA method for assessing the alternative fuel vehicles with sustainability perspectives. *Sustainability*, *14*(9), 5463.
11. Yu, L., & Wang, R. (2022). Researches on adaptive cruise control system: A state of the art review. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, *236*(2–3), 211–240.

12. Chen, J., Ye, Y., Wu, Q., Langari, R., & Tang, C. (2023). Low-cost and high-performance adaptive cruise control based on inertial-triggered mechanism and multi-objective optimization. *IEEE Transactions on Vehicular Technology*, *72*(6), 7279–7289.
13. Batayneh, W., Al-Araidah, O., Bataineh, K., & Al-Ghasem, A. (2013). Fuzzy-based adaptive cruise controller with collision avoidance and warning system. *Mechanical Engineering Research*, *3*(1), 143.
14. Zhu, M., & Tan, G. (2023). *Research on Cooperative Adaptive Cruise Control (CACC) Based on Fuzzy PID Algorithm* (No. 2023-01-0682). SAE Technical Paper.
15. Lin, Y. C., & Nguyen, H. L. T. (2019). Adaptive neuro-fuzzy predictor-based control for cooperative adaptive cruise control system. *IEEE Transactions on Intelligent Transportation Systems*, *21*(3), 1054–1063.
16. Almadi, A. I., Al Mamlook, R. E., Almarhabi, Y., Ullah, I., Jamal, A., & Bandara, N. (2022). A fuzzy-logic approach based on driver decision-making behavior modeling and simulation. *Sustainability*, *14*(14), 8874.
17. Malik, H., Larue, G. S., Rakotonirainy, A., & Maire, F. (2014). Fuzzy logic to evaluate driving maneuvers: An integrated approach to improve training. *IEEE Transactions on Intelligent Transportation Systems*, *16*(4), 1728–1735.
18. Hentout, A., Maoudj, A., & Aouache, M. (2023). A review of the literature on fuzzy-logic approaches for collision-free path planning of manipulator robots. *Artificial Intelligence Review*, *56*(4), 3369–3444.
19. Miranda, M. H., Silva, F. L., Lourenço, M. A., Eckert, J. J., & Silva, L. C. (2022). Vehicle drivetrain and fuzzy controller optimization using a planar dynamics simulation based on a real-world driving cycle. *Energy*, *257*, 124769.
20. Moslem, S., Farooq, D., Esztergár-Kiss, D., Yaseen, G., Senapati, T., & Deveci, M. (2023). A novel spherical decision-making model for measuring the separateness of preferences for drivers' behavior factors associated with road traffic accidents. *Expert Systems with Applications*, *238*, 122318.
21. Elallid, B. B., Benamar, N., Hafid, A. S., Rachidi, T., & Mrani, N. (2022). A comprehensive survey on the application of deep and reinforcement learning approaches in autonomous driving. *Journal of King Saud University-Computer and Information Sciences*, *34*(9), 7366–7390.
22. Fisac, J. F., Bajcsy, A., Herbert, S. L., Fridovich-Keil, D., Wang, S., Tomlin, C. J., & Dragan, A. D. (2018). Probabilistically safe robot planning with confidence-based human predictions. *arXiv preprint arXiv:1806.00109*.
23. David, M. (2019). AI and the illusion of human-algorithm complementarity. *Social Research: An International Quarterly*, *86*(4), 887–908.
24. Ali, M. A., Mailah, M., Jabbar, W. A., Moiduddin, K., Ameen, W., & Alkhalefah, H. (2020). Autonomous road roundabout detection and navigation system for smart vehicles and cities using laser simulator–fuzzy logic algorithms and sensor fusion. *Sensors*, *20*(13), 3694.
25. Deveci, M., Pamucar, D., & Gokasar, I. (2021). Fuzzy Power Heronian function based CoCoSo method for the advantage prioritization of autonomous vehicles in real-time traffic management. *Sustainable Cities and Society*, *69*, 102846.
26. Nakrani, N. M., & Joshi, M. M. (2022). A human-like decision intelligence for obstacle avoidance in autonomous vehicle parking. *Applied Intelligence*, *52*, 3728–3747.
27. Kamil, F., & Moghrabiah, M. Y. (2022). Multilayer decision-based fuzzy logic model to navigate mobile robot in unknown dynamic environments. *Fuzzy Information and Engineering*, *14*(1), 51–73.

28. Lopez, I., & Sarigul-Klijn, N. (2010). A review of uncertainty in flight vehicle structural damage monitoring, diagnosis and control: Challenges and opportunities. *Progress in Aerospace Sciences*, *46*(7), 247–273.
29. Jafari, S., Shahbazi, Z., & Byun, Y. C. (2022). Improving the road and traffic control prediction based on fuzzy logic approach in multiple intersections. *Mathematics*, *10*(16), 2832.
30. Jafari, S., Shahbazi, Z., & Byun, Y. C. (2021). Traffic control prediction design based on fuzzy logic and Lyapunov approaches to improve the performance of road intersection. *Processes*, *9*(12), 2205.
31. Nyholm, S., & Smids, J. (2020). Automated cars meet human drivers: Responsible human-robot coordination and the ethics of mixed traffic. *Ethics and Information Technology*, *22*, 335–344.
32. Yu, H., Jiang, R., He, Z., Zheng, Z., Li, L., Liu, R., & Chen, X. (2021). Automated vehicle-involved traffic flow studies: A survey of assumptions, models, speculations, and perspectives. *Transportation Research Part C: Emerging Technologies*, *127*, 103101.
33. Yilin, C., & Jianhua, W. (2022). Optimization and implementation of fuzzy logic controllers for precise path tracking in autonomous driving. *Journal of Sustainable Urban Futures*, *12*(12), 1–15.
34. Rahman, Z., Yi, X., Khalil, I., Anwar, A., & Pal, S. (2023). Blockchain-based and fuzzy logic-enabled false data discovery for the intelligent autonomous vehicular system. In: *Proceedings of the Third International Symposium on Advanced Security on Software and Systems*, pp. 1–11.
35. Sadaf, M., Iqbal, Z., Javed, A. R., Saba, I., Krichen, M., Majeed, S., & Raza, A. (2023). Connected and automated vehicles: Infrastructure, applications, security, critical challenges, and future aspects. *Technologies*, *11*(5), 117.
36. Mata-Carballeira, Ó., Díaz-Rodríguez, M., del Campo, I., & Martínez, V. (2020). An intelligent system-on-a-chip for a real-time assessment of fuel consumption to promote eco-driving. *Applied Sciences*, *10*(18), 6549.
37. Reddy, N. R. (2019). *Driving Behaviour Classification: An Eco-driving Approach* (Master's thesis, University of Twente).
38. Li, P., Jiao, X., & Li, Y. (2021). Adaptive real-time energy management control strategy based on fuzzy inference system for plug-in hybrid electric vehicles. *Control Engineering Practice*, *107*, 104703.
39. Nie, Z., Jia, Y., Wang, W., & Outbib, R. (2022). Eco-Co-Optimization strategy for connected and automated fuel cell hybrid vehicles in dynamic urban traffic settings. *Energy Conversion and Management*, *263*, 115690.
40. Xu, N., Li, X., Liu, Q., & Zhao, D. (2021). An overview of eco-driving theory, capability evaluation, and training applications. *Sensors*, *21*(19), 6547.
41. Deb, M., Majumder, P., Majumder, A., Roy, S., & Banerjee, R. (2016). Application of artificial intelligence (AI) in characterization of the performance–emission profile of a single cylinder CI engine operating with hydrogen in dual fuel mode: An ANN approach with fuzzy-logic based topology optimization. *International Journal of Hydrogen Energy*, *41*(32), 14330–14350.
42. Tarafdar, A., Majumder, P., Deb, M., & Bera, U. K. (2023). Application of a q-rung orthopair hesitant fuzzy aggregated Type-3 fuzzy logic in the characterization of performance-emission profile of a single cylinder CI-engine operating with hydrogen in dual fuel mode. *Energy*, *269*, 126751.

43. Sittichompoo, S., Theinnoi, K., Sawatmongkhon, B., Wongchang, T., Iamcheerangkoon, T., & Phugot, S. (2022). Promotion effect of hydrogen addition in selective catalytic reduction of nitrogen oxide emissions from diesel engines fuelled with diesel-biodiesel-ethanol blends. *Alexandria Engineering Journal*, *61*(7), 5383–5395.
44. Jung, Y., Pyo, Y. D., Jang, J., Kim, G. C., Cho, C. P., & Yang, C. (2019). NO, NO2 and N2O emissions over a SCR using DOC and DPF systems with Pt reduction. *Chemical Engineering Journal*, *369*, 1059-–1067.
45. Alves de Araujo Junior, C. A., Mauricio Villanueva, J. M., Almeida, R. J. S. D., & Azevedo de Medeiros, I. E. (2021). Digital twins of the water cooling system in a power plant based on fuzzy logic. *Sensors*, *21*(20), 6737.
46. Tarafdar, A., Majumder, P., Deb, M., & Bera, U. K. (2023). Performance-emission optimization in a single cylinder CI-engine with diesel hydrogen dual fuel: A spherical fuzzy MARCOS MCGDM based Type-3 fuzzy logic approach. *International Journal of Hydrogen Energy*, *48*, 28601–28627.
47. Ghadi, Y. Y., Rasul, M. G., & Khan, M. M. K. (2016). Design and development of advanced fuzzy logic controllers in smart buildings for institutional buildings in subtropical Queensland. *Renewable and Sustainable Energy Reviews*, *54*, 738–744.
48. Liu, Z., Zhang, X., Sun, Y., & Zhou, Y. (2023). Advanced controls on energy reliability, flexibility, resilience, and occupant-centric control for smart and energy-efficient buildings—A state-of-the-art review. *Energy and Buildings*, *297*, 113436.
49. Rajeswari Subramaniam, K., Cheng, C. T., & Pang, T. Y. (2023). Fuzzy logic controlled simulation in regulating thermal comfort and indoor air quality using a vehicle heating, ventilation, and air-conditioning system. *Sensors*, *23*(3), 1395.
50. Fayaz, M., Ullah, I., Shah, A. S., & Kim, D. (2019). An efficient energy consumption and user comfort maximization methodology based on learning to optimization and learning to control algorithms. *Journal of Intelligent & Fuzzy Systems*, *37*(5), 6683–6706.
51. Bruno, D. R., Berri, R., Barbosa, F., & Osorio, F. S. (2023). CARINA Project: Visual perception systems applied for autonomous vehicles and advanced driver assistance systems (ADAS). *IEEE Access*, *11*, 69720–69749.
52. Capitaine, M. P., & Cárdenas, H. M. G. (2023). Artificial intelligence and advanced driver assistance systems absorption (ADAS) in Mexico. *Ciencia Nicolaita*, (88).
53. Kim, W., Yang, H., & Kim, J. (2023). Blind spot detection radar system design for safe driving of smart vehicles. *Applied Sciences*, *13*(10), 6147.
54. Makarova, I., Shepelev, V. D., Mukhametdinov, E. M., & Pashkevich, A. (2020). Changing the maintenance and repair system while expanding the connected vehicles fleet. In: *VEHITS*, pp. 622–633.
55. Ineza Havugimana, L. F., Liu, B., Liu, F., Zhang, J., Li, B., & Wan, P. (2023). Review of artificial intelligent algorithms for engine performance, control, and diagnosis. *Energies*, *16*(3), 1206.
56. Djelloul, I., Sari, Z., & Latreche, K. (2018). Uncertain fault diagnosis problem using neuro-fuzzy approach and probabilistic model for manufacturing systems. *Applied Intelligence*, *48*, 3143–3160.
57. Gougam, F., Rahmoune, C., Benazzouz, D., Afia, A., & Zair, M. (2020). Bearing faults classification under various operation modes using time domain features, singular value decomposition, and fuzzy logic system. *Advances in Mechanical Engineering*, *12*(10), 1687814020967874.

58. Dowdeswell, B., Sinha, R., & MacDonell, S. G. (2020). Finding faults: A scoping study of fault diagnostics for industrial cyber–physical systems. *Journal of Systems and Software*, *168*, 110638.
59. Mazzoleni, M., Sarda, K., Acernese, A., Russo, L., Manfredi, L., Glielmo, L., & Del Vecchio, C. (2022). A fuzzy logic-based approach for fault diagnosis and condition monitoring of industry 4.0 manufacturing processes. *Engineering Applications of Artificial Intelligence*, *115*, 105317.
60. Miraz, M. H., Ali, M., & Excell, P. S. (2021). Adaptive user interfaces and universal usability through plasticity of user interface design. *Computer Science Review*, *40*, 100363.
61. Khan, M., & Khusro, S. (2023). Towards the design of personalized adaptive user interfaces for smart TV viewers. *Journal of King Saud University-Computer and Information Sciences*, *35*(9), 101777.
62. Erdoğan, M., Kaya, İ., Karaşan, A., & Çolak, M. (2021). Evaluation of autonomous vehicle driving systems for risk assessment based on three-dimensional uncertain linguistic variables. *Applied Soft Computing*, *113*, 107934.
63. Vahidi, A., & Eskandarian, A. (2003). Research advances in intelligent collision avoidance and adaptive cruise control. *IEEE Transactions on Intelligent Transportation Systems*, *4*(3), 143–153.
64. Alcalá, R., Alcalá-Fdez, J., Casillas, J., Cordón, O., & Herrera, F. (2006). Hybrid learning models to get the interpretability–accuracy trade-off in fuzzy modeling. *Soft Computing*, *10*, 717–734.
65. Lokhande, S. A., & Chauhan, N. (2023). SPHA-VC: Secure passengers health assessment via vehicular communications. *Microprocessors and Microsystems*, *98*, 104799.
66. Tanwar, N., & Akhai, S. (2017). Survey analysis for quality control comfort management in air conditioned classroom. *Journal of Advanced Research in Civil and Environmental Engineering*, *4*(1&2), 20–23.
67. Akhai, S., Mala, S., & Jerin, A. A. (2021). Understanding whether air filtration from air conditioners reduces the probability of virus transmission in the environment. *Journal of Advanced Research in Medical Science & Technology (ISSN: 2394-6539)*, *8*(1), 36–41.
68. Akhai, S., Mala, S., & Jerin, A. A. (2020). Apprehending air conditioning systems in context to COVID-19 and human health: A brief communication. *International Journal of Healthcare Education & Medical Informatics (ISSN: 2455-9199)*, *7*(1&2), 28–30.
69. Akhai, S., Singh, V. P., & John, S. (2016). Investigating indoor air quality for the split-type air conditioners in an office environment and its effect on human performance. *Journal of Mechanical Civil Engineering*, *13*(6), 113–118.
70. Kumar, P., & Akhai, S. (2022). Effective energy management in smart buildings using VRV/VRF systems. In *Additive Manufacturing in Industry 4.0: Methods, Techniques, Modeling, and Nano Aspects*. p. 27.
71. Akhai, S., Thareja, P., & Singh, V. P. (2017). Assessment of indoor environment health sustenance in air conditioned class rooms. *Advanced Research in Civil and Environmental Engineering*, *4*(1&2), 1–9.
72. Furizal, F., Sunardi, S., & Yudhana, A. (2023). Temperature and humidity control system with air conditioner based on fuzzy logic and internet of things. *Journal of Robotics and Control (JRC)*, *4*(3), 308–322.

73. Belman-Flores, J. M., Rodríguez-Valderrama, D. A., Ledesma, S., García-Pabón, J. J., Hernández, D., & Pardo-Cely, D. M. (2022). A review on applications of fuzzy logic control for refrigeration systems. *Applied Sciences*, *12*(3), 1302.
74. Mounica, V., & Obulesu, Y. P. (2022). Hybrid power management strategy with fuel cell, battery, and supercapacitor for fuel economy in hybrid electric vehicle application. *Energies*, *15*(12), 4185.
75. Bakdi, A., & Vanem, E. (2022). Fullest COLREGs evaluation using fuzzy logic for collaborative decision-making analysis of autonomous ships in complex situations. *IEEE Transactions on Intelligent Transportation Systems*, *23*(10), 18433–18445.

CHAPTER 14

Fuzzy Logic in Image Processing and Pattern Recognition

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ABSTRACT

Fuzzy logic is a problem-solving tool and a mathematical framework that deals with the logical reasoning of approximation rather than precision. In the last few years, classical image processing has faced difficulty dealing with real-world images containing noise and distortions due to their vagueness and uncertainty. So, this chapter explores the recent developments in image processing and pattern recognition by applying fuzzy logic. Furthermore, the integration of fuzzy logic along with machine learning algorithms and deep learning algorithms is explored and reported as a significant development in the field of image classification for target identification and classification in defense, object detection, medical image analysis, scenario recognition in video surveillance, and many other fields of applications. Finally, it concludes with areas for further advancement and the future scope of interest for research and development.

14.1 INTRODUCTION

An attempt to mimic human reasoning and decision-making ability becomes essential to incorporate mathematically, resulting in a logic system called fuzzy logic. Unlike Boolean logic, an infinite-valued logic was introduced

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to deal with the object's belongingness in different classes at the same time. To define belongingness, membership functions are introduced. It provides the machine an extra provision to make a decision based upon partial belongingness rather than complete belongingness. Especially for the image processing tasks, different kinds of vagueness and ambiguity in the images in the form of pixel value need to be processed in order to reach the final decision. Filtering out those things sometimes leads to the loss of essential information that is actually needed for the best decision-making. Fuzzy image processing introduces the fuzzy version of an image and processes it through the inference rule engine which has expert knowledge in the form of rules. After that, perform defuzzification to get the actual result. Apart from that, in the different steps of the image processing, the researchers use fuzzy logic to get the precise output from that step which again becomes the input for the next step. The neural network has incorporated fuzzy logic to enhance the power to solve complex problems in lack of expert knowledge. A hierarchical fuzzy logic system is organized into subsystems, each of which is further divided into fuzzy logic units that are connected hierarchically.

Fuzzy logic is a mathematical tool dealing with uncertainty. It is the extension of the Boolean logic which only deals with 0 and 1 or true and false. It is the more generalized form of the crisp set theory that contains those objects having some properties for membership. On the other hand, a fuzzy set contains those objects that are imprecisely defined in varying degrees. For example, suppose I want to define a set of numbers between 16 to 19 either completely present or partially present in a particular group. So, the fuzzy set a can be defined as

$$A_f = \{(16,0.2), (17,0.1), (18,0.7), (19,1.0) \mid x \in X\}$$

Here, X is the universe of discourse of all positive integers.

So, the fuzzy set is the set of ordered pairs of the element and its membership in the set A. The membership defines belongingness in a set. As opposed to that if this set is defined in crisp set, then it will be $A_c = \{19\}$. Because the crisp set contains the element with a hundred percent presence. In this way, fuzzy logic gives the provision to represent more information than the crisp set. Furthermore, suppose I ask a question: Is it cold today? The answer could be very cold, moderately cold, a little cold, or not at all. The fuzzy logic addresses the problem in a better way by representing it between 0 and 1 as opposed to only 0 or 1 in Boolean logic. This theory tries to mimic human reasoning for decision-making. Due to the ambiguity and uncertainty, real-world images containing noise and distortions have proven challenging for classical image processing to handle. Thus, using fuzzy logic, the latest advances in image processing and pattern recognition are investigated in the different domains of application like agriculture, biomedical image analysis, and many more fields.

14.2 HISTORY

In the year 1920, fuzzy logic was studied by Lukasiewicz and Tarski as infinite-valued logic. In the year 1965, Zadeh introduced the fuzzy theory which allows partial membership [1]. In 1962, the decision-making process in pattern recognition was published by McMillan Press. In the year 1970, the fuzzy control system was developed. In the year 1973, a famous paper by Prof. Zadeh was published introducing an outline of an approach that could be used for decision-making and complex system analysis. In the year 1977, fuzzy logic in pattern recognition was implemented in the speech recognition and the speaker recognition problem. In the year 1980, the Fuzzy expert system was developed. In the later years of 1982 and onwards, The development of fuzzy (gray) image processing was introduced. In the year 1986, The fuzzy syntactic recognition approach was developed for various skeletal maturity identification from X-ray images of the radius and ulna of the wrist. In the late 1980s, neurofuzzy models were introduced for clustering, rule generation, classification, and feature selection that enable linguistic input accepted by the artificial neural network. During 1990–1994, rough sets and the genetic algorithm are used for large data mining. Besides, fuzzy logic was first applied in image processing tasks like noise reduction, edge detection, and image segmentation. After that, in the year 2020, fuzzy logic techniques were further developed and applied in medical image processing like brain disease prediction. In the next few years, fuzzy logic works for quality improvement of the images using fuzzy logic systems [2]. In accordance, effective unsupervised feature selection models as well as certain application-specific models, such as, fuzzy clustering networks for hardware realization and mixed category perception, were also developed. In the year 2023, fuzzy neural networks evolve and models to solve complex problems like cyber invasion and fraud detection in auctions using binary pattern classification tests.

14.3 FUZZY LOGIC IN PATTERN RECOGNITION

Pattern recognition is a big spectrum for the understanding of the different systems and working further in the application domain. Nowadays, all types of advanced machine learning methods and data analysis techniques are busy understanding some sort of underlying hidden pattern that could immensely help to deep dive into the research along with the development of the new application domain for the betterment of mankind. Fuzzy logic in pattern recognition just stimulates the urge to search along with some more flexibility of belongingness.

A subtle difference exists between pattern recognition and clustering in their goals. The clustering method aims to uncover the natural structures within the data without predefined classes or labels whereas pattern recognition aims to focus on identifying and categorizing data based on the predefined patterns or classes. So, clustering is all about exploring and grouping the data rather than identifying and categorizing data based on known patterns or classes. Pattern recognition in image processing is the process of identifying the pattern and the regularities of the image data automatically through the machine learning algorithm for data analysis. Through the process of pattern recognition, a machine-learning algorithm can recognize familiar and unfamiliar objects. So, pattern recognition plays a very crucial role in image processing. A pattern recognition system consists of three blocks that are feature space, measurement space, and decision space. As we know, a deficiency of information creates uncertainties in the system that could arise from contradictory, vague, unreliable, and ill-defined information in different stages of the pattern recognition system. The different stages of pattern recognition are varied from system to system to find useful patterns. The lack of precision or ambiguity can occur due to experimental error or limitation of the instrument or measurement can lead to vagueness in the measurement space. In the same way, Occasionally, it could be suitable and convenient to represent the input feature value in interval form, with one or both sides of the interval being ambiguous. The corresponding classes in the decision space might become unmanageable by becoming nonconvex, extended, and overlapping. That is the decision space can be affected to decide the 100% belongingness of a data point. However, in human perception, that could be fine if the data point has 90% membership of a class which represents partial belongingness. So, these all kinds of problems are addressed by the fuzzy logic in pattern recognition. Fuzzy logic in pattern recognition provides the capability to produce a classifier that can model overlapping class boundaries and generate linear or nonlinear boundaries. Fuzzy logic in pattern recognition was applied to speaker recognition and speech recognition problems in 1977. The characteristics of the speech depend on the health, age, sex, mind, and temperament of the speaker consisting certain amount of fuzziness and overlapping classes. So, For vowel sound recognition, classification analysis of the machine recognition using the fuzzy sets gives 82%accuracy based on the highest membership values. Furthermore, incorporating the linguistic constraints-based supervisory learning improved the accuracy by 15%.

14.4 GRAY IMAGE PROCESSING

Another fuzzy set theory application is gray image processing. As the image is gray, the segment, skeleton, edge and their relation have no precise definition makes it a suitable candidate for implementation of the fuzzy logic.

As can be seen in Figure 14.1, the uncertainty or imperfection of the image can be represented in three ways. Grayness ambiguity is the uncertainty associated with the gray level or the intensity value of the pixels in an image whether the pixel value is considered as white or black. It is the kind of vagueness where the intensity of a pixel in an image appears to have poor color contrast or has imprecise boundaries. Geometric fuzziness in the images contains those images where boundaries, edges, and shapes are not very prominent. That means both the location of the pixels and the gray level characterize the geometry of the image subset. The uncleared boundaries, blurriness, and the multiple objects' presence in the images are considered complex and ill data. Different types of operators like max and min operators, Zadeh's contrast enhancement operator (INT), S & π membership functions, index of fuzziness, and entropy of fuzzy sets were used to develop an efficient algorithm to process the gray images and reduce the difficulty to decide the pixel is white or black, in turn, decrease the index of fuzziness and entropy. The best-segmented output of object extraction can be obtained from the minimized index of entropy and fuzziness. The degree of the fuzziness of an image can be defined using fuzziness measures that could be linear index, quadratic index, logarithmic fuzzy entropy, fuzzy entropy of r-order Yager's measures, and hybrid entropy. The measure of fuzziness is used in many applications like thresholding.

The whole task of image processing can also be visualized as low-level image processing, medium-level image processing, and high-level image processing. In low-level image processing, visualization of the images has been improved by some basic techniques like contrast enhancement [3], image smoothening, and edge detection. Apart from that, low light enhancement is another significant process for some image processing tasks, especially for color images. A significant study has shown that intuitionistic fuzzy sets along with histogram equalization outperform all the existing methods, such as, adaptive histogram equalization with limited contrast, histogram equalization, histogram specification, dynamic fuzzy histogram equalization preserving brightness, and discrete cosine transform (DCT) coefficient [4]. The main purpose of medium-level image processing is to extract some features of the images. High-level image processing results in the description of the content of the images.

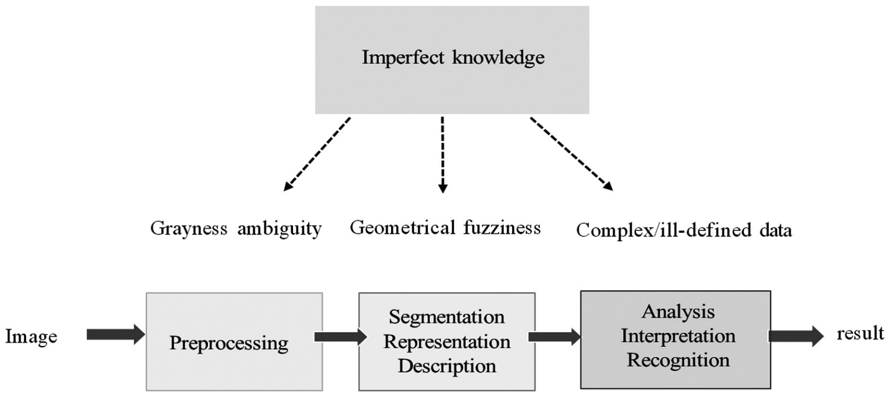

FIGURE 14.1 Imperfect knowledge in gray image processing.

The intention behind investigating fuzzy logic is to represent and process expert knowledge and efficiently manage vagueness and ambiguity. In the context of that, a scheme has been introduced earlier in fuzzy image processing consisting of three applications that are fuzzy binarization, definition of fuzzy edge, and measurement of fuzzy geometry [5]. Fuzzy set-based image processing consists of many steps. First, the input image gets into the process of fuzzification and then goes through the membership function modification. The role of expert knowledge plays here a crucial role and then goes through defuzzification [6].

14.5 FUZZIFICATION

In the process of fuzzification, image data has transformed from a gray-level plane to a membership plane. So, the images can be represented in fuzzy logic. The fuzzification of the image can be done in two ways. First, without changing the pixel values, we represent an image as a collection of fuzzy singletons. Second, represents the property of darkness by introducing a fuzzy set that is determined by an appropriate membership function. The suitable member function that converts an image to a fuzzy image is called a fuzzifier. Suppose an image G of dimension (M×N) with L gray level is defined as the array of fuzzy singletons that can be defined as

$$G = \bigcup_m \bigcup_n \mu_{mn} \tag{14.1}$$

Here, $\mu_{mn} \in [0,1]$ is the membership value and is the predefined image property like homogeneity, noisiness, brightness, etc. [7, 8].

14.6 MEMBERSHIP FUNCTION MODIFICATION

This is the most important step where appropriate fuzzy techniques can modify the membership values. The degree to which an object satisfies particular properties is indicated by its membership value. Additionally, the membership values show how fuzzy a set is. Fuzzy clustering is the unsupervised learning technique that induces rules by categorizing and organizing data into partitions to form clusters. The fuzzy clustering method which is the fuzzy c-means (FCMs) algorithm is widely used in many applications, including pattern recognition, image segmentation, and data analysis. The fuzzy clustering consists of the fuzzy partitioning of the input space and the creation of the fuzzy set that consists of the data points along with the partial membership of the multiple clusters.

That clustering algorithm is used to create rule-based classification models where each rule is associated with a fuzzy cluster. Unlike fuzzy image processing, a methodology has been developed for converting a fuzzy logic model that is based on transparent linguistic rules from a fuzzy clustering-based classification model. Furthermore, optimized algorithms are established by combining the FCMs algorithm with genetic algorithms and particle swarm optimization to improve the rule-based fuzzy clustering process. The membership function for the image fuzzy processing is thresholding by selecting an α-cut. A study shows that the fuzzy rule-based approach for disease detection performs well over various methods and techniques, such as, support vector machines (SVMs), artificial neural networks, fuzzy logic, convolution neural networks, etc. Fuzzy rules are developed from the values of the parameters obtained from the feature extraction method, that is, blob analysis and then implemented using the membership function [9].

14.7 IMAGE DEFUZZIFICATION

As we do not have any fuzzy hardware, fuzzification of an image and then defuzzification are required to process an image in fuzzy techniques. Defuzzification means decoding the result by converting the fuzzy set to the crisp set again. It is observed that the defuzzification results in the loss of information about the spatial characteristics of the images, such as, shape, topology, and geometry. As opposed to the crisp segmentation, feature distance minimization is proposed [10]. The Minkowski distance between the fuzzy set and the crisp sets is defined through their selected feature-based representation. Disease detection in Orchid plants is an application domain of fuzzy image processing that consists of two parts, that is image processing like gray-scaling, noise removal, and threshold segmentation. The fuzzy logic system works on it through fuzzification, inference, and defuzzification [11]. The classification of the unhealthy region in the leaf of the plant has been done using the fuzzy inference system [12].

14.8 IMAGE PROCESSING

In image processing, image analysis requires cooperative operations and image recognition can be performed through the formulation of complex decision regions. Image acquisition involves capturing visual data from the real world for digital processing and analysis. Cameras, scanners, satellites, and medical imaging machines are used for image acquisition. Each device employs specific sensors or technologies to capture visual information. Image enhancement refers to techniques used to improve the quality, clarity, and visual appearance of digital images. It involves altering an image to make it more suitable for a specific application or to improve its interpretability. Several methods are employed in image enhancement. Spatial domain technique directly manipulates pixel values to enhance contrast, brightness, or sharpness. Operations like histogram equalization, contrast stretching, and spatial filtering fall into this category. Frequency domain techniques are transformations, such as, Fourier transforms are used to enhance images by modifying their frequency components. Filters, such as, high-pass, low-pass, or band-pass filters can sharpen or smooth images by accentuating or suppressing certain frequencies. Histogram modification adjusting the distribution of pixel intensities in the histogram can improve overall contrast and brightness. Multiscale transformations are techniques like wavelet transformation that enhance images by decomposing them into multiple scales, allowing for localized enhancement. Image restoration involves the process of recovering the original image from a degraded or corrupted version. It aims to undo the effects of various factors that deteriorate image quality, such as, blurring, noise, or compression artifacts. Several methods are used in image restoration. Deconvolution is the technique that attempts to reverse the blurring caused by factors like motion or optical imperfections. Algorithms, such as, Wiener deconvolution or Richardson–Lucy deconvolution aim to restore sharpness and clarity. Noise reduction is a method like median filtering, Gaussian smoothing, or wavelet denoising that helps eliminate or reduce unwanted noise, enhancing image quality. Super-resolution is the approach that reconstructs a higher-resolution image from low-resolution versions, aiming to restore finer details. Inpainting is used to fill in missing or damaged parts of an image, inpainting algorithms estimate and reconstruct the missing information. Color image processing involves manipulating and analyzing images that contain color information. It's crucial for various applications where color plays a vital role, such as, in photography, medicine, art, and computer vision. The primary aspects of color image processing include many steps. Color models are those various color models, such as, red, green, blue; cyan, magenta, yellow, black; hue, saturation, lightness; and hue, saturation, value that represent colors differently, allowing for different manipulations and analyses based on their properties. Color enhancement uses techniques, such as, color correction, white balance adjustment, and histogram equalization to enhance the overall appearance and quality of color images. Color segmentation involves partitioning an image into regions or objects based on color information. This technique is vital in object detection, tracking, and classification. Color image compression methods for compressing color images without significant loss of quality, considering the characteristics of human perception and the redundancy in color data. Wavelet representation is a powerful method used to analyze and represent images at multiple degrees of resolution. It employs wavelet transforms to break down an image into different frequency components, capturing both fine details and coarse approximations. This representation facilitates a multi-resolution view of the image, allowing for more efficient storage, analysis, and manipulation. Wavelet transforms such as, the discrete wavelet transform or the continuous wavelet transform, decompose the image into different levels or scales, each representing a different degree of detail. Higher levels capture finer details while lower levels or scales provide broader approximations of the image. This multiresolution approach enables tasks such as, compression, denoising, and analysis at various levels of detail, catering to specific requirements in applications such as, image processing, data compression, and signal analysis. Image compression is a technique used to reduce the size of digital images, enabling efficient storage, transmission, and processing while minimizing loss of image quality. There are two main types of image compression. The lossless compression methods retain all original image information while reducing file size. It is commonly used for images where maintaining pixel-perfect accuracy is crucial, like medical imaging or technical drawings. Lossy compression achieves higher compression ratios by discarding some image data. While it reduces file size significantly, there is a tradeoff with image quality. Popular lossy compression methods include joint photographic experts group, where users can adjust the compression level to balance between file size and image quality. Image compression algorithms leverage techniques like predictive coding, transform coding (such as, DCT), and quantization to reduce redundant information and compress the image efficiently. These methods are integral in digital photography, web applications, and various industries where managing large volumes of image data is essential. Image morphological processing involves analyzing and manipulating the structure and shapes within an image using mathematical operations based on set theory and geometry. It focuses on extracting, enhancing, and modifying features such as, edges, shapes, and patterns within images. Erosion shrinks or erodes the boundaries of objects in an image, useful for removing small structures or fine details. Dilation is the opposite of erosion, dilation enlarges or fattens the boundaries of objects, enhancing or joining nearby structures. The opening combines erosion followed by dilation helps in removing noise, small objects, or thin structures from an image. Closing is dilation followed by erosion fills small gaps or holes and joins nearby structures in an image. Image segmentation involves dividing an image into meaningful and distinct regions or objects based on certain characteristics such as, color, intensity, texture, or boundaries. It is a critical step in image analysis and computer vision, enabling the extraction of specific areas for further processing and interpretation. Various techniques are employed for image segmentation. Thresholding separates regions based on pixel intensity values, where pixels above or below a certain threshold are grouped. Edge-based segmentation detects discontinuities or edges in an image to separate different objects or regions based on abrupt changes in pixel intensity. Region-based segmentation divides the image into regions with similar properties, using algorithms such as, clustering or region growth. Contour-based segmentation is identifying and delineating object boundaries or contours for segmentation. Image segmentation finds applications in medical imaging (tumor detection), object recognition, autonomous vehicles, and scene understanding, providing crucial information for subsequent analysis and decision-making in various fields. Feature extraction involves identifying and selecting the most relevant and distinctive characteristics from raw data, facilitating easier analysis, classification, and pattern recognition. In image processing, it involves capturing and representing meaningful information from images that aid in subsequent tasks like object detection, recognition, and analysis. Various methods are used for feature extraction. Pixel-based features are basic features derived directly from pixel values, such as, color, intensity, and texture. Edge detection is to identify edges and contours within an image to extract information about object boundaries. Shape Descriptors are extracting features related to shapes, such as, area, perimeter, or circularity, crucial for object recognition. Histograms and statistical features describe the distribution of pixel values or statistical properties, such as, mean, variance, or skewness. Feature extraction is pivotal in fields such as, computer vision, pattern recognition, and machine learning, where these extracted features serve as inputs for algorithms to make decisions, classify objects, or perform complex analyses on images or data. Image pattern classification involves the categorization or labeling of images into predefined classes or categories based on their features. It is a fundamental task in image processing and computer vision, aiming to identify patterns, objects, or structures within images. The process typically involves many steps. Feature extraction is performed to extract relevant features from images such as, texture, color, edges, or shapes. Training a classifier using machine learning algorithms (such as SVMs, neural networks, or decision trees), a model is trained on a labeled dataset, learning to associate extracted features with specific classes. Classification: The trained model is applied to new, unlabeled images to predict or assign them to appropriate classes based on the learned patterns.

The image processing steps consist of some substeps such as, noise removal and distortion correction in the image preprocessing, object boundary identification and object feature identification in the feature extraction phases, and false positive removal in the postprocessing phase. Although all the steps are not necessarily required for a single image processing task rather the steps are added or omitted depending upon the application.

A comparative study has been performed on the different classification and pattern recognition algorithms and observed that the control chart approach is the decision methodology that gives promising results but cannot detect overlapping events. So, to overcome this problem fuzzy logic technique is used and increases the accuracy from 95.6% to 97.2% [13]. However, in image processing and pattern recognition, uncertainties can happen in any phase of the image processing tasks like enhancement, noise reduction, filtering, contour extraction, segmentation, and skeleton extraction to extract the features from the image pattern.

14.8.1 NOISE REMOVAL AND DISTORTION CORRECTION

Fuzzy logic can enhance the quality of images by reducing the noise in the pre-processing phase. A fuzzy filter is used to remove the additive noise and they use the member function corresponding to the fuzzy rule of the different stages of the filter [14]. A recursive double-action fuzzy filter is introduced which performs the fuzzy reasoning into two phases and strongly cancels the noise without any degradation of the image structure [15]. Another adaptive fuzzy filter is proposed by the researcher that can potentially enhance the image quality by performing edge detection for the smeared images. That fuzzy filter has two mechanisms: Adaptive weighted fuzzy mean and fuzzy normed inference system. The member function of the fuzzy set used for the filters is adaptively determined for the different images. This filter can cancel the random impulse noise and Gaussian impulse noise effectively [16]. The article proposes the use of fuzzy logic and an alpha-trimmed mean-based filter to smooth out uniform impulse noise from grayscale images that have been distorted. To prevent the outlier effect, the suggested method combines fuzzy logic with the idea of an alpha-trimmed mean. The alpha-trimmed mean and median values are used to develop a fuzzy membership function, in turn, is used to find the noisy pixels estimated value. The method described in [17] outperforms all the previous impulse noise removal methods. The impulse noise of the sequence-based images is also removed [18]. Furthermore, the impulse noise which is salt pepper noise can be removed using an adaptive switching median filter [19]. In recent studies of biomedical image analysis, Gaussian blur is applied to remove unwanted noises from the optical coherence tomography B scan images to identify diabetic macular edema [20].

14.8.2 OBJECT IDENTIFICATION AND SEGMENTATION

For reliable image segmentation, an automatic fuzzy algorithm has been introduced in the study by the researcher and compared with the existing method by various test images, noisy synthetic images, and simulated magnetic resonance Image datasets [21]. Research work has been published for skin cancer detection using fuzzy logic-based segmentation with an advanced deep-learning model. Furthermore, to enhance the segmentation results, the L–R fuzzy defuzzification method is used [22].

In computer vision, fuzzy logic can be incorporated with the image segmentation process to detect damages in a traffic accident where a c-means fuzzy clustering algorithm is used with a particle optimization algorithm for image segmentation [23]. A hybrid character recognition method is introduced using fuzzy logic, SVMs, and the stroke Bayesian program learning using naïve Bayes in an industrial environment [24].

To automate some production chain in agriculture, intelligent systems was developed that uses the intensification operator to enhance the contrast of the image. To segment the images fuzzy divergence is used and fruit identification is performed using the Hough transform [25].

14.8.3 FEATURE EXTRACTION

For the high-level image analysis, the objects are segmented and recognized by some algorithm. However, clustered objects cannot be segmented properly. So, multistage segmentation approaches are introduced. However, the problem of multistage segmentation is that at each step a new structure is detected which creates ambiguity. So, to propose an improved version on top of this a metaheuristic optimization algorithm that is ant-colony optimization and fuzzy logic-based technique is proposed to solve the problem [26]. Many machine learning algorithms are used for the feature extraction processes but fuzzy logic is used very rarely.

14.8.4 CLASSIFICATION

At the initial time or the early age of the image processing, classification approaches are mainly pixel-based rather than utilizing the spatial and context information of the object in the images and their surroundings. As time goes on, approaches are modified and start incorporating spatial and context information. The classification of the segmented object can be performed by object feature tracking, and supervised segmentation [27] can be done for the object-oriented classification. Tissue abnormality can be detected using fuzzy-neuro logic by determining the suitable object parameters. The medical images are classified and segmented perfectly [28].

14.8.4.1 FUZZY CLUSTERING ALGORITHM

The fuzzy clustering techniques are widely used to assign the degree of membership of the data points that belong to one or more clusters. The grouping of the data is performed based on their proximity to each other. The c-mean clustering algorithm provides the hard assignment in the data point clustering. Although, the c-means clustering is computationally complex and sensitive to initialization. It is very difficult to get an exact number of clusters and get the suboptimal segmentation. By tuning the parameters perfectly, the performance can be achieved up to a certain extent. Recent advancements in fuzzy clustering algorithms like FCMs clustering algorithms and their different variations like standard FCM, kernelized fuzzy c-means (KFCMs) clustering, and wavelet fuzzy c-means clustering algorithms [29] have improved the accuracy significantly by the assignment of the partial membership to different clusters. The wavelet FCMs clustering gives a satisfactory result over the standard FCM or KFCM [30]. The benefit of this technique is that we can deal with overlapping regions of the images. Fuzzy clustering enables better segmentation and categorization of image data by allowing a pixel to belong to multiple clusters with varying degrees of membership as opposed to the hard membership function. A fuzzy model has been developed by integrating fuzzy clustering techniques along with fuzzy neural network-based models for prediction. Rough fuzzy pattern recognition techniques or rough fuzzy clustering algorithm was introduced for clustering similar genes from microarray gene expression data and segmenting the brain magnetic resonance images. This is the generalized hybrid unsupervised learning algorithm called rough fuzzy possibilistic c-means algorithm that can give a generalization of all combinations of the c-means algorithm. The combined principle of the rough set and fuzzy set incorporates the probabilistic and the possibilistic memberships simultaneously where uncertainty, vagueness, and approximation can be dealt with in the rough set and the overlapping portion can be handled by the membership function of the fuzzy sets [31]. Pattern recognition is improved by modifying the objective function algorithm [32]. A fuzzy gravitational search algorithm has been introduced for automatic segmentation using brain magnetic resonance imaging (MRI) images [33, 34]. However, the parallel algorithm is introduced in FCMs for brain tumor segmentation on different MRI images which improves the computational time and is twice as fast as the conventional FCM [35]. The performance of the fuzzy clustering algorithm has been improved using the task pipeline concept in using compute unified device architecture technology by parallelly implementing the algorithm. The experimental results indicate 23.35 times boost in performance. The final segmentation is then achieved by applying the watershed algorithm [36, 37].

14.8.5 REMOVAL OF FALSE POSITIVES

Removal of false positive features in the post-processing is performed in such a manner that the true target features still remain. Removal of false positives in mammographic images in postprocessing is an important problem. In fuzzy logic-based false positive reduction, a fuzzy logic classifier assigns each region of interest into two values: one for the probability of being a true positive and another for the probability of being a false positive [38].

Nonmaximum suppression is a standard postprocessing algorithm for merging all the detected objects in the same object. This algorithm is very simple and follows greedy clustering having a fixed distance threshold. This algorithm is used for making a tradeoff between the percentage of accurately identified positive cases relative to all positive cases, in reality, that is, recall, and the ratio of precisely categorized positive cases among all cases classified as positives, that is, precision [39]. Another method is to filter out detection below a certain level, that is, thresholding, geometric consistency checks the relationship between detected objects, and re-ranking using machine learning [40]. Two-stage postprocessing scheme which comprises the area-thresholding sieving and the morphological closing for object detection in wide-area aerial imagery is used [41].

14.9 FUZZY LOGIC WITH NEURAL NETWORKS

The neural network is a big interconnected network of simple processing elements aligned parallelly and has the capability of performing cooperative operations as well as making complex decisions. The huge connection among the neurons ensures that the system is fault tolerant irrespective of the presence of the noise and the component failure, but to handle the uncertainty and incorporate human reasoning, the fuzzy set-theoretic model is introduced along with them. As seen earlier, the design of the fuzzy rule-based system is the mandatory thing to express human knowledge in IF–THEN rules. The process consists of identifying and labeling the input and output variables, specifying the value range of each input and output variable, and specifying the member function to characterize the fuzzy sets. To carry out this process there already exists a general-purpose tool like fuzzy inference system professional that provides an interactive environment for designing and optimizing the fuzzy inference systems. But the flip side is that defining the rule-based system for image processing is difficult to define manually. Furthermore, it models a simple process based on the qualitative model. For the complex process, defining and tuning the parameters are very time-consuming results limiting the incorporation of the fuzzy logic up to the field where domain expert knowledge is available. But we are interested in those fuzzy logic-based models, that can learn from the examples in case of lack of expert knowledge. Besides, a better version of the neural network gets introduced that exploits the advantages of linguistic information. So, neurofuzzy models are being proposed. It eventually reduces time and cost and enhances efficiency. An automatic microaneurysms detection method has been developed using deep learning along with fuzzy image processing in the retinal images [42]. Nowadays, neurofuzzy models have immense applications in the fields of agriculture, biomedical, and many more fields [43–45].

14.10 HIERARCHICAL FUZZY LOGIC

The studies have shown that the conventional fuzzy system has several limitations over the dimensionality of the data [46, 47]. This restricts it from solving large complex problems having large dimensionality of the data. So, hierarchical fuzzy systems have been introduced to solve the problem related to those huge dimensional data [48, 49]. The hierarchical fuzzy system can be classified into two categories: type 1 fuzzy hierarchical inference system where crisp membership function is defined [50] and type 2 fuzzy hierarchical inference system where fuzzy membership function is defined [51–54]. The segmentation of the brain tumor in the magnetic resonance images is performed by a hierarchical combination of fuzzy logic and cellular automata [55].

The main difference between the hierarchical fuzzy logic and the neural network is that in the hierarchical fuzzy system, the system is divided into subsystems and each subsystem is divided into fuzzy logic units that are connected in a hierarchy form in the hierarchical fuzzy logic. The output of each subsystem is used as the input of the next subsystem and it reduces the overall complexity of the system by the reduced rule base. However, in the neurofuzzy modeling, the input set is used to design a fuzzy rule base for the IF-THEN statements and then the neural network is used to learn and optimize the fuzzy rule base with feedback connections. So, the application of these techniques can be used in different places depending upon their requirements where the tradeoff is made between cost and efficiency.

14.11 SUMMARY

Fuzzy logic has its history dating back to 1920 and has been developed in many systems specifically fuzzy control systems, fuzzy expert systems, and fuzzy image processing. As we know, real-world images are ambiguous and unpredictable, traditional image processing has had trouble handling them when they contain noise and distortions. So, fuzzy set-based image processing is introduced and that consists of several steps, including fuzzification, membership function modification, and defuzzification. In this study, we broadly describe the different kinds of ambiguity and the uncertainty of the images. Different kinds of fuzzy filters are used for removing additive noise and impulse noise. Furthermore, the different study shows that low light enhancement and contrast enhancement can be performed through fuzzy logic in image processing. To automate the production chain in agriculture, a fuzzy system has been developed. The plant disease can be detected through fuzzy image processing. Traffic accident detection and hybrid character recognition model are proposed by the researcher by object identification and segmentation using fuzzy logic. The problem of multistage segmentation is removed by the improved version of the model following ant-colony optimization and fuzzy logic-based technique. The FCMs clustering and its different variations are efficiently deal with different overlapping regions of the images and very popular in biomedical image processing. Fuzzy-based postprocessing algorithm is developed that improves the efficiency. Fuzzy neural networks are introduced for those complex applications that are learned by themselves. Finally, the hierarchical fuzzy logic has been discussed which significantly speeds up the research in the biomedical fields using the type 1 and type 2 fuzzy logic. Fuzzy logic has immensely improved the classification phase of image processing. So, the implementation of fuzzy logic significantly advances image processing tasks.

14.12 FUTURE WORK

The research is open to developing the new algorithm or implementing the existing technology to a suitable application that could be best fitted to achieve a perfect tradeoff between cost and efficiency. Furthermore, new technology could be developed for the existing problem domain or different real-life applications to provide a better solution that could be more sustainable for the future.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

KEYWORDS

- **fuzzy logic**
- **image processing**
- **fuzzification**
- **hierarchical fuzzy logic**
- **fuzzy neural network**

REFERENCES

1. Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*(3), 338–353, https://doi.org/10.1016/S0019-9958(65)90241-X.
2. Sharma, Y. K. A design and development of novel framework to enhance the quality of image using fuzzy set based image processing; 2020. [Online]. Available: www.ijiset.com
3. Sharma, S., & Bhatia, A. (2015). Contrast enhancement of an image using fuzzy logic. *International Journal of Computers and Applications*, *111*(17), 14–20, https://doi.org/10.5120/19757-1410.
4. Lepcha, D. C., Goyal, B., Dogra, A., Sharma, K. P., & Gupta, D. N. (2023).A deep journey into image enhancement: A survey of current and emerging trends. *Information Fusion*, *93*, 36–76, https://doi.org/10.1016/j.inffus.2022.12.012.
5. Chacon, M. I., Aguilar, L., & Delgado, A. Definition and applications of a fuzzy image processing scheme. In: *Proceedings of 2002 IEEE 10th Digital Signal Processing Workshop, 2002 and the 2nd Signal Processing Education Workshop.* IEEE, pp. 102–107. https://doi.org/10.1109/DSPWS.2002.1231085.
6. Gonzalez, R. C., Woods, R. E., & Hall, P. P. *Digital Image Processing*, 3rd edn. Pearson International.
7. Jähne, B., Haußecker, H., & Geißler, P. *Handbook of Computer Vision and Applications Volume 2 Signal Processing and Pattern Recognition*. Academic Press.
8. Caponetti, L., & Castellano, G. Fuzzy logic for image processing a gentle introduction using java. [Online]. Available: http://www.springer.com/series/10059
9. Kour, V. P., & Arora, S. (2019). Fruit disease detection using rule-based classification. In: *Smart Innovations in Communication and Computational Sciences*.pp. 295–312. https://doi.org/10.1007/978-981-13-2414-7_28.
10. Sladoje, N., Lindblad, J., & Nyström, I. (2011). Defuzzification of spatial fuzzy sets by feature distance minimization. *Image and Vision Computing*, *29*(2–3), 127–141, https://doi.org/10.1016/j.imavis.2010.08.007.

11. bin MohamadAzmi, M. T., & Isa, N. M. (2013). Orchid disease detection using image processing and fuzzy logic. In: *2013 International Conference on Electrical, Electronics and System Engineering (ICEESE)*. IEEE, pp. 37–42. https://doi.org/10.1109/ICEESE.2013.6895039.
12. Muthukannan, K., & Latha, P. (2014). Fuzzy inference system based unhealthy region classification in plant leaf image.
13. Elbaşi, E. (2013). Fuzzy logic-based scenario recognition from video sequences. *Journal of Applied Research and Technology*, *11*(5), 702–707, https://doi.org/10.1016/S1665-6423(13)71578-5.
14. Van De Ville, D., Nachtegael, M., Van der Weken, D., Kerre, E. E., Philips, W., & Lemahieu, I. (2003). Noise reduction by fuzzy image filtering. *IEEE Transactions on Fuzzy Systems*, *11*(4), 429–436, https://doi.org/10.1109/TFUZZ.2003.814830.
15. Russo, F., & Ramponi, G. (1996). A fuzzy filter for images corrupted by impulse noise. *Ieee Signal Processing Letters*, *3*(6), 168–170, https://doi.org/10.1109/97.503279.
16. Kerre, E., & Nachtegael, M. (2000). *Fuzzy Techniques in Image Processing*. Physica-Verlag HD: Heidelberg, Vol. *52*. https://doi.org/10.1007/978-3-7908-1847-5.
17. Hussain, A., Javaid, Q., & Siddique, M. (2011). Impulse noise removal using fuzzy logic and alpha-trimmed mean. In: *2011 IEEE International Conference on Signal and Image Processing Applications (ICSIPA)*, IEEE, pp. 216–220. https://doi.org/10.1109/ICSIPA.2011.6144066.
18. Mélange, T. (2011). Random impulse noise removal from image sequences based on fuzzy logic. *Journal of Electronic Imaging*, *20*(1), 013024, https://doi.org/10.1117/1.3564922.
19. Thirilogasundari, V., babu, V. S., & Janet, S. A. (2012). Fuzzy based salt and pepper noise removal using adaptive switching median filter. *Procedia Engineering*, *38*, 2858–2865, https://doi.org/10.1016/j.proeng.2012.06.334.
20. Tripathi, A. et al. (2023). Fuzzy logic-based system for identifying the severity of diabetic macular edema from OCT B-scan images using DRIL, HRF, and cystoids. *Diagnostics*, *13*(15), 2550, https://doi.org/10.3390/diagnostics13152550.
21. Zanaty, E. A., & Aljahdali, S. (2012). Automatic fuzzy algorithms for reliable image segmentation. [Online]. Available: https://www.researchgate.net/publication/284182671
22. Singh, S. K., Abolghasemi, V., & Anisi, M. H. (2023). Fuzzy logic with deep learning for detection of skin cancer. *Applied Sciences*, *13*(15), 8927, https://doi.org/10.3390/app13158927.
23. Amirfakhrian, M., & Parhizkar, M. (2021). Integration of image segmentation and fuzzy theory to improve the accuracy of damage detection areas in traffic accidents. *Journal of Big Data*, *8*(1), https://doi.org/10.1186/s40537-021-00539-2.
24. Xu, L., Wang, Y., Li, R., Yang, X., & Li, X. (2020). A hybrid character recognition approach using fuzzy logic and stroke bayesian program learning with naïve bayes in industrial environments. *IEEE Access*, *8*, 124767–124782, https://doi.org/10.1109/ACCESS.2020.3007487.
25. Argote Pedraza, I. L., Faber Archila Diaz, J., Pinto, R. M., Becker, M., & Tronco, M. L. (2019). Sweet citrus fruit detection in thermal images using fuzzy image processing. In: *2019 IEEE Colombian Conference on Applications in Computational Intelligence (ColCACI)*, IEEE, pp. 1–6. https://doi.org/10.1109/ColCACI.2019.8781965.
26. Katteda, S. R. (2011). Feature extraction for image classification and analysis with ant colony optimization using fuzzy logic approach. *Signal Image Process*, *2*(4), 137–143, https://doi.org/10.5121/sipij.2011.2412.

27. Zhang, Y., & Maxwell, T. A fuzzy logic approach to supervised segmentation for object-oriented classification.
28. Kumar, S. S., Moorthi, M., Madhu, M., & Amutha, R. (2010). An improved method of segmentation using fuzzy-neuro logic. In: *2010 Second International Conference on Computer Research and Development*, IEEE, pp. 671–675. https://doi.org/10.1109/ICCRD.2010.155.
29. Zanaty, E. A. (2012). Determining the number of clusters for kernelized fuzzy C-means algorithms for automatic medical image segmentation. *Egyptian Informatics Journal*, *13*(1), 39–58, https://doi.org/10.1016/j.eij.2012.01.004.
30. khalifa, I., Youssif, A., & Youssry, H. (2012). MRI brain image segmentation based on wavelet and FCM algorithm. *International Journal of Computers and Applications*, *47*(16), 32–39, https://doi.org/10.5120/7275-0446.
31. Maji, P., & Pal, S. K., *Rough-Fuzzy Pattern Recognition: Applications in Bioinformatics and Medical Imaging*. Wiley-IEEE Computer Society Pr.
32. Bezdek, J. C. (1981). *Pattern Recognition with Fuzzy Objective Function Algorithms*. Springer US: Boston, MA. https://doi.org/10.1007/978-1-4757-0450-1.
33. Hooda, H., & Verma, O. P. (2022). Fuzzy clustering using gravitational search algorithm for brain image segmentation. *Multimedia Tools and Applications*, *81*(20), 29633–29652, https://doi.org/10.1007/s11042-022-12336-x.
34. Kaul, H. (2013). Fuzzy clustering using gravitational search algorithm master of technology in software engineering.
35. Ravi, A., Suvarna, A., D'Souza, A., Reddy, G. R. M., & Megha. (2012). A parallel fuzzy c means algorithm for brain tumor segmentation on multiple MRI images. In: *Proceedings of International Conference on Advances in Computing*.
36. Hoseini, F., & Shahbahrami, A. (2016). An efficient implementation of Fuzzy C-Means and watershed algorithms for MRI segmentation. In: *2016 8th International Symposium on Telecommunications (IST)*, IEEE, pp. 178–184. https://doi.org/10.1109/ISTEL.2016.7881806.
37. Hoseini, F., & Dekahi, G. M. (2019). High performance implementation of fuzzy C-means and watershed algorithms for MRI segmentation. [Online]. Available: www.jacr.iausari.ac.ir
38. Mencattini, A., Rabottino, G., Tamilia, E., Salmeri, M., & Lojacono, R. (2011). Features extraction and fuzzy logic based classification for false positives reduction in mammographic images. *Features Extraction and Fuzzy Logic Based Classification for False Positives Reduction in Mammographic Images*. [Online]. Available: https://www.researchgate.net/publication/221334072
39. Hosang, J., Benenson, R., & Schiele, B. Learning non-maximum suppression.
40. Zhang, X., Jiang, M., Zheng, Z., Tan, X., Ding, E., & Yang, Y. (2020). Understanding image retrieval re- ranking: A graph neural network perspective. [Online]. Available: http://arxiv.org/abs/2012.07620
41. Gao, X., Ram, S., & Rodrí Guez, J. J. Object sieving and morphological closing to reduce false detections in wide-area aerial imagery.
42. Rahim, S. S., Palade, V., Almakky, I., & Holzinger, A. (2020). Fuzzy image processing and deep learning for microaneurysms detection. In: *Artificial Intelligence and Machine Learning for Digital Pathology. Lecture Notes in Computer Science*. Springer, pp. 321–339. https://doi.org/10.1007/978-3-030-50402-1_19.

43. Mandal, D. (2019). Adaptive neuro-fuzzy inference system based grading of basmati rice grains using image processing technique. *Romanian Journal of Information Science and Technology*, *22*(3–4), https://doi.org/10.3390/asi1020019.
44. Meenu, M., Kurade, C., Neelapu, B. C., Kalra, S., Ramaswamy, H. S., & Yu, Y. (2021). A concise review on food quality assessment using digital image processing. *Trends in Food Science & Technology*, *118*, 106–124, https://doi.org/10.1016/j.tifs.2021.09.014.
45. Alghamdi, M. I. (2022). Neutrosophic set with adaptive neuro-fuzzy inference system for liver tumor segmentation and classification model. *International Journal of Neutrosophic Science*, *18*(2).
46. Kamthan, S., & Singh, H. (2023). Hierarchical fuzzy deep learning system for various classes of images. *Memories - Materials, Devices, Circuits and Systems*, *4*, 100023, https://doi.org/10.1016/j.memori.2022.100023.
47. Singh, H. et al. (2013). Real-life applications of fuzzy logic. *Advances in Fuzzy Systems*, *2013*, 1–3, https://doi.org/10.1155/2013/581879.
48. Hung, L., & Chung, H. (2006). Design of hierarchical fuzzy logic control for mobile robot system. In: *2006 IEEE Conference on Robotics, Automation and Mechatronics*, IEEE. pp. 1–6. https://doi.org/10.1109/RAMECH.2006.252616.
49. Wang, D., Zeng, X. - J., & Keane, J. A. (2006). A survey of hierarchical fuzzy systems (Invited Paper).
50. Kamthan, S., Singh, H., & Meitzler, T. (2022). Hierarchical fuzzy deep learning for image classification. *Memories - Materials, Devices, Circuits and Systems*, *2*, 100016, https://doi.org/10.1016/j.memori.2022.100016.
51. Castillo, O., Sanchez, M., Gonzalez, C., & Martinez, G. (2017). Review of recent type-2 fuzzy image processing applications. *Information*, *8*(3), 97, https://doi.org/10.3390/info 8030097.
52. Kamthan, S. (2021). *Hierarchical Intelligent Systems and Their Applications to Survivability*.
53. Kamthan, S., & Singh, H. (2020). Hierarchical fuzzy logic for multi-input multi-output systems. *IEEE Access*, *8*, 206966–206981, https://doi.org/10.1109/ACCESS.2020.3037901.
54. Mittal, K., Jain, A., Vaisla, K. S., Castillo, O., & Kacprzyk, J. (2020). A comprehensive review on type 2 fuzzy logic applications: Past, present and future. *Engineering Applications of Artificial Intelligence*, *95*, 103916, https://doi.org/10.1016/j.engappai.2020.103916.
55. Kalantari, R., Moqadam, R., Loghmani, N., Allahverdy, A., Shiran, M., & Zare-Sadeghi, A. (2022). Brain tumor segmentation using hierarchical combination of fuzzy logic and cellular automata. *Journal of Medical Signals and Sensors*, *12*(3), 263, https://doi.org/10.4103/jmss.jmss_128_21.

CHAPTER 15

Novel Distance–Similarity Measures for Intuitionistic Fuzzy Sets: A Comparative Analysis from Medical Diagnosis and Pattern Recognition Perspective

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ABSTRACT

The idea of intuitionistic fuzzy sets (IFS) represents a valuable expansion of the fuzzy set theory introduced by Atanassov, designed to effectively harness uncertainty. The concept of similarity and distance measure proves to be the best technique of dealing with modeling activities. While numerous measures are theoretically available, they lack precision and require enhancement to achieve improved results. In this chapter, we propose distance and its twin similarity measure based on IFS. Also, application like medical diagnosis and pattern recognition have been discussed and compared with existing measures. Different attributes are analyzed, and practical numerical cases are utilized to evaluate the measure's trustworthiness. Comparative analysis show case the utility of the novel distance-similarity measure. The outcomes illustrate that the suggested measure can be trusted, is adaptable, and handles situations with uncertainty more effectively.

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15.1 INTRODUCTION

Decision-making is the skill of selecting the most favorable course of action from a range of options, leading to success for either an individual or an organization. It is not a one-step process and requires careful understanding of the preferences which leads to the better functioning of the organization. In our everyday experiences, we encounter situations that demand effective decision-making. This skill finds application in diverse fields, such as healthcare diagnostics, identifying patterns, business management, and economics. Formulating a decision can often be a complex process, entangled in uncertainties and scenarios that do not neatly fit into binary "yes" or "no" resolutions. Zadeh [1] realizes this problem and extended Cantor's classical set theory to the theory of fuzzy sets. In this theory, Zadeh highlighted that the extent of belongingness does not always fall strictly into a "yes" or "no" category; rather, there exists considerable ambiguity or fuzziness in between these definitive states. To simplify and take in account the concerned problem, Zadeh formulated $\wp(\mathfrak{a}_i)$ where $\wp(\mathfrak{a}_i) \in [0, 1]$ and is known as degree of membership. It was realized later that the degree of nonmembership is not always equal to 1—degree of membership as sometimes vagueness is present. To overcome this problem Atanassov [2, 3] proposed intuitionistic fuzzy sets in which hesitancy is also included and can be stated as $\wp(\mathfrak{a}_i) + \mathfrak{H}(\mathfrak{a}_i) \leq 1$, where $\mathfrak{H}(\mathfrak{a}_i)$ is degree of nonmembership and also stated operations that are defined over IFS.

After its formulation it quickly seized the attention of many researchers who used IFS as a tool in various fields like medical diagnosis, pattern recognition, image segmentation, clustering, etc. De et al. [4] applied IFS to medical diagnosis, Li and Cheng [5] used IFS as a tool for pattern recognition, Xu [6] smeared it in multicriteria decision-making and Xu et al. [7] extended its application in cluster analysis. Some correlation measures have also been proposed with the help of IFS in diverse fields like Thao [8, 9] correlated it in pattern recognition and later in medical diagnosis. Ejegwa and Oyenke [10] applied it to various multi-criteria decision-making (MCDM) problems.

The concept of IFS was used extensively with distance and similarity measures as it serves as a means to be a reasonable source of information. Distance measures are used to find the distance between two fuzzy sets whereas similarity measures are used to find the closeness among them. Burillo and Bustince [11] coined the notion of distance with IFS. Szmidt and Kacprzk [12] extended the work further by using all three parameters constituting IFS for calculating distance. Wang and Xin [13] discussed a weighted distance measure and applied it to pattern recognition. The application in this field was also utilized by Park et al. [14], Hatzimichailidis et al. [15], Solanki et al. [16], etc. Davaz and Sadrabadi [17] suggested a distance measure and extended its application to diagnosis problems. Dutta and Goala [18] formulated advanced distance measures in medical diagnosis. Further, Goala and Bora [19] proposed multicriteria intuitionistic fuzzy sets in medical diagnosis. Garg and Kaur [20] discovered a novel distance measure with its applications in medical diagnosis and pattern recognition. Further, Mahanta and Panda [21] introduced a distance measure and studied its applications in medical diagnosis and pattern recognition. Dutta et al. [22] suggested distance and similarity measure and discussed its various applications. Ohlan [23] discussed novel distance measure for interval-valued IFS with applications in multicriteria group decision-making. Zeng et al. [24] suggested an exponential distance measure to study pattern recognition. Szmidt and Kacprzk [25] and Chen and Radyanto [26] proposed similarity measures based on IFS and extended its use in medicine. Ye [27] formulated some similarity measures based on cosine function and demonstrated its applications in mechanical design schemes. Luo and Liang [28] proposed a similarity measure for interval-valued IFS with its applications in pattern recognition. Further, Iqbal and Rizwan [29] suggested a similarity measure and discussed its significance in the field of medical diagnosis and pattern recognition. Kumari and Mishra [30] discussed multicriteria fuzzy techniques based on the principles of IFS and studied its applications in supplier selection. Adamu [31] applied IFS to make better decisions related to environmental management. Augustine [32] proposed distance- similarity measure with its roots extending to demonstrating its real-life use in medical diagnosis and pattern recognition. Gohain et al. suggested two new similarity measures with cross evaluation factor as its key feature. Thao and Chou [33] have proposed similarity measures and studied decision-making in evaluation of software quality. Gupta and Kumar [34] discussed IFS with applications in pattern recognition and clustering. Further, Kumar and Kumar [35] proposed an article on IFS discussing its possibility in pattern recognition. Patel et al. [36] suggested a similarity measure based on IFS and discussed its utility in face recognition and software quality assessment. Dutta et al. [37] formulated a measure based on IFS with its roots extended to decision-making in scenarios related to COVID-19. Bajaj et al. [38] proposed a correlation coefficient measure based on IFS to streamline decision-making problems. Patel et al. [39] discussed a measure based on IFS with applications in pattern recognition and medical diagnosis. Chakraborty et al. [40] recommended a similarity measure for making a universal decision-making problem of selecting a smartphone based on different criteria. Meanwhile, Panda et al. [41] proposed a measure for identifying bugs in software based on IFS.

15.1.1 RESEARCH GAP

At the forefront are various similarity and distance measures rooted in IFS, yet these methods confront inherent limitations demanding careful consideration and improvement. The measures proposed by Li et al. [5] and Ye [27] take into consideration only two parameters of IFS thus not utilizing its use fully. Further, trigonometric measures help in further enhancing the decision-making and overcoming the drawbacks. The cosine similarity measures in vector space have some drawbacks which lead to unreasonable results. The cotangent similarity measures help to overcome the drawbacks and show its decision-making capability in various fields.

This chapter introduces a cosine similarity measure, akin to the cotangent measure, demonstrating enhanced flexibility and efficiency in decision-making, establishing itself as a valuable tool in this context. The chapter also shows the applications of measures in pattern recognition and medical diagnosis, but not limited to this to demonstrate its use in decision-making process.

To fulfill the purpose, the chapter is structured as: Section 15.2 takes us through the fundamentals of the article. Section 15.3 is dedicated to distance–similarity measure. Section 15.4 shows the numerical illustrations of the measures and Section 15.5 studies its real-life applications. Section 15.6 compares it with work done by other authors to show the novelty of the measure. Section 15.7 concludes the chapter with references.

15.2 PRELIMINARIES

Before going through the new measures we need to revisit some of the existing definitions.

Definition 15.1. [1] Let $\mathbb{Q}$ be a fuzzy set in $\mathbb{A}$ then $\mathbb{Q} = \{\mathfrak{a}, \wp_{\mathbb{Q}}(\mathfrak{a}) \mid \mathfrak{a} \in \mathbb{A}\}$ where $\wp_{\mathbb{Q}}(\mathfrak{a})$: $\mathbb{A} \to [0, 1]$ Where $\wp_{\mathbb{Q}}(\mathfrak{a})$ is the degree of membership of $\mathbb{Q}$.

Definition 15.2. [2] Let $\mathbb{Q}$ be intuitionistic fuzzy set $\mathbb{Q}$ in $\mathbb{A}$ then $\mathbb{Q} = \{\mathfrak{a}, \wp_{\mathbb{Q}}(\mathfrak{a}), \mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}) \mid \mathfrak{a} \in \mathbb{A}\}$ where $\wp_{\mathbb{Q}}(\mathfrak{a})$: $\mathbb{A} \to [0, 1]$ and $\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a})$: $\mathbb{A} \to [0, 1]$.

Where $\wp(\mathfrak{a}_i)$ is the degree of membership and $\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a})$ is the degree of nonmembership such that $0 \geq \wp_{\mathbb{Q}}(\mathfrak{a}) + \mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}) \leq 1$.

Definition 15.3. [4] An IFS $\mathbb{Q}$ in universe of discourse $\mathbb{A}$ is defined as $\mathbb{Q} = \{\mathfrak{a}, \wp_{\mathbb{Q}}(\mathfrak{a}), \mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}) \mid \mathfrak{a} \in \mathbb{A}\}$ where $\wp_{\mathbb{Q}}(\mathfrak{a})$: $\mathbb{A} \rightarrow [0, 1]$ and $\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a})$: $\mathbb{A} \rightarrow [0, 1]$.

Where $\wp_{\mathbb{Q}}(\mathfrak{a})$ is the degree of membership and $\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a})$ is the degree of nonmembership such that $0 \leq \wp_{\mathbb{Q}}(\mathfrak{a}_i) + \mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}) \geq 1$ and $\omega_{\mathbb{Q}}(\mathfrak{a}) = 1 - \wp_{\mathbb{Q}}(\mathfrak{a}) - \mathfrak{H}_{\mathbb{Q}}(\mathfrak{a})$ where $\omega_{\mathbb{Q}}(\mathfrak{a})$ is called hesitancy.

Then, the relation between the two IFSs can be stated as follows.

1. $\mathbb{Q} \subseteq \mathbb{P}$ iff $\wp_{\mathbb{Q}}(\mathfrak{a}) \leq \wp_{\mathbb{P}}(\mathfrak{a})$ and $\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}) \geq \mathfrak{H}_{\mathbb{P}}(\mathfrak{a})$ for any $\mathfrak{a} \in \mathbb{A}$.
2. $\mathbb{Q} = \mathbb{P}$ iff $\wp_{\mathbb{Q}}(\mathfrak{a}) = \wp_{\mathbb{P}}(\mathfrak{a})$ and $\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}) = \mathfrak{H}_{\mathbb{P}}(\mathfrak{a})$ for any $\mathfrak{a} \in \mathbb{A}$.
3. $\overline{\mathbb{Q}} = \{<\mathfrak{a}, \mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}), \mathfrak{H}_{\mathbb{P}}(\mathfrak{a})>: \mathfrak{a} \in \mathbb{A}\}$
4. $\mathbb{Q} \cup \mathbb{P} = \{<\mathfrak{a}, \max(\wp_{\mathbb{Q}}(\mathfrak{a}), \wp_{\mathbb{P}}(\mathfrak{a})), \min(\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}), \mathfrak{H}_{\mathbb{P}}(\mathfrak{a}))>: \mathfrak{a} \in \mathbb{A}\}$.
5. $\mathbb{Q} \cap \mathbb{P} = \{<\mathfrak{a}, \min(\wp_{\mathbb{Q}}(\mathfrak{a}), \wp_{\mathbb{P}}(\mathfrak{a})), \max(\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}), \mathfrak{H}_{\mathbb{P}}(\mathfrak{a}))>: \mathfrak{a} \in \mathbb{A}\}$.

Definition 15.4. Let $\mathbb{Q}$ and $\mathbb{P}$ be two IFS in $\mathbb{A}$ then similarity measure $\dot{\underset{\cdot}{S}}(\mathbb{Q}, \mathbb{P})$ between them is defined as follows.

1. $0 \leq \dot{\underset{\cdot}{S}}(\mathbb{Q}, \mathbb{P}) \leq 1$.
2. $\dot{\underset{\cdot}{S}}(\mathbb{Q}, \mathbb{P}) = 1 \Leftrightarrow \mathbb{Q} = \mathbb{P}$.
3. $\dot{\underset{\cdot}{S}}(\mathbb{Q}, \mathbb{P}) = \dot{\underset{\cdot}{S}}(\mathbb{P}, \mathbb{Q})$.
4. $\dot{\underset{\cdot}{S}}(\mathbb{Q}, \mathbb{O}) \leq \dot{\underset{\cdot}{S}}(\mathbb{Q}, \mathbb{P}) + \dot{\underset{\cdot}{S}}(\mathbb{P}, \mathbb{O})$, where $\mathbb{O}$ is an IFS in $\mathbb{A}$.

Definition 15.5. Let $\mathbb{Q}$ and $\mathbb{P}$ be two IFS in $\mathbb{A}$ then distance measure $\dot{\mathrm{D}}(\mathbb{Q}, \mathbb{P})$ between them is defined as follows.

1. $0 \leq \dot{\mathrm{D}}(\mathbb{Q}, \mathbb{P}) \leq 1$.
2. $\dot{\mathrm{D}}(\mathbb{Q}, \mathbb{P}) = 0 \Leftrightarrow \mathbb{Q} = \mathbb{P}$.
3. $\dot{\mathrm{D}}(\mathbb{Q}, \mathbb{P}) = \dot{\mathrm{D}}(\mathbb{P}, \mathbb{Q})$.
4. $\dot{\mathrm{D}}(\mathbb{Q}, \mathbb{O}) \leq \dot{\mathrm{D}}(\mathbb{Q}, \mathbb{P}) + \dot{\mathrm{D}}(\mathbb{P}, \mathbb{Q})$, where $\mathbb{O}$ is an IFS in $\mathbb{A}$.

15.3 DISTANCE–SIMILARITY MEASURES BASED ON IFS

In this section, we will discuss some existing and new distance–similarity measures based on IFS.

15.3.1 EXISTING DISTANCE AND SIMILARITY MEASURE

Definition 15.6. [Hong and Kim 1999] Let $\mathbb{Q}$ and $\mathbb{P}$ be two IFS in $\mathbb{A}$ then similarity measure between them is defined as

$$\underset{\cdot}{S}1(\mathbb{Q},\mathbb{P}) = 1-\frac{1}{2n}\sum_{i-1}^{n}\left[\left|\wp_{\mathbb{Q}}(\mathfrak{a}_i)-\wp_{\mathbb{P}}(\mathfrak{a}_i)\right|+\left|\mathfrak{h}_{\mathbb{Q}}(\mathfrak{a}_i)-\mathfrak{h}_{\mathbb{P}}(\mathfrak{a}_i)\right|\right]$$

$$\dot{D}1(\mathbb{Q},\mathbb{P}) = \frac{1}{2n}\sum_{i=1}^{n}\left[\left|\wp_{\mathbb{Q}}(\mathfrak{a}_i)-\wp_{\mathbb{P}}(\mathfrak{a}_i)\right|+\left|\mathfrak{h}_{\mathbb{Q}}(\mathfrak{a}_i)-\mathfrak{h}_{\mathbb{P}}(\mathfrak{a}_i)\right|\right]$$

Definition 15.7. [Szmidt and Kacprzyk 2000] Let $\mathbb{Q}$ and $\mathbb{P}$ be two IFS in $\mathbb{A}$ then similarity measure between them is defined as

$$\underset{\cdot}{S}2(\mathbb{Q},\mathbb{P}) = 1-\frac{1}{2}\sum_{i=1}^{n}\left[\left|\wp_{\mathbb{Q}}(\mathfrak{a}_i)-\wp_{\mathbb{P}}(\mathfrak{a}_i)\right|+\left|\mathfrak{h}_{\mathbb{Q}}(\mathfrak{a}_i)-\mathfrak{h}_{\mathbb{P}}(\mathfrak{a}_i)\right|+\left|\omega_{\mathbb{Q}}(\mathfrak{a}_i)-\omega_{\mathbb{P}}(\mathfrak{a}_i)\right|\right]$$

$$\dot{D}2(\mathbb{Q},\mathbb{P}) = \frac{1}{2}\sum_{i=1}^{n}\left[\left|\wp_{\mathbb{Q}}(\mathfrak{a}_i)-\wp_{\mathbb{P}}(\mathfrak{a}_i)\right|+\left|\mathfrak{h}_{\mathbb{Q}}(\mathfrak{a}_i)-\mathfrak{h}_{\mathbb{P}}(\mathfrak{a}_i)\right|+\left|\omega_{\mathbb{Q}}(\mathfrak{a}_i)-\omega_{\mathbb{P}}(\mathfrak{a}_i)\right|\right]$$

$$\underset{\cdot}{S}3(\mathbb{Q},\mathbb{P}) = 1-\sqrt{\frac{1}{2}\sum_{i=1}^{n}\left[\left|\wp_{\mathbb{Q}}(\mathfrak{a}_i)-\wp_{\mathbb{P}}(\mathfrak{a}_i)\right|^2+\left|\mathfrak{h}_{\mathbb{Q}}(\mathfrak{a}_i)-\mathfrak{h}_{\mathbb{P}}(\mathfrak{a}_i)\right|^2+\left|\omega_{\mathbb{Q}}(\mathfrak{a}_i)-\omega_{\mathbb{P}}(\mathfrak{a}_i)\right|^2\right]}$$

$$\dot{D}3(\mathbb{Q},\mathbb{P}) = \sqrt{\frac{1}{2}\sum_{i=1}^{n}\left[\left|\wp_{\mathbb{Q}}(\mathfrak{a}_i)-\wp_{\mathbb{P}}(\mathfrak{a}_i)\right|^2+\left|\mathfrak{h}_{\mathbb{Q}}(\mathfrak{a}_i)-\mathfrak{h}_{\mathbb{P}}(\mathfrak{a}_i)\right|^2+\left|\omega_{\mathbb{Q}}(\mathfrak{a}_i)-\omega_{\mathbb{P}}(\mathfrak{a}_i)\right|^2\right]}$$

$$\underset{\cdot}{S}4(\mathbb{Q},\mathbb{P}) = 1-\frac{1}{2n}\sum_{i=1}^{n}\left[\left|\wp_{\mathbb{Q}}(\mathfrak{a}_i)-\wp_{\mathbb{P}}(\mathfrak{a}_i)\right|+\left|\mathfrak{h}_{\mathbb{Q}}(\mathfrak{a}_i)-\mathfrak{h}_{\mathbb{P}}(\mathfrak{a}_i)\right|+\left|\omega_{\mathbb{Q}}(\mathfrak{a}_i)-\omega_{\mathbb{P}}(\mathfrak{a}_i)\right|\right]$$

$$\dot{D}4(\mathbb{Q},\mathbb{P}) = \frac{1}{2n}\sum_{i=1}^{n}\left[\left|\wp_{\mathbb{Q}}(\mathfrak{a}_i)-\wp_{\mathbb{P}}(\mathfrak{a}_i)\right|+\left|\mathfrak{h}_{\mathbb{Q}}(\mathfrak{a}_i)-\mathfrak{h}_{\mathbb{P}}(\mathfrak{a}_i)\right|+\left|\omega_{\mathbb{Q}}(\mathfrak{a}_i)-\omega_{\mathbb{P}}(\mathfrak{a})\right|\right]$$

$$\underset{\cdot}{S}5(\mathbb{Q},\mathbb{P}) = 1-\sqrt{\frac{1}{2n}\sum_{i=1}^{n}\left[\left|\wp_{\mathbb{Q}}(\mathfrak{a}_i)-\wp_{\mathbb{P}}(\mathfrak{a}_i)\right|^2+\left|\mathfrak{h}_{\mathbb{Q}}(\mathfrak{a}_i)-\mathfrak{h}_{\mathbb{P}}(\mathfrak{a}_i)\right|^2+\left|\omega_{\mathbb{Q}}(\mathfrak{a}_i)-\omega_{\mathbb{P}}(\mathfrak{a}_i)\right|^2\right]}$$

$$\dot{D}5(\mathbb{Q},\mathbb{P}) = \sqrt{\frac{1}{2n}\sum_{i=1}^{n}\left[\left|\wp_{\mathbb{Q}}(\mathfrak{a}_i)-\wp_{\mathbb{P}}(\mathfrak{a}_i)\right|^2+\left|\mathfrak{h}_{\mathbb{Q}}(\mathfrak{a}_i)-\mathfrak{h}_{\mathbb{P}}(\mathfrak{a}_i)\right|^2+\left|\omega_{\mathbb{Q}}(\mathfrak{a}_i)-\omega_{\mathbb{P}}(\mathfrak{a}_i)\right|^2\right]}$$

Definition 15.8. [Li 2007] Let $\mathbb{Q}$ and $\mathbb{P}$ be two IFS in $\mathbb{A}$ then similarity measure between them is defined as

$$\underset{\cdot}{S}6(\mathbb{Q},\mathbb{P}) = 1-\sqrt{\frac{1}{2n}\sum_{i=1}^{n}\left[\left|\wp_{\mathbb{Q}}(\mathfrak{a}_i)-\wp_{\mathbb{P}}(\mathfrak{a}_i)\right|^2+\left|\mathfrak{h}_{\mathbb{Q}}(\mathfrak{a}_i)-\mathfrak{h}_{\mathbb{P}}(\mathfrak{a}_i)\right|^2\right]}$$

$$\dot{D}6(\mathbb{Q},\mathbb{P}) = \sqrt{\frac{1}{2n}\sum_{i=1}^{n}\left[\left|\wp_{\mathbb{Q}}(\mathfrak{a}_i)-\wp_{\mathbb{P}}(\mathfrak{a}_i)\right|^2+\left|\mathfrak{h}_{\mathbb{Q}}(\mathfrak{a}_i)-\mathfrak{h}_{\mathbb{P}}(\mathfrak{a}_i)\right|^2\right]}$$

Definition 15.9. [Sharma and Tripathi 2020] Suppose $\mathbb{A}$ be the universal set then sine distance measure and cosine similarity measure between two IFS $\mathbb{Q}$ and $\mathbb{P}$ can be defined as

$$\dot{D}7(\mathbb{Q},\mathbb{P})=\frac{1}{2n}\sum_{i=1}^{n}\left(\sin\left(\frac{\left|\wp_{\mathbb{Q}}(\mathfrak{a}_i)-\wp_{\mathbb{P}}(\mathfrak{a}_i)\right|}{2}\right)\pi+\sin\left(\frac{\left|\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}_i)-\mathfrak{H}_{\mathbb{P}}(\mathfrak{a}_i)\right|}{2}\right)\pi\right)$$

$$\dot{D}8\,(\mathbb{Q},\mathbb{P})=\frac{1}{2n}\sum_{i=1}^{n}\left(\sin\left(\frac{\left|\sqrt{\wp_{\mathbb{Q}}(\mathfrak{a}_i)}-\sqrt{\wp_{\mathbb{P}}(\mathfrak{a}_i)}\right|}{2}\right)\pi+\sin\left(\frac{\left|\sqrt{\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}_i)}-\sqrt{\mathfrak{H}_{\mathbb{P}}(\mathfrak{a}_i)}\right|}{2}\right)\pi\right)$$

$$\underset{\cdot}{S}7(\mathbb{Q},\mathbb{P})=\frac{1}{2n}\sum_{i=1}^{n}\left(\cos\left(\frac{\left|\wp_{\mathbb{Q}}(\mathfrak{a}_i)-\wp_{\mathbb{P}}(\mathfrak{a}_i)\right|}{2}\right)\pi+\cos\left(\frac{\left|\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}_i)-\mathfrak{H}_{\mathbb{P}}(\mathfrak{a}_i)\right|}{2}\right)\pi\right)$$

$$\underset{\cdot}{S}8(\mathbb{Q},\mathbb{P})=\frac{1}{2n}\sum_{i=1}^{n}\left(\cos\left(\frac{\left|\sqrt{\wp_{\mathbb{Q}}(\mathfrak{a}_i)}-\sqrt{\wp_{\mathbb{P}}(\mathfrak{a}_i)}\right|}{2}\right)\pi+\cos\left(\frac{\left|\sqrt{\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}_i)}-\sqrt{\mathfrak{H}_{\mathbb{P}}(\mathfrak{a}_i)}\right|}{2}\right)\pi\right)$$

Definition 15.10. [Ejegwa 2022] Suppose $\mathbb{Q}$ and $\mathbb{P}$ be two IFS in the universe of discourse $\mathbb{A}$ then the distance similarity measure between them can be defined as

$$\underset{\cdot}{S}9(\mathbb{Q},\mathbb{P})=\frac{1}{n}\sum_{i-=1}^{n}\sqrt{\wp_{\mathbb{Q}}(\mathfrak{a}_i)\wp_{\mathbb{P}}(\mathfrak{a}_i)}+\sqrt{\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}_i)\,\mathfrak{H}_{\mathbb{P}}(\mathfrak{a}_i)}+\sqrt{\omega_{\mathbb{Q}}(\mathfrak{a}_i)\omega_{\mathbb{P}}(\mathfrak{a}_i)}$$

$$\dot{D}9\,(\mathbb{Q},\mathbb{P})=1-\frac{1}{n}\sum_{i=1}^{n}\sqrt{\wp_{\mathbb{Q}}(\mathfrak{a}_i)\wp_{\mathbb{P}}(\mathfrak{a}_i)}+\sqrt{\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}_i)\,\mathfrak{H}_{\mathbb{P}}(\mathfrak{a}_i)}+\sqrt{\omega_{\mathbb{Q}}(\mathfrak{a}_i)\omega_{\mathbb{P}}(\mathfrak{a}_i)}$$

15.3.2 PROPOSED DISTANCE–SIMILARITY MEASURE

In the following section, the proposed distance measures are discussed. As similarity measure is a twin concept of distance measure, we shall discuss both in this section.

Let $\mathbb{Q}$ and $\mathbb{P}$ be two IFS in the universe of discourse $\mathbb{A}$ then the distance similarity measure between them can be defined as follows:

$$\dot{D}10\,(\mathbb{Q},\mathbb{P})=1-\frac{1}{n}\sum_{i=1}^{n}\left[\sin\frac{\pi}{2}\left(\sqrt{\wp_{\mathbb{Q}}(\mathfrak{a}_i)\wp_{\mathbb{P}}(\mathfrak{a}_i)}+\sqrt{\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}_i)\,\mathfrak{H}_{\mathbb{P}}(\mathfrak{a}_i)}+\sqrt{\omega_{\mathbb{Q}}(\mathfrak{a}_i)\omega_{\mathbb{P}}(\mathfrak{a}_i)}\right)\right]$$

$$\underset{\cdot}{S}10(\mathbb{Q},\mathbb{P})=\frac{1}{n}\sum_{i=1}^{n}\left[\sin\frac{\pi}{2}\left(\sqrt{\wp_{\mathbb{Q}}(\mathfrak{a}_i)\wp_{\mathbb{P}}(\mathfrak{a}_i)}+\sqrt{\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}_i)\,\mathfrak{H}_{\mathbb{P}}(\mathfrak{a}_i)}+\sqrt{\omega_{\mathbb{Q}}(\mathfrak{a}_i)\omega_{\mathbb{P}}(\mathfrak{a}_i)}\right)\right]$$

$$\dot{D}11\,(\mathbb{Q},\mathbb{P}) = 1 - \frac{1}{n}\sum_{i=1}^{n} w_i \left[\sin\frac{\pi}{2}\left(\sqrt{\wp_{\mathbb{Q}}(\mathfrak{a}_i)\wp_{\mathbb{P}}(\mathfrak{a}_i)} + \sqrt{\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}_i)\,\mathfrak{H}_{\mathbb{P}}(\mathfrak{a}_i)} + \sqrt{\omega_{\mathbb{Q}}(\mathfrak{a}_i)\omega_{\mathbb{P}}(\mathfrak{a}_i)}\right)\right]$$

$$\dot{S}11(\mathbb{Q},\mathbb{P}) = \frac{1}{n}\sum_{i=1}^{n} w_i \left[\sin\frac{\pi}{2}\left(\sqrt{\wp_{\mathbb{Q}}(\mathfrak{a}_i)\wp_{\mathbb{P}}(\mathfrak{a}_i)} + \sqrt{\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}_i)\,\mathfrak{H}_{\mathbb{P}}(\mathfrak{a}_i)} + \sqrt{\omega_{\mathbb{Q}}(\mathfrak{a}_i)\omega_{\mathbb{P}}(\mathfrak{a}_i)}\right)\right]$$

15.4 NUMERICAL ILLUSTRATION

In this section, we offer numerical validation for the suggested measure. To test the validity of the proposed measure we shall carry out calculations for the proposed distance measure with the help of an example.

Let $\mathbb{Q}$, $\mathbb{P}$ and $\mathbb{O}$ be three IFS in $\mathbb{A} = \{\mathfrak{a}_1, \mathfrak{a}_2, \ldots, \mathfrak{a}_{n-1}, \mathfrak{a}_n\}$ then

$\mathbb{Q} = \{\langle\mathfrak{a}_1, 0.6,0.2\rangle, \langle\mathfrak{a}_2, 0.4,0.6\rangle, \langle\mathfrak{a}_3, 0.5,0.3\rangle\}$,

$\mathbb{P} = \{\langle\mathfrak{a}_1, 0.8,0.1\rangle, \langle\mathfrak{a}_2, 0.7,0.3\rangle, \langle\mathfrak{a}_3, 0.6,0.1\rangle\}$

$\mathbb{O} = \{\langle\mathfrak{a}_1, 0.9,0.1\rangle, \langle\mathfrak{a}_2, 0.8,0.2\rangle, \langle\mathfrak{a}_3, 0.7,0.3\rangle\}$.

$$\dot{D}11\,(\mathbb{Q},\mathbb{P}) = 1 - \frac{1}{n}\sum_{i=1}^{n} \left[\sin\frac{\pi}{2}\left(\sqrt{\wp_{\mathbb{Q}}(\mathfrak{a}_i)\wp_{\mathbb{P}}(\mathfrak{a}_i)} + \sqrt{\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}_i)\,\mathfrak{H}_{\mathbb{P}}(\mathfrak{a}_i)} + \sqrt{\omega_{\mathbb{Q}}(\mathfrak{a}_i)\omega_{\mathbb{P}}(\mathfrak{a}_i)}\right)\right]$$

$$= \frac{1}{3}\left[\sin\frac{\pi}{2}\left|\left(\left[\left(\sqrt{0.6\times 0.8} + \sqrt{0.2\times 0.1} + \sqrt{0.2\times 0.1}\right) + \left(\sqrt{0.4\times 0.7} + \sqrt{0.6\times 0.3} + \sqrt{0\times 0}\right)\right]\right.\right.\right.$$

$$\left.\left.\left. + \left(\sqrt{0.5\times 0.6} + \left|\sqrt{0.3\times 0.1}\right| + \sqrt{0.2\times 0.3}\right)\right)\right|\right]$$

$= 0.001614$

$$\dot{D}10\,(\mathbb{P},\mathbb{O}) = 1 - \frac{1}{n}\sum_{i=1}^{n} \left[\sin\frac{\pi}{2}\left(\sqrt{\wp_{\mathbb{P}}(\mathfrak{a}_i)\wp_{\mathbb{O}}(\mathfrak{a}_i)} + \sqrt{\mathfrak{H}_{\mathbb{P}}(\mathfrak{a}_i)\,\mathfrak{H}_{\mathbb{O}}(\mathfrak{a}_i)} + \sqrt{\omega_{\mathbb{P}}(\mathfrak{a}_i)\omega_{\mathbb{O}}(\mathfrak{a}_i)}\right)\right]$$

$$= \frac{1}{3}\left[\sin\frac{\pi}{2}\left|\left(\left[\left(\sqrt{0.8\times 0.9} + \sqrt{0.1\times 0.1} + \sqrt{0.1\times 0}\right) + \left(\sqrt{0.7\times 0.8} + \sqrt{0.3\times 0.2} + \sqrt{0\times 0}\right)\right]\right.\right.\right.$$

$$\left.\left.\left. + \left(\sqrt{0.6\times 0.7} + \left|\sqrt{0.1\times 0.3}\right| + \sqrt{0.3\times 0}\right)\right)\right|\right]$$

$= 0.014157$

$$\dot{D}10\,(\mathbb{Q},\mathbb{O}) = 1 - \frac{1}{n}\sum_{i=1}^{n} \left[\sin\frac{\pi}{2}\left(\sqrt{\wp_{\mathbb{Q}}(\mathfrak{a}_i)\wp_{\mathbb{O}}(\mathfrak{a}_i)} + \sqrt{\mathfrak{H}_{\mathbb{Q}}(\mathfrak{a}_i)\,\mathfrak{H}_{\mathbb{O}}(\mathfrak{a}_i)} + \sqrt{\omega_{\mathbb{Q}}(\mathfrak{a}_i)\omega_{\mathbb{O}}(\mathfrak{a}_i)}\right)\right]$$

$$= \frac{1}{3}\left[\sin\frac{\pi}{2}\left|\left(\left[\left(\sqrt{0.8\times 0.9} + \sqrt{0.1\times 0.1} + \sqrt{0.1\times 0}\right) + \left(\sqrt{0.7\times 0.8} + \sqrt{0.3\times 0.2} + \sqrt{0\times 0}\right)\right]\right.\right.\right.$$

$$\left.\left.\left. + \left(\sqrt{0.6\times 0.7} + \left|\sqrt{0.1\times 0.3}\right| + \sqrt{0.3\times 0}\right)\right)\right|\right]$$

$= 0.014268,$

Similarly, we can prove for $\dot{D}11(\mathbb{Q}, \mathbb{O})$, $\dot{S}10(\mathbb{Q}, \mathbb{P})$, $\dot{S}11(\mathbb{Q}, \mathbb{P})$.

Numerical Rationale: From the above computations, it can be concluded as follows.

1. $0 \leq \dot{D}^{i}(\mathbb{Q}, \mathbb{P}) \leq 1$.
2. $\dot{D}^{i}(\mathbb{Q}, \mathbb{P}) = 0 \Leftrightarrow \mathbb{Q} = \mathbb{P}$.
3. $\dot{D}^{i}(\mathbb{Q}, \mathbb{P}) = \dot{D}^{i}(\mathbb{P}, \mathbb{Q})$
4. $\dot{D}^{i}(\mathbb{Q}, \mathbb{O}) \leq \dot{D}^{i}(\mathbb{Q}, \mathbb{P}) + \dot{D}^{i}(\mathbb{P}, \mathbb{O})$.

Table 15.1 shows the value of proposed distance measure and weighted distance measure.

TABLE 15.1 Proposed Distance Measure for $\mathbb{Q}$, $\mathbb{P}$, and $\mathbb{O}$ ⏎

Distance Measure	$\dot{D}10(\mathbb{Q}, \mathbb{P})$	$\dot{D}10(\mathbb{P}, \mathbb{O})$	$\dot{D}10(\mathbb{Q}, \mathbb{O})$
$\dot{D}10(\mathbb{Q}, \mathbb{P})$	0.001614	0.014157	0.014268
$\dot{D}10(\mathbb{Q}, \mathbb{P})$	0.667305	0.670701	0.670644

15.5 APPLICATIONS

Here, we have presented the applications related to the proposed distance measure to show the reliability of the proposed measure.

15.5.1 PATTERN RECOGNITION

Suppose there are three patterns $\mathbb{Q}$, $\mathbb{P}$, and $\mathbb{O}$ and we wish to determine which among the following is closest to $\mathbb{Y}$ where

$$\mathbb{Q} = \left\{\left\langle\frac{1,0}{a_1}\right\rangle, \left\langle\frac{0.8,0}{a_2}\right\rangle, \left\langle\frac{0.7,0.1}{a_3}\right\rangle\right\}, \mathbb{P} = \left\{\left\langle\frac{0.8,0.1}{a_1}\right\rangle, \left\langle\frac{1,0}{a_2}\right\rangle, \left\langle\frac{0.9,0.1}{a_3}\right\rangle\right\},$$

$$\mathbb{O} = \left\{\left\langle\frac{0.6,0.2}{a_1}\right\rangle, \left\langle\frac{0.8,0}{a_2}\right\rangle, \left\langle\frac{1,0}{a_3}\right\rangle\right\}.$$

and let $\mathbb{Y} = \left\{\left\langle\frac{0.5,0.3}{a_1}\right\rangle, \left\langle\frac{0.6,0.2}{a_2}\right\rangle, \left\langle\frac{0.8,0.1}{a_3}\right\rangle\right\}$

Let the weights w_i are 0.5, 0.3, and 0.2, respectively.

Table 15.2 indicates that P exhibits the closest proximity to Y, as it showcases the least distance, suggesting that Y is the acknowledged and nearest pattern.

TABLE 15.2 Distance Measure Between ℚ, ℙ, and 𝕆 ⏎

Distance Measure	$\dot{D}^i(\mathbb{Q}, \mathbb{Y})$	$\dot{D}^i(\mathbb{P}, \mathbb{Y})$	$\dot{D}^i(\mathbb{Q}, \mathbb{Y})$
$\dot{D}10(\mathbb{Q}, \mathbb{P})$	0.07	**0.02**	0.04
$\dot{D}11(\mathbb{Q}, \mathbb{P})$	0.08	**0.02**	0.03

15.5.2 MEDICAL DIAGNOSIS

Suppose a patient has been examined by a medical consultant on the basis of five symptoms like body temperature (α_1), tiredness (α_2), stomach issues (α_3), headache (α_4), and chest pain (α_5) and set of diagnosis $\mathbb{O}$ = {Viral Fever, Typhoid, Stomach problems, Malaria, and chest problem}. Using the feedback provided by patients, we aim to identify the disease that most closely aligns with their symptoms or conditions

$$\mathbb{Q}_1 = \left\{ \left\langle \frac{0.4, 0}{a_1} \right\rangle, \left\langle \frac{0.3, 0.5}{a_2} \right\rangle, \left\langle \frac{0.1, 0.7}{a_3} \right\rangle, \left\langle \frac{0.4, 0.3}{a_4} \right\rangle, \left\langle \frac{0.1, 0.7}{a_5} \right\rangle \right\}$$

$$\mathbb{Q}_2 = \left\{ \left\langle \frac{0.7, 0}{a_1} \right\rangle, \left\langle \frac{0.2, 0.6}{a_2} \right\rangle, \left\langle \frac{0.0, 0.9}{a_3} \right\rangle, \left\langle \frac{0.7, 0}{a_4} \right\rangle, \left\langle \frac{0.1, 0.8}{a_5} \right\rangle \right\}$$

$$\mathbb{Q}_3 = \left\{ \left\langle \frac{0.3, 0.3}{a_1} \right\rangle, \left\langle \frac{0.6, 0.1}{a_2} \right\rangle, \left\langle \frac{0.2, 0.7}{a_3} \right\rangle, \left\langle \frac{0.2, 0.6}{a_4} \right\rangle, \left\langle \frac{0.1, 0.9}{a_5} \right\rangle \right\}$$

$$\mathbb{Q}_4 = \left\{ \left\langle \frac{0.1, 0.7}{a_1} \right\rangle, \left\langle \frac{0.2, 0.4}{a_2} \right\rangle, \left\langle \frac{0.8, 0}{a_3} \right\rangle, \left\langle \frac{0.2, 0.7}{a_4} \right\rangle, \left\langle \frac{0.2, 0.7}{a_5} \right\rangle \right\}$$

$$\mathbb{Q}_5 = \left\{ \left\langle \frac{0.1, 0.8}{a_1} \right\rangle, \left\langle \frac{0, 0.8}{a_2} \right\rangle, \left\langle \frac{0.2, 0.8}{a_3} \right\rangle, \left\langle \frac{0.2, 0.8}{a_4} \right\rangle, \left\langle \frac{0.8, 0.1}{a_5} \right\rangle \right\}$$

and let $\mathbb{O} = \left\{ \left\langle \frac{0.8, 0.1}{a_1} \right\rangle, \left\langle \frac{0.6, 0.1}{a_2} \right\rangle, \left\langle \frac{0.2, 0.8}{a_3} \right\rangle, \left\langle \frac{0.6, 0.1}{a_4} \right\rangle, \left\langle \frac{0.1, 0.6}{a_5} \right\rangle \right\}$.

Let the weights w_i are 0.15, 0.2, 0.1, 0.25, and 0.3, respectively.

Table 15.3 gives that $\mathbb{O}$ is closest to $\mathbb{Q}_1$ as it has the least distance, which implies person is likely to be suffering from viral fever.

TABLE 15.3 Distance Measure Between Medical Diagnosis and Patient ⏎

Distance Measure	$\dot{D}^i(\mathbb{O}, \mathbb{Q}_1)$	$\dot{D}^i(\mathbb{O}, \mathbb{Q}_2)$	$\dot{D}^i(\mathbb{O}, \mathbb{Q}_3)$	$\dot{D}^i(\mathbb{O}, \mathbb{Q}_4)$	$\dot{D}^i(\mathbb{O}, \mathbb{Q}_5)$
$\dot{D}10(\mathbb{Q}, \mathbb{P})$	0.01	0.01	0.01	0.12	0.13
$\dot{D}11(\mathbb{Q}, \mathbb{P})$	0.01	0.01	0.02	0.07	0.14

15.6 COMPARATIVE ANALYSIS

Comparative analysis serves as a valuable tool by allowing for the examination and assessment of similarities, differences, patterns, and relationships between different variables, subjects, or phenomena. In this article, our objective is to assess the dependability of the proposed measure by applying it to real-world scenarios such as pattern recognition and medical diagnosis.

Comparison between proposed distance measures by some renowned researchers has been done and the result obtained from them is unified for pattern recognition and medical diagnosis. Tables 15.4 and 15.5 show the result obtained for pattern recognition and medical diagnosis, respectively, for all the distance measure listed in this article.

TABLE 15.4 Comparative Analysis of Distance Measure Between $\mathbb{Q}$,$\mathbb{P}$, $\mathbb{O}$ with $\mathbb{G}$ for Pattern Recognition ⏎

Distance Measure	$\dot{D}^i(\mathbb{Q}, \mathbb{G})$	$\dot{D}^i(\mathbb{P}, \mathbb{G})$	$\dot{D}^i(\mathbb{O}, \mathbb{G})$
$\dot{D}1(\mathbb{Q}, \mathbb{P})$	0.37	0.35	0.15
$\dot{D}2(\mathbb{Q}, \mathbb{P})$	1	1	1
$\dot{D}3(\mathbb{Q}, \mathbb{P})$	0.56	0.56	0.25
$\dot{D}4(\mathbb{Q}, \mathbb{P})$	0.5	0.5	0.22
$\dot{D}5(\mathbb{Q}, \mathbb{P})$	0.40	0.40	0.18
$\dot{D}6(\mathbb{Q}, \mathbb{P})$	0.37	0.35	0.15
$\dot{D}7(\mathbb{Q}, \mathbb{P})$	0.55	0.52	0.23
$\dot{D}8(\mathbb{Q}, \mathbb{P})$	0.39	1.07	0.53
$\dot{D}9(\mathbb{Q}, \mathbb{P})$	0.20	0.10	0.14
$\dot{D}10(\mathbb{Q}, \mathbb{P})$	0.07	**0.02**	0.04
$\dot{D}11(\mathbb{Q}, \mathbb{P})$	0.08	**0.02**	0.03

Figure 15.1 shows the graphical representation of the result obtained for comparative analysis for pattern recognition.

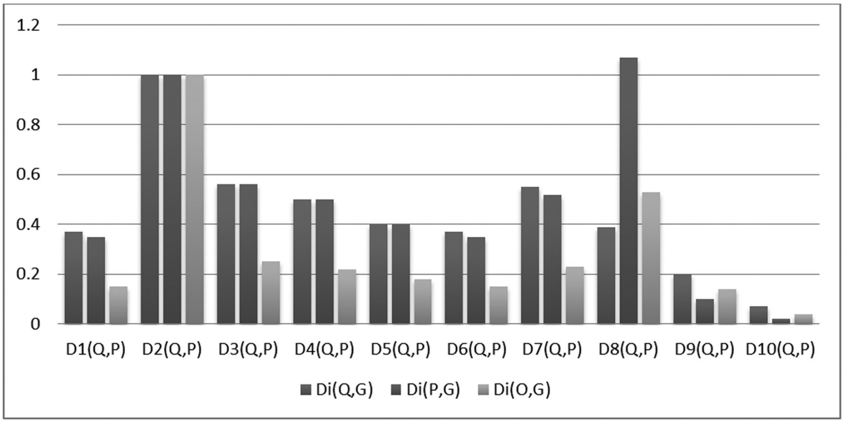

FIGURE 15.1 Comparative analysis of distance measure for pattern recognition. ⏎

TABLE 15.5 Comparative Analysis of Distance Measure Between Patient and Symptoms ⏎

Distance Measure	$\dot{\mathbf{D}}^i(\mathbb{O}, \mathbb{Q}_1)$	$\dot{\mathbf{D}}^i(\mathbb{O}, \mathbb{Q}_2)$	$\dot{\mathbf{D}}^i(\mathbb{O}, \mathbb{Q}_3)$	$\dot{\mathbf{D}}^i(\mathbb{O}, \mathbb{Q}_4)$	$\dot{\mathbf{D}}^i(\mathbb{O}, \mathbb{Q}_5)$
$\dot{D}1(\mathbb{Q}, \mathbb{P})$	0.19	0.18	0.20	0.46	0.50
$\dot{D}2(\mathbb{Q}, \mathbb{P})$	1.4	1.2	1.4	2.7	2.8
$\dot{D}3(\mathbb{Q}, \mathbb{P})$	0.64	0.56	0.70	1.17	1.29
$\dot{D}4(\mathbb{Q}, \mathbb{P})$	0.18	0.16	0.18	0.36	0.37
$\dot{D}5(\mathbb{Q}, \mathbb{P})$	0.23	0.20	0.25	0.43	0.40
$\dot{D}6(\mathbb{Q}, \mathbb{P})$	0.23	0.23	0.28	0.51	0.56
$\dot{D}7(\mathbb{Q}, \mathbb{P})$	0.28	0.26	0.29	0.62	0.65
$\dot{D}8(\mathbb{Q}, \mathbb{P})$	0.27	0.32	0.23	0.56	0.60
$\dot{D}9(\mathbb{Q}, \mathbb{P})$	0.30	0.30	0.29	0.24	0.23
$\dot{D}10(\mathbb{Q}, \mathbb{P})$	**0.01**	0.01	0.01	0.12	0.13
$\dot{D}11(\mathbb{Q}, \mathbb{P})$	**0.01**	0.01	0.02	0.07	0.14

Figure 15.2 shows the graphical representation of the result obtained for comparative analysis for medical diagnosis.

Comparative analysis for pattern recognition and medical diagnosis shows that the proposed distance measure is the best measure among the existing measures and give more accurate results. The measure due to its reliability and flexibility can be used in different MCDM situations to solve complex problems. Its reliability and adaptability make it a versatile tool applicable across various scenarios in multiple-criteria decision-making, as evidenced in both pattern classification and medical diagnosis.

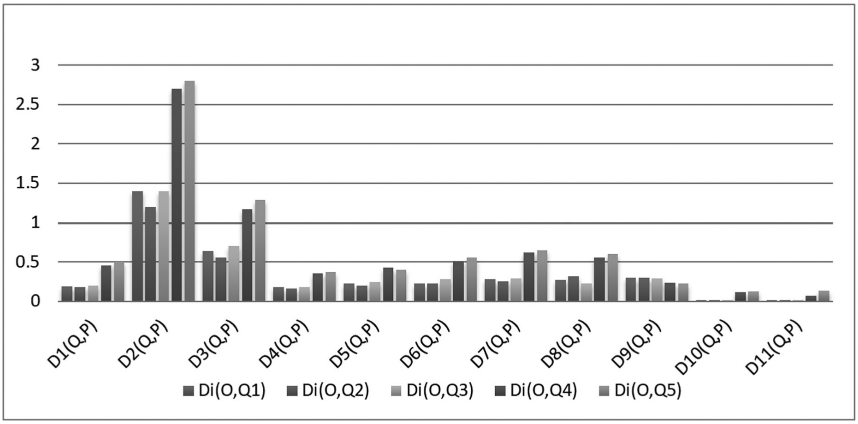

FIGURE 15.2 Comparative analysis of distance measure for medical diagnosis. ⏎

15.7 SENSITIVITY ANALYSIS

Initially, decision-makers were granted equal importance in ranking the options. Yet, there might arise instances where the preferences attributed to the opinions of decision-makers do not align. These kinds of situations have been taken into consideration in this section.

We have taken six cases where priority has been given to each decision-maker in first three cases and also in next three cases where equal priority has been given to two decision-maker at a time.

Case I: If $w_1 = 0.45$, $w_2 = 0.35$, $w_3 = 0.20$, case II: If $w_1 = 0.10$, $w_2 = 0.55$, $w_3 = 0.35$, case III: If $w_1 = 0.33$, $w_2 = 0.27$, $w_3 = 0.40$, case IV: If $w_1 = 0.40$, $w_2 = 0.40$, $w_3 = 0.20$, case V: If $w_1 = 0.30$, $w_2 = 0.35$, $w_3 = 0.35$, and case VI: If $w_1 = 0.30$, $w_2 = 0.40$, $w_3 = 0.30$.

The result of above six cases is tabulated in Table 15.6.

15.8 CONCLUSION

Distance measures serve as instrumental tools for analyzing numerous real-life decision-making scenarios. This chapter explores both distance measures and their corresponding similarity measures. The purpose of the measure is to provide a reliable and flexible tool for decision-making. The measure is applied in situations related to pattern recognition and medical diagnosis in this article but it can be combined with other decision-making situations as well. The measure can be applied on MCDM problems to study other aspects of decision-making as well. Numerical calculations are shown to prove capability of the measure. Comparison with renowned authors has been to show the novelty of the measure. Sensitivity analysis done demonstrates the effectiveness of the measure even if priorities of decision-makers are changed. The limitation of the study was restriction because of inadequacy in deliberating assessment from individual decision-maker during decision result. From the results shown, we can conclude that anticipated distance–similarity measures are good to manage the real-life problem. We look forward for extensions and generalizations of the proposed measures and their applications in MCDM problems.

TABLE 15.6 Sensitivity Analysis Using Six Different Weight Criteria ⏎

Distance Measure	$\dot{D}11(\mathbb{Q}, \mathbb{P})$	$\dot{D}11(\mathbb{Q}, \mathbb{P})$	$\dot{D}11(\mathbb{Q}, \mathbb{P})$
Case I	0.70	0.30	0.81
Case II	0.78	0.30	0.80
Case III	0.73	0.30	0.75
Case IV	0.72	0.30	0.82
Case V	0.74	0.30	0.78
Case VI	0.74	0.30	0.79

KEYWORDS

- **decision-making**
- **distance measures**
- **intuitionistic fuzzy sets**
- **medical diagnosis**
- **pattern recognition**
- **similarity measures**

REFERENCES

1. Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*, 338–356.

2. Atanassov, K. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, *20*, 87–96.
3. Atanassov, K. (1989). More on intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, *33*, 37–46.
4. De, S. K., Biswas, R., & Roy, A. R. (2001). An application of intuitionistic fuzzy sets in medical diagnosis. *Fuzzy Sets and Systems*, *117*(2), 209–213.
5. Li, D., & Cheng, C. (2002). New similarity measures of intuitionistic fuzzy sets and application to pattern recognition. *Pattern Recognition Letters, 23*, 221–225.
6. Xu, Z. (2007). Multi-person multi-attribute decision making models under intuitionistic fuzzy environment. *Fuzzy Optim Decis Making*, *6*, 221–236, https://doi.org/10.1007/s10700-007-9009-7.
7. Xu, Z., Chen, J., & Wu, J. (2008). Clustering algorithm for intuitionistic fuzzy sets. *Information Sciences*, *178*(19), 3775–3790.
8. Thao, N. X. (2018). A new correlation coefficient of the intuitionistic fuzzy sets and its application. *Journal of Intelligent and Fuzzy Systems*, *35*(2), 1959–1968.
9. Thao, N. X., Ali, M., & Smarandache, F. (2019). An intuitionistic fuzzy clustering algorithm based on a new correlation coefficient with application in medical diagnosis. *Journal of Intelligent &Fuzzy Systems*, *36*(1), 189–198. https://doi.org/10.3233/jifs-181084.
10. Ejegwa, P., & Onyeke, I. (2020). Intuitionistic fuzzy statistical correlation algorithm with applications to multi-criteria based decision-making processes. *International Journal of Intelligent Systems*. *36*(10). https://doi.org/10.1002/int.22347.
11. Burillo, P., & Bustince, H. (1996). Entropy on intuitionistic fuzzy sets and on interval-valued fuzzy sets. *Fuzzy Sets and Systems, 78*(3), 305–316. https://doi.org/10.1016/0165-0114(96)84611-2.
12. Szmidt, E., & Kacprzyk, J. (2006). Distances between intuitionistic fuzzy sets: Straightforward approaches may not work. In: *3rd International IEEE Conference Intelligent Systems*, pp. 716–721, https://doi.org/10.1109/IS.2006.348507.
13. Wang, W., & Xin, X. (2005). Distance measure between intuitionistic fuzzy sets. *Pattern Recognition Letters*, *26*, 2063–2069. https://doi.org/10.1016/j.patrec.2005.03.018.
14. Park, J. H., Lim, K. M., & Kwun, Y. C. (2009). Distance measure between intuitionistic fuzzy sets and its application to pattern recognition. *Journal of Korean Institute of Intelligent Systems, 19*(4). https://doi.org/10.5391/jkiis.2009.19.4.556.
15. Hatzimichailidis, A., Papakostas, G., & Kaburlasos, V. (2012). A novel distance measure of intuitionistic fuzzy sets and its application to pattern recognition problems. *International Journal of Intelligent Systems*, *27*(4), 396–409. https://doi.org/10.1002/int.21529
16. Solanki, R; Rahman, M.M; Kaushal, M., Lohani, M. Q., & Muhuri, P. (2018). A novel distance measure over intuitionistic fuzzy sets with its applications in pattern recognition. In: *IEEE Symposium Series on Computational Intelligence (SSCI)*, pp. 1466–1471, https://doi.org/10.1109/SSCI.2018.8628798.
17. Davvaz, B., & Sadrabadi, E. (2015). An application of intuitionistic fuzzy sets in medicine. *International Journal of Biomathematics*. *9*(3), 150813193917005. https://doi.org/10.1142/S1793524516500376.
18. Dutta, P., & Goala, S. (2018). Fuzzy decision making in medical diagnosis using an advanced distance measure on intuitionistic fuzzy sets. *The Open Cybernetics & Systemics Journal*, *12*, 136–149. https://doi.org/10.2174/1874110X01812010136.
19. Goala, S., & Bora, S. L. (2020). Intuitionistic fuzzy multicriteria decision making in medical diagnosis via novel distance measure. *International Journal of Scientific & Technology Research (IJSTR)*, *9*(1), 2277–8616.

20. Garg, H., & Kaur, G. (2020). Novel distance measures for cubic intuitionistic fuzzy sets and their applications to pattern recognitions and medical diagnosis. *Granular Computing*, *5*, 169–184. https://doi.org/10.1007/s41066-018-0140-3.
21. Mahanta, J., & Panda, S. (2021). A novel distance measure for intuitionistic fuzzy sets with diverse applications. *International Journal of Intelligent Systems*, 36. https://doi.org/10.1002/int.22312.
22. Gohain, B., Chutia, R., Dutta, P., & Gogoi, S. (2022). Two new similarity measures for intuitionistic fuzzy sets and its various applications. *International Journal of Intelligent Systems*, *37*, 5557–5596. https://doi.org/10.1002/int.22802.
23. Ohlan, A. (2022). Novel entropy and distance measures for interval-valued intuitionistic fuzzy sets with application in multi-criteria group decision-making, *International Journal of General Systems*, *51*(4), 413–440, https://doi.org/10.1080/03081079.2022.2036138.
24. Zeng, W., Cui, H., Liu, Y., Yin, Q., & Xu, Z. (2022). Novel distance measure between intuitionistic fuzzy sets and its application in pattern recognition. *Iranian Journal of Fuzzy Systems*, *19*(3), 127–137. https://doi.org/10.22111/ijfs.2022.6947.
25. Szmidt, E., & Kacprzyk, J. (2004). Medical diagnostic reasoning using a similarity measure for intuitionistic fuzzy sets. *Note on Intuitionistic Fuzzy Sets, 10*(4), 61–69.
26. Chen, S. M., & Randyanto, Y. (2013). A novel similarity measure between intuitionistic fuzzy sets and its applications. *International Journal of Pattern Recognition and Artificial Intelligence. 27*, 350021. https://doi.org/10.1142/S0218001413500213.
27. Ye, J. (2016). Similarity measures of intuitionistic fuzzy sets based on cosine function for the decision making of mechanical design schemes. *Journal of Intelligent & Fuzzy Systems, 30*, 151–158. https://doi.org/10.3233/IFS-151741.
28. Luo, M., & Liang, J. (2019). A novel similarity measure for interval-valued intuitionistic fuzzy sets and its applications. *Symmetry*, *10*(10), 441, https://doi.org/0.5281/zenodo.3047937.
29. Iqbal, M., & Rizwan, U. (2019). Some applications of intuitionistic fuzzy sets using new similarity measure. *Journal of Ambient Intelligence and Humanized Computing*, https://doi.org/10.1007/s12652-019-01516-7.
30. Kumari, R., & Mishra, A. R. (2020). Multi-criteria COPRAS method based on parametric measures for intuitionistic fuzzy sets: Application of green supplier selection. *The Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, *44*, 1645–1662. https://doi.org/10.1007/s40998-020-00312-w.
31. Adamu, I. M. (2021). Application of intuitionistic fuzzy sets to environmental management. *Notes on Intuitionistic Fuzzy Sets*. *27*(3), 40–50, https://doi.org/10.7546/nifs.2021.27.3.40-50.
32. Ejegwa, P. A., & Agbetayo, J. M. (2022). Similarity-distance decision-making technique and its applications via intuitionistic Fuzzy Pairs. *Journal of Computational and Cognitive Engineering*, 2(1). https://doi.org/10.47852/bonviewJCCE512522514.
33. Thao, N. X., & Chou, S. Y. (2022). Novel similarity measures, entropy of intuitionistic fuzzy sets and their application in software quality evaluation. *Soft Computing*, *26*(4), 2009–2020**,** https://doi.org/10.1007/s00500-021-06373-1.
34. Gupta, R., & Kumar, S. (2022). Intuitionistic fuzzy similarity-based information measure in the application of pattern recognition and clustering. *International Journal of Fuzzy Systems*, *24*, 2493–2510. https://doi.org/10.1007/s40815-022-01272-5.

35. Kumar, R., & Kumar, S. (2023). A novel intuitionistic fuzzy similarity measure with applications in decision-making, pattern recognition, and clustering problems. *Granular Computing*, *8*, 1027–1050. https://doi.org/10.1007/s41066-023-00366-1.
36. Patel, A., Jana, S., & Mahanta, J. (2024). Construction of similarity measure for intuitionistic fuzzy sets and its application in face recognition and software quality evaluation. *Expert Systems with Applications*, *237*, 121491.
37. Dutta, P., & Borah, G. (2023). Multicriteria group decision making via generalized trapezoidal intuitionistic fuzzy number-based novel similarity measure and its application to diverse COVID-19 scenarios. *Artificial Intelligence Review*, *56*, 3543–3617. https://doi.org/10.1007/s10462-022-10251-z.
38. Bajaj, J., & Kumar, S. (2023). A new intuitionistic fuzzy correlation coefficient approach with applications in multi-criteria decision-making. *Decision Analytics Journal*, *9*, 100340.
39. Patel, A., Lemtur, S., & Mahanta, J. (2023). A novel distance measure for intuitionistic fuzzy sets with its application in pattern classification and decision-making. In: *AIP Conference Proceedings*, AIP Publishing, *2819*(1).
40. Chakraborty, J., Mukherjee, S., & Sahoo, L. (2023). Intuitionistic fuzzy multi-index multi-criteria decision-making for smart phone selection using similarity measures in a fuzzy environment. *Journal of Industrial Intelligence*, *1*(1), 1–7.
41. Panda, R. R., & Nagwani, N. K. (2024). Software bug priority prediction technique based on intuitionistic fuzzy representation and class imbalance learning. *Knowledge and Information Systems*, *66*, 2135–2164.

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