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Research article

A Fuzzy Control System for Performance Optimization in Wireless Sensor Networks

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ARTICLE INFO

Article history:
Received February 21st, 2025
Revised May 19th, 2025
Accepted June 17th, 2025
Available online June 27th, 2025

Keywords:
Fuzzy Logic;
Wireless Sensor Networks (WSNs);
Energy Efficiency;
Packet Delivery Ratio;
Network Lifetime.

Please cite this article in IEEE style as:
A. Motwakel, R. M. Almohamedh, and H. T. A. Abdalrahman, "A Fuzzy Control System for Performance Optimization in Wireless Sensor Networks," *Register: Jurnal Ilmiah Teknologi Sistem Informasi*, vol. 11, no. 1, pp. 41-60, 2025.

ABSTRACT

Wireless Sensor Networks (WSNs) play a vital role in numerous domains such as environmental monitoring, healthcare, industrial automation, and smart city infrastructures. Despite their growing significance, WSNs face persistent challenges, including limited energy resources, high data loss, network instability, and latency issues. To address these concerns, this study explores the integration of fuzzy logic to optimize WSN performance under uncertain and dynamic conditions. A fuzzy logic-based control system was designed to adaptively regulate key parameters, such as node energy, packet loss, and connectivity. Simulations were conducted with varying node densities (100, 200, and 300 nodes) to assess the effectiveness of the approach. The results revealed notable improvements: energy consumption was reduced by up to 0.65%, network lifetime extended by up to 0.28%, packet delivery ratio increased by up to 3.10%, and average latency decreased by up to 43.8%. These outcomes underscore the potential of fuzzy logic to enhance the adaptability, efficiency, and reliability of WSNs, offering a practical and scalable solution for performance optimization in real-world deployments.

1. Introduction

Wireless Sensor Networks (WSNs) have become a cornerstone of modern communication systems, with applications spanning critical sectors such as environmental monitoring, healthcare, industrial automation, and smart cities. These networks consist of distributed sensors that collect data on physical or environmental variables such as temperature, humidity, and motion, and transmit this data to a central system for analysis. However, despite their potential, WSNs encounter significant challenges related to energy efficiency, data reliability, network lifespan, and real-time performance [1][2].

The inherent challenges in WSNs stem from the limited power resources of sensor nodes, unpredictable wireless communication, and fluctuating environmental conditions [3]. Conventional methods to optimize WSN performance, which rely on deterministic approaches, are often inadequate in addressing the uncertainties and imprecision that characterize these factors. This paper proposes integrating fuzzy logic into WSNs to overcome these limitations. Fuzzy logic, a powerful tool for managing uncertainty and approximate reasoning, offers a promising solution to enhance decision-making processes under uncertain conditions [4].

Fuzzy logic, introduced by Lotfi Zadeh in 1965, extends classical binary logic by allowing partial truth values between completely true and false [5]. Its application in WSNs enables the development of algorithms that adapt more effectively to the dynamic and unpredictable nature of wireless

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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communication, optimizing performance parameters such as energy consumption, data accuracy, and network robustness.

Despite the significant progress made in WSNs research, most existing studies focus on isolated aspects such as energy consumption or routing efficiency, often under static or ideal network conditions. These approaches lack adaptability to dynamic environmental factors, unpredictable node behavior, and uncertain data transmission quality. Furthermore, they seldom address multiple performance metrics simultaneously within a unified framework. This study aims to fill that gap by proposing a fuzzy logic-based control system that adaptively manages key WSN parameters to enhance energy efficiency, reliability, and responsiveness. The objective is to provide a comprehensive and intelligent performance optimization model capable of handling real-world uncertainties across diverse network scenarios.

This study specifically explores how fuzzy logic can enhance the operational efficiency and reliability of WSNs, focusing on the design and implementation of algorithms that address challenges in energy management, data precision, and overall network durability. By leveraging fuzzy logic, WSNs can achieve greater adaptability and resilience, making them more suitable for large-scale and mission-critical deployments.

The remainder of the paper is structured as follows: Section 2 reviews related work, Section 3 describes the system design, Section 4 presents the implementation, Section 5 evaluates performance, Section 6 discusses simulation results, Section 7 provides a discussion, and Section 8 concludes the study.

2. Materials and Methods

2.1. Related Works

Wireless Sensor Networks (WSNs) have become integral to various applications such as environmental monitoring, healthcare, and industrial automation, due to their ability to autonomously monitor physical and environmental conditions. However, the effectiveness of WSNs is often hindered by challenges including limited energy resources, unreliable wireless communication, and dynamic environmental conditions [7]. Traditional deterministic approaches have limitations in adapting to these uncertainties, prompting researchers to explore alternative methodologies such as fuzzy logic. This section reviews previous studies that have investigated the application of fuzzy logic to enhance the performance of WSNs.

Hamzah, Abdulmughni, et al. [8] present several clustering and hierarchical routing protocols proposed to enhance energy efficiency in WSNs. LEACH, a probabilistic CH selection approach, and its centralized variant, LEACH-C, aimed to improve energy distribution. TEEN and APTEEN optimize data transmission by balancing reactive and proactive communication strategies. HEED periodically selects CHs based on residual energy and proximity to neighbors, ensuring network scalability. PEGASIS employs a chain-based transmission method to minimize energy consumption. Additionally, fuzzy logic-based clustering approaches utilize multiple parameters, such as residual energy and node density, to optimize CH selection, often requiring centralized processing due to computational demands. Recent advancements integrate optimization techniques such as k-means clustering, Discrete Particle Swarm Optimization (DPSO), and genetic algorithms, significantly improving network lifetime and energy efficiency [8].

Al Dallal [9] introduces an energy-efficient routing protocol that integrates Deep Q-Network (DQN) and fuzzy logic for cluster head selection. Additionally, it incorporates Predictive Coding Theory for data compression, significantly reducing energy consumption. Simulation results demonstrate the superiority of the proposed model over conventional routing protocols in terms of both energy efficiency and Quality of Service (QoS) [9].

Bagwari et al. [10] present an enhanced energy optimization model for Industrial WSNs using machine learning techniques. The model analyzes and optimizes energy consumption patterns, achieving 35.28% savings in transmission energy and 32.73% in reception energy. The proposed approach improves network lifetime and operational efficiency [10].

Gupta and Yadav [11] propose a study that focuses on optimizing the LEACH protocol by applying mathematical modeling and probability analysis to enhance network lifetime, energy

http://doi.org/10.26594/register.v11i1.5431

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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efficiency, and data throughput. The Improved LEACH (ILEACH) protocol outperforms the traditional LEACH in terms of energy savings and network longevity [11]. Shalu and Sarobin [12] present an optimized clustering approach using the Improved Squirrel Search Algorithm (ISSA). The model considers node residual energy, distance from neighbors and the base station, and node load balancing. The results show superior energy efficiency compared to SSA, GWO, and LEACH algorithms [12]. Bhimshetty and Agughasi [13] present a reinforcement learning-based routing protocol using Deep Q-Network (DQN) and Q-learning for WSN optimization. The proposed model outperforms LEACH and fuzzy C-means (FCM) in network longevity, active node count, and energy conservation [13].

2.2. Design

The proposed method enhances the functionality and efficiency of WSNs. WSNs are pivotal in various domains such as environmental monitoring, healthcare, and industrial automation, but they face challenges including limited energy resources, unpredictable wireless communication, and dynamic environmental conditions. Fuzzy logic allows for more adaptive decision-making in complex and uncertain environments. By applying fuzzy logic to WSNs, this paper aims to enhance energy efficiency, data accuracy, network reliability, and real-time performance.

2.2.1. Fuzzy Control System Design

WSNs comprise spatially distributed sensor nodes that monitor and collect data from their surroundings, transmitting this information to a central processing unit. The effectiveness of WSNs is often challenged by issues such as energy constraints, data accuracy, and network scalability. To address these challenges, the implementation of fuzzy control systems presents a promising solution. Fuzzy control systems utilize fuzzy logic to manage the inherent uncertainties and dynamic nature of WSNs, thereby enhancing their overall performance. Figure 1 represents the flowchart of a fuzzy logic-based system for enhancing the performance of WSNs:

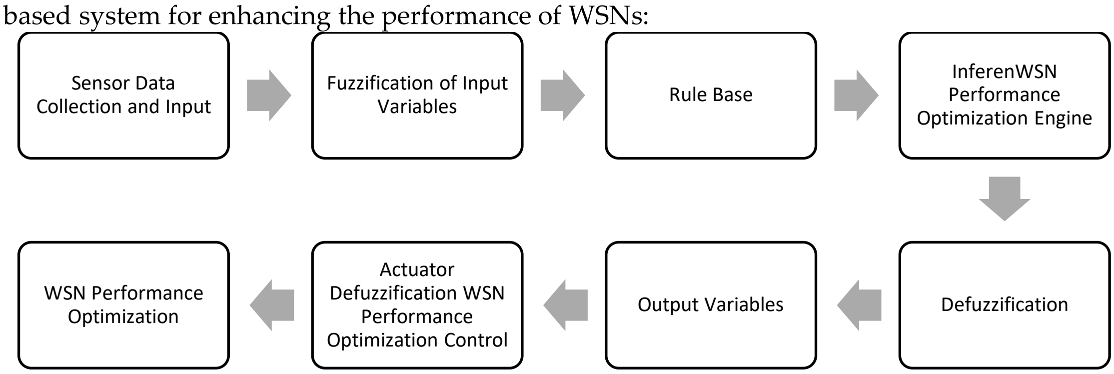

Fig. 1. Fuzzy Control System Design

2.2.2. Sensor Data Collection and Input Variables

WSNs consist of distributed sensor nodes that autonomously monitor and collect data from the environments in which they are deployed. These nodes continuously sense various physical or environmental parameters and transmit the collected data to a central base station or gateway. This data is crucial for performing analysis, making decisions, and optimizing the performance of the network.

Real-time data collection involves gathering sensor readings from nodes as they operate in the field. This data is typically transmitted wirelessly to a central location for processing and analysis. First key parameters relevant to WSNs is node energy. Energy is a critical resource in WSNs, as sensor nodes are often powered by batteries or energy-harvesting techniques (e.g., solar, kinetic). Monitoring node energy levels helps predict when nodes may need to be recharged or replaced to maintain network operation. Second, Packet Loss Rate, packet loss refers to the percentage of data packets that fail to reach their destination due to network congestion, transmission errors, or node failures. High packet loss rates can degrade the reliability and efficiency of data transmission in WSNs. Third, Node Density, node density refers to the number of sensor nodes deployed per unit area within the network. While high node density improves coverage and redundancy, it also increases energy consumption and communication overhead. Fourth, Signal-to-Noise Ratio (SNR), SNR quantifies the strength of the desired signal relative to background noise and interference. In WSNs, a high SNR indicates good signal quality, leading to reliable data transmission and improved network performance. Fifth, Node Connectivity, connectivity refers to the ability of sensor nodes to communicate directly or indirectly

 http://doi.org/10.26594/register.v11i1.5431

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with each other within the network. Monitoring node connectivity helps assess network topology, identify potential communication bottlenecks, and ensure robust data routing.

2.2.3. Fuzzification of Input Variables:

Fuzzification is the process of converting crisp input variables into fuzzy sets using triangular membership functions. This step is crucial in a fuzzy control system for WSNs, as it translates precise sensor readings into linguistic terms that can be processed by the inference engine. For instance, membership functions must be defined for input variables: (a) Node Energy (NE): The remaining energy level of sensor nodes, expressed as a percentage, (b) Data Packet Loss Rate (DPLR): The rate at which data packets are lost during transmission, represented as a percentage, (c) Node Density (ND): The number of sensor nodes within a given area, (d) Signal-to-Noise Ratio (SNR): The ratio of the strength of the received signal to the background noise level, (e) Node Connectivity (NC): The degree of connectivity between sensor nodes in the network.

Each of these variables is mapped to fuzzy sets using shapes like triangular functions, enabling the system to handle the inherent uncertainties and variabilities in sensor data more effectively. This fuzzified input allows for more flexible and adaptive decision-making, which is essential for optimizing the performance and reliability of WSNs.

2.2.4. Rule Base

In a fuzzy logic system for WSNs, the input variables include Node Energy (NE), Data Packet Loss Rate (DPLR), Node Density (ND), Signal-to-Noise Ratio (SNR), and Node Connectivity (NC). The output variables include Transmission Power Adjustment (TPA), Data Aggregation Level (DAL), Routing Path Selection (RPS), Sleep/Wake Schedule (SWS), and Error Correction Mechanism (ECM). Table 1 shows the attribute and membership of input variables and output variables. Table 2 is a comprehensive rule base that maps the input conditions to the appropriate actions [10].

Table 1. Input and Output Variables

Input Variables:		Output Variables:	
Atribute	**Membership**	**Atribute**	**Membership**
Node Energy (NE)	Low, Medium, High	Transmission Power Adjustment (TPA):	Decrease, Maintain, Increase
Data Packet Loss Rate (DPLR)	Low, Medium, High	Data Aggregation Level (DAL):	Low, Medium, High
Node Density (ND)	Sparse, Moderate, Dense	Routing Path Selection (RPS):	Change, Maintain
Signal-to-Noise Ratio (SNR)	Low, Medium, High	Sleep/Wake Schedule (SWS):	Increase Sleep, Maintain, Decrease Sleep
Node Connectivity (NC)	Poor, Fair, Good	Error Correction Mechanism (ECM):	Low, Medium, High

This comprehensive rule base on Table 2 allows the fuzzy logic system to adaptively optimize WSN performance based on varying network conditions and input parameters. The fuzzy rules are constructed based on expert knowledge, enabling the system to make context-aware decisions in uncertain environments. By dynamically adjusting transmission power, data aggregation levels, routing paths, sleep/wake schedules, and error correction mechanisms, the system enhances energy efficiency, data accuracy, latency, and overall network reliability.

2.2.5. Inference Engine

The inference engine is a core component of a fuzzy logic system, playing a crucial role in processing and making decisions based on fuzzy rules and inputs. In the context of WSNs, the inference engine is instrumental in interpreting sensor data, managing uncertainties, and enhancing overall network performance through intelligent decision-making.

The inference engine in a fuzzy logic system is vital for enhancing the performance of WSNs. Its ability to process fuzzy inputs, apply expert rules, and make intelligent decisions enables WSNs to operate more efficiently, reliably, and adaptively. This capability is essential for addressing the challenges posed by the dynamic and often harsh environments in which WSNs are deployed, ultimately leading to more robust and efficient network operations.

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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Table 2. Rule Base

Rule 1:	If NE is Low, DPLR is High, ND is Sparse, SNR is Low, and NC is Poor, then: TPA is Decrease, DAL is Low, RPS is Change, SWS is Increase Sleep, and ECM is High.
Rule 2:	If NE is Medium, DPLR is Medium, ND is Moderate, SNR is Medium, and NC is Fair, then: TPA is Maintain, DAL is Medium, RPS is Maintain, SWS is Maintain, and ECM is Medium
Rule 3:	If NE is High, DPLR is Low, ND is Dense, SNR is High, and NC is Good, then: TPA is Increase, DAL is High, RPS is Maintain, SWS is Decrease Sleep, and ECM is Low.
Rule 4:	If NE is Low, DPLR is Low, ND is Sparse, SNR is Medium, and NC is Fair then: TPA is Decrease, DAL is Medium, RPS is Change, SWS is Increase Sleep, and ECM is Medium
Rule 5:	If NE is Medium, DPLR is High, ND is Dense, SNR is Low, and NC is Poor then: TPA is Maintain, DAL is Low, RPS is Change, SWS is Maintain, and ECM is High
Rule 6:	If NE is High, DPLR is Medium, ND is Sparse, SNR is High, and NC is Good then: TPA is Increase, DAL is High, RPS is Maintain, SWS is Decrease Sleep, and ECM is Medium
Rule 7:	If NE is Low, DPLR is Medium, ND is Moderate, SNR is Low, and NC is Poor then: TPA is Decrease, DAL is Low, RPS is Change, SWS is Increase Sleep, and ECM is High
Rule 8:	If NE is Medium, DPLR is Low, ND is Dense, SNR is Medium, and NC is Fair then: TPA is Maintain, DAL is Medium, RPS is Maintain, SWS is Maintain, and ECM is Low
Rule 9:	If NE is High, DPLR is High, ND is Sparse, SNR is Low, and NC is Poor then: TPA is Increase, DAL is Low, RPS is Change, SWS is Decrease Sleep, and ECM is High
Rule 10:	If NE is Low, DPLR is High, ND is Moderate, SNR is High, and NC is Fair then: TPA is Decrease, DAL is Medium, RPS is Change, SWS is Increase Sleep, and ECM is Medium
Rule 11:	If NE is Medium, DPLR is Medium, ND is Sparse, SNR is Low, and NC is Poor then: TPA is Maintain, DAL is Low, RPS is Change, SWS is Maintain, and ECM is High
Rule 12:	If NE is High, DPLR is Low, ND is Moderate, SNR is Medium, and NC is Fair then: TPA is Increase, DAL is Medium, RPS is Maintain, SWS is Decrease Sleep, and ECM is Low
Rule 13:	If NE is Low, DPLR is Low, ND is Dense, SNR is High, and NC is Good then: TPA is Decrease, DAL is High, RPS is Maintain, SWS is Increase Sleep, and ECM is Low
Rule 14:	If NE is Medium, DPLR is High, ND is Sparse, SNR is Medium, and NC is Fair then: TPA is Maintain, DAL is Medium, RPS is Change, SWS is Maintain, and ECM is Medium
Rule 15:	If NE is High, DPLR is Medium, ND is Moderate, SNR is Low, and NC is Poor then: TPA is Increase, DAL is Low, RPS is Change, SWS is Decrease Sleep, and ECM is High
Rule 16:	If NE is Low, DPLR is Medium, ND is Dense, SNR is High, and NC is Good then: TPA is Decrease, DAL is High, RPS is Maintain, SWS is Increase Sleep, and ECM is Medium
Rule 17:	If NE is Medium, DPLR is Low, ND is Sparse, SNR is Medium, and NC is Fair then: TPA is Maintain, DAL is Medium, RPS is Maintain, SWS is Maintain, and ECM is Low
Rule 18:	If NE is High, DPLR is High, ND is Moderate, SNR is Low, and NC is Poor then: TPA is Increase, DAL is Low, RPS is Change, SWS is Decrease Sleep, and ECM is High
Rule 19:	If NE is Low, DPLR is High, ND is Sparse, SNR is High, and NC is Fair then: TPA is Decrease, DAL is Medium, RPS is Change, SWS is Increase Sleep, and ECM is Medium
Rule 20:	If NE is Medium, DPLR is Medium, ND is Dense, SNR is Medium, and NC is Fair then: TPA is Maintain, DAL is Medium, RPS is Maintain, SWS is Maintain, and ECM is Medium

2.2.6. Defuzzification

Defuzzification is a critical process in the implementation of fuzzy logic systems, involving the conversion of fuzzy output generated by the inference engine into a precise, crisp value that can be used for decision-making in real-world applications. In a fuzzy logic system, inputs are first processed through fuzzification, which transforms precise values into fuzzy sets. The inference engine then applies a set of rules to these fuzzy sets to derive fuzzy outputs. Defuzzification is the final step, essential for interpreting these outputs in a meaningful and actionable way. The centroid method used in this paper which it calculates the center of the area under the curve of the fuzzy set.

2.2.7. Output Variables and Actions

In the context of fuzzy logic for enhancing the performance of WSNs, output variables represent specific actions taken based on the system's decisions. These actions are critical for optimizing various aspects of WSN performance, including energy efficiency, data accuracy, latency, and network reliability. The primary output variables in this framework are Transmission Power Adjustment (TPA), Data Aggregation Level (DAL), Routing Path Selection (RPS), Sleep/Wake Schedule (SWS), and Error Correction Mechanism (ECM).

http://doi.org/10.26594/register.v11i1.5431

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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2.2.8. Actuator Control

Actuator control is the process of implementing the crisp decisions derived from the fuzzy logic controller to manage and optimize various aspects of WSN operations. The fuzzy logic system processes various inputs and generates fuzzy outputs, which are then defuzzified into specific, actionable commands. These commands are executed by actuators to adjust transmission power, data aggregation levels, routing paths, sleep/wake schedules, and error correction mechanisms. Actuator control is essential for translating the adaptive, context-aware decisions of the fuzzy logic system into tangible improvements in overall network performance.

3. Results and Discussion

3.1. Implementation

3.1.1. Sensor Data Collection

The initial step in implementing a fuzzy logic system to enhance the performance of WSNs involves the efficient collection of real-time data from sensor nodes. This data collection process is crucial, as it provides the necessary input for the fuzzy logic controller to make informed decisions.

The implementation of sensor data collection is a fundamental component in enhancing the performance of WSNs using fuzzy logic. By employing suitable communication protocols such as Zigbee, Bluetooth, and Wi-Fi, along with effective data aggregation and error-handling techniques, the system can gather accurate and timely data from sensor nodes. This real-time data serves as a critical input for the fuzzy logic controller, enabling it to make informed decisions that optimize network performance, energy efficiency, and reliability.

The simulations were conducted using MATLAB R2021a, utilizing the Fuzzy Logic Toolbox to develop and test the fuzzy inference system. The network topology was assumed as a square area of size 100m × 100m. Sensor nodes (100, 200, and 300) were randomly deployed within this area. The key simulation parameters are as follows: Topology Size: 100m × 100m, Packet Size: 512 bytes, Traffic Model: Constant Bit Rate (CBR) with packets generated every 1 second, Energy Model: Initial node energy: 2 Joules, Transmission energy: 50 nJ/bit, Reception energy: 50 nJ/bit, Data aggregation energy: 5 nJ/bit/signal, Simulation Time: 1500 seconds, MAC Protocol: IEEE 802.15.4, Routing Protocol: Simple gradient-based routing. These settings simulate typical scenarios in environmental monitoring WSNs and allow for a controlled comparison between fuzzy-based and non-fuzzy approaches.

3.1.2. FLC Development

Figure 2 shows the system architecture for implementing Fuzzy Logic Control (FLC) in WSNs, designed to optimize network performance by dynamically adjusting operational parameters based on the network's current state. This architecture comprises several interconnected components that work together to process input data, make decisions, and apply the necessary adjustments to the network. Below is a detailed description of the system architecture.

Input Fuzzification Module is responsible for converting the crisp input values from sensor nodes into fuzzy values. Input parameters include: Node Energy (NE), Data Packet Loss Rate (DPLR), Node Density (ND), Signal-to-Noise Ratio (SNR), and Node Connectivity (NC). Inference Engine processes the fuzzy input values according to a predefined set of rules. This module applies fuzzy reasoning to determine the appropriate actions for the network. A comprehensive set of IF-THEN rules defines how the system should respond under various conditions, and Mamdani-type inference is typically used for its straightforward rule representation and interpretability. Output Defuzzification Module converts the fuzzy output from the inference engine back into crisp values that can be used to adjust the network's operational parameters. The Centroid method is used for defuzzification to ensure smooth and consistent output. Output parameters include Transmission Power Adjustment (TPA), Data Aggregation Level (DAL), Routing Path Selection (RPS), Sleep/Wake Schedule (SWS), and Error Correction Mechanism (ECM).

Figures 3, 4, 5, 6, and 7 show the Input Fuzzification Module, which is essential for converting raw sensor data into a format that the fuzzy logic system can utilize effectively. By fuzzifying critical network parameters such as node energy, data packet loss rate, node density, signal-to-noise ratio, and node connectivity, the module enables the FLC system to make informed and nuanced decisions, ultimately enhancing the performance and reliability of WSNs.

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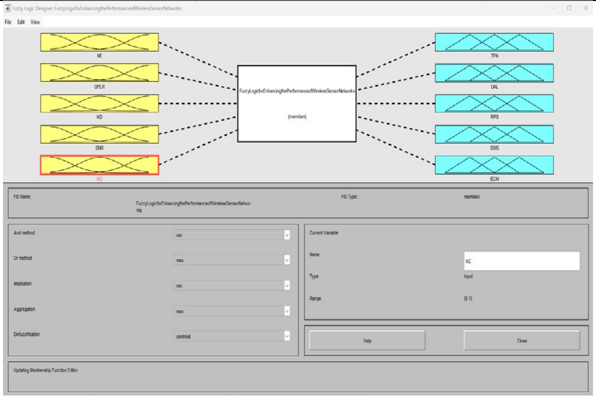

Fig. 2. FLC Development

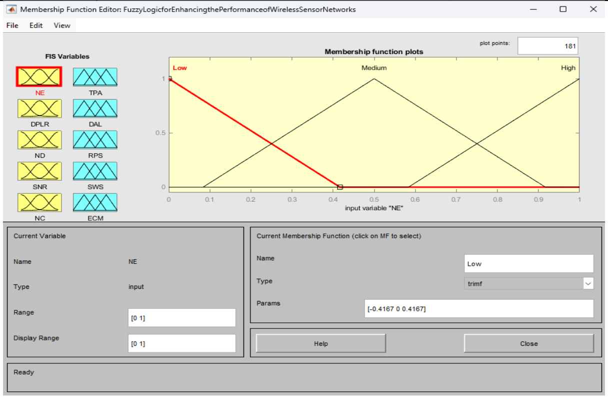

Fig. 3. The input fuzzification variable Node Energy (NE)

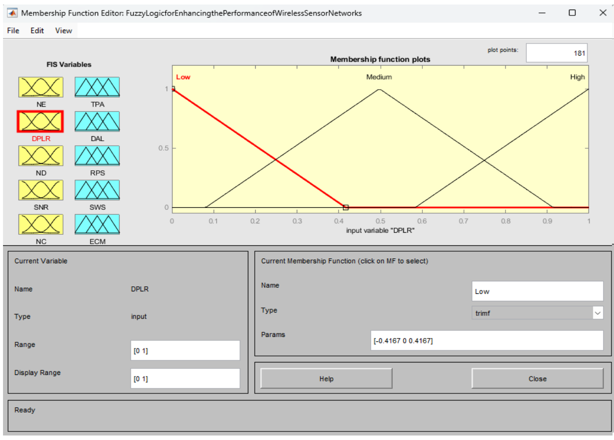

Fig. 4. The input fuzzification variable Data Packet Loss Rate (DPLR)

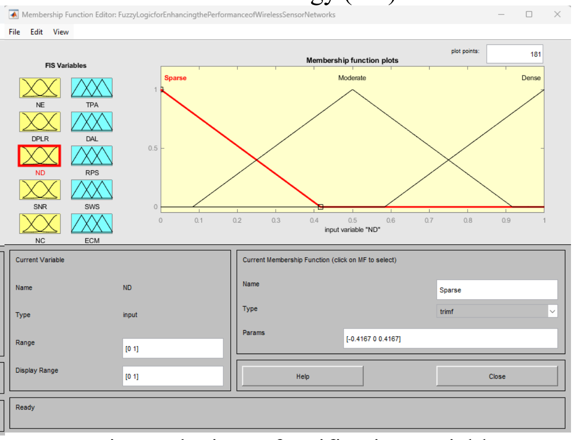

Fig. 5 The input fuzzification variable Node Density (ND)

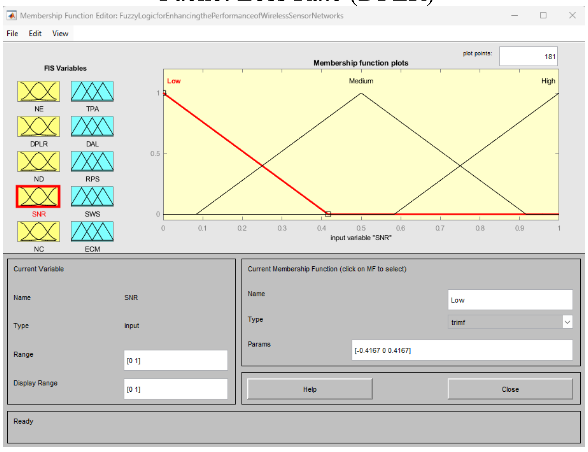

Fig. 6. The input fuzzification variable Signal-to-Noise Ratio (SNR)

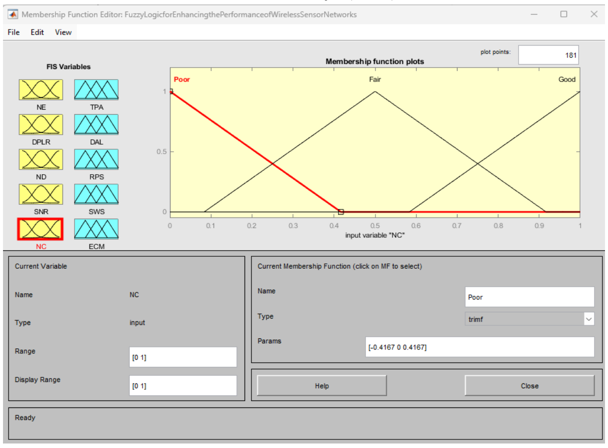

Fig. 7. The input fuzzification variable Node Connectivity (NC)

Figure 8 show the implementation of the fuzzy logic rules for enhancing the performance of WSNs). It involves a systematic process in which the fuzzy logic controller evaluates current network conditions and applies the appropriate rules to determine optimal actions. For instance, according to Rule 1, if the sensor node energy (NE) is low, data packet loss rate (DPLR) is high, node density (ND) is sparse, signal-to-noise ratio (SNR) is low, and node connectivity (NC) is poor, the system will decrease transmission power adjustment (TPA), set data aggregation level (DAL) to low, change the routing path selection (RPS), increase sleep/wake schedule (SWS), and set the error correction mechanism (ECM) to high. Similarly, Rule 2 dictates that if NE is medium, DPLR is medium, ND is moderate, SNR is medium, and NC is fair, the system will maintain TPA, set DAL to medium, maintain RPS and maintain SWS, and set ECM to medium. Each rule caters to specific network conditions, such as in Rule 3 where high NE, low DPLR, dense ND, high SNR, and good NC prompt an increase in TPA, a high DAL, maintenance of RPS, decrease in SWS, and a low ECM. The fuzzy logic system continuously monitors these input variables and adjusts the network parameters accordingly to ensure optimal performance,

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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energy efficiency, and reliability of the WSN.

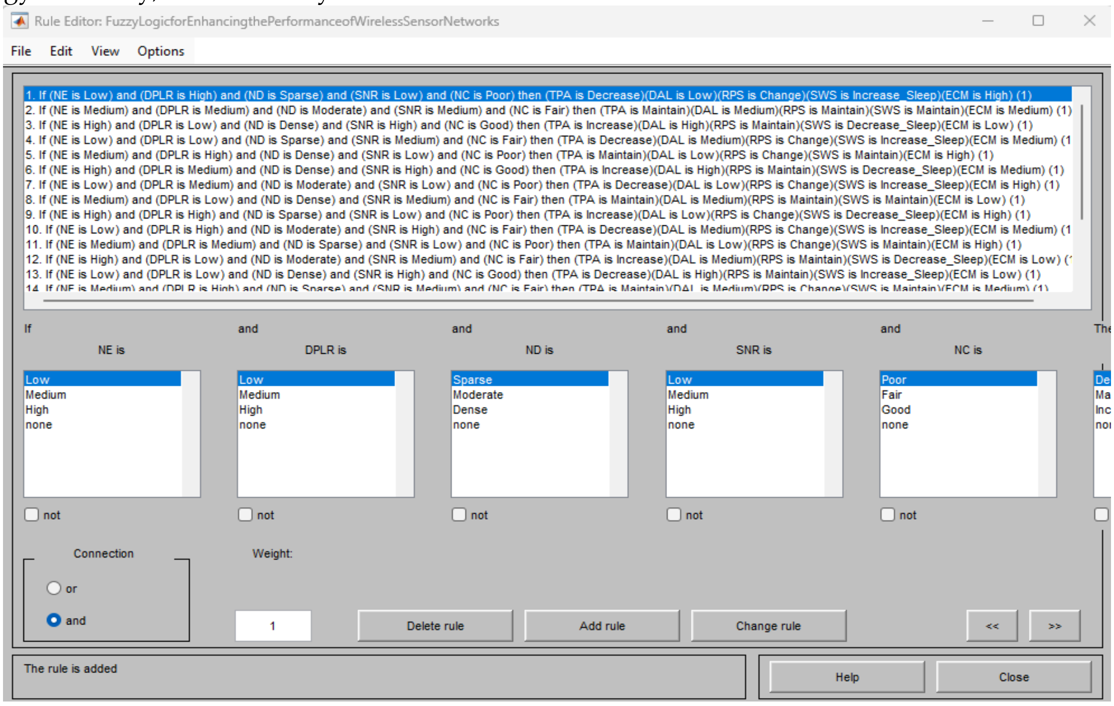

Fig. 8. The implementation of the rule base

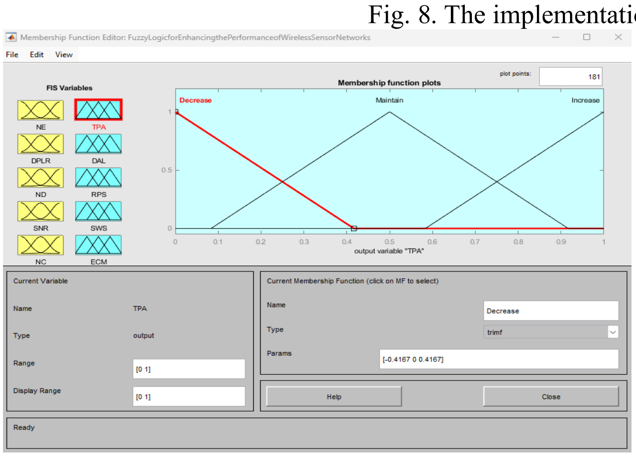

Fig. 9. Output defuzzification for Transmission Power Adjustment (TPA) variable

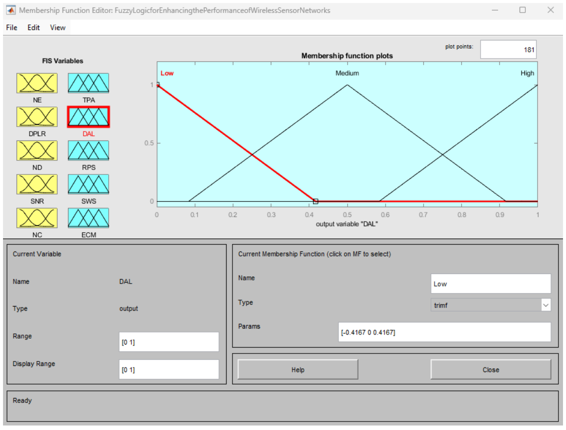

Fig. 10. Output defuzzification for Data Aggregation Level (DAL) variable

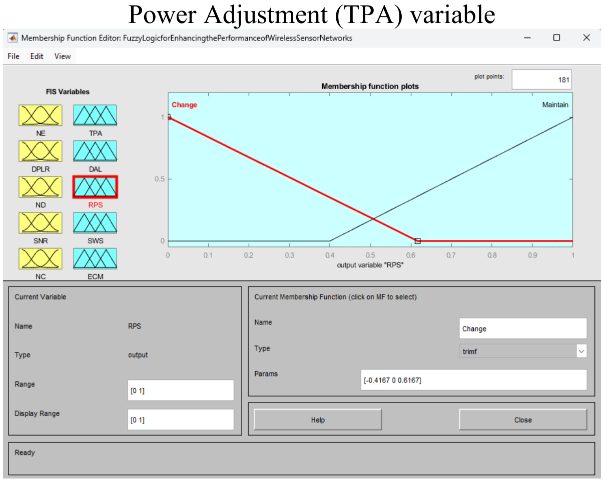

Fig. 11. Output defuzzification for Routing Path Selection (RPS) variable

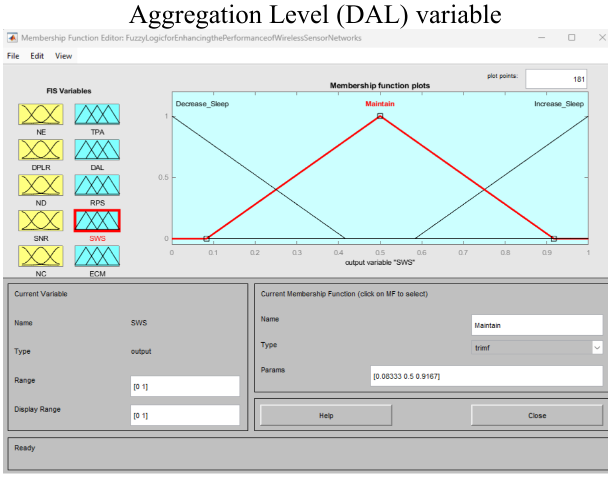

Fig. 12. Output defuzzification for Sleep/Wake Schedule (SWS) variable

 http://doi.org/10.26594/register.v11i1.5431

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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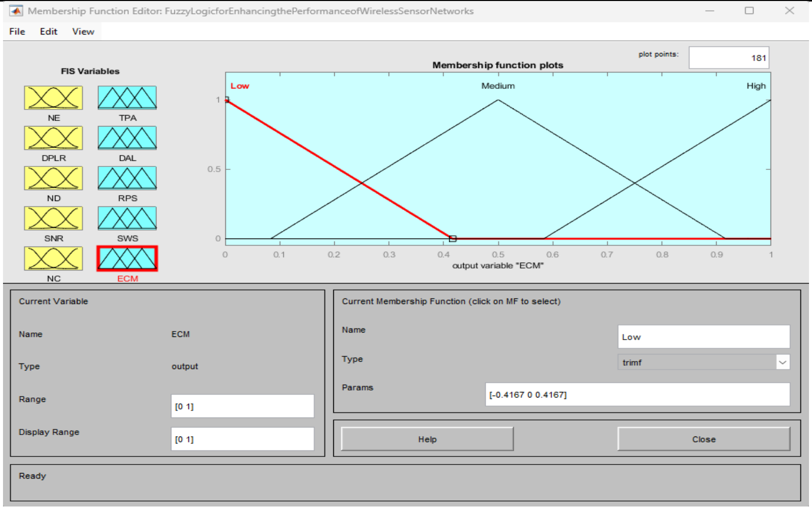

Fig. 13. Output defuzzification for Error Correction Mechanism (ECM) variable

Figures 9, 10, 11 ,12 , and 13 show the Output Defuzzification Module in a fuzzy logic system for enhancing the performance of WSNs. This module plays a critical role in converting fuzzy outputs from the inference engine into precise, actionable values that adjust the network's operational parameters. Utilizing the Centroid method for defuzzification, it ensures smooth and consistent outputs. The module translates fuzzy logic decisions into specific adjustments for Transmission Power Adjustment (TPA), Data Aggregation Level (DAL), Routing Path Selection (RPS), Sleep/Wake Schedule (SWS), and Error Correction Mechanism (ECM). By precisely adjusting these parameters, it helps to optimize the network's energy efficiency, data accuracy, latency, and overall reliability, ensuring the WSN operates effectively under varying conditions.

Figure 14 shows the Rule Viewer, which provides a detailed visualization of each rule's impact on the final decision based on current inputs such as Node Energy (NE), Data Packet Loss Rate (DPLR), Node Density (ND), Signal-to-Noise Ratio (SNR), and Node Connectivity (NC). By adjusting these inputs, users can see how the fuzzy logic rules activate and interact to determine specific output actions, including Transmission Power Adjustment (TPA), Data Aggregation Level (DAL), Routing Path Selection (RPS), Sleep/Wake Schedule (SWS), and Error Correction Mechanism (ECM). This tool is essential for analyzing and refining the rule set to ensure that network behavior meets the desired performance criteria.

For example, if NE is low, DPLR is high, ND is sparse, SNR is medium, and NC is poor, the rule viewer will show how these conditions influence the output actions such as decreasing transmission power, setting a low data aggregation level, maintaining the current routing path, increasing the sleep schedule, and selecting a high error correction mechanism. By observing the rule activation patterns and their contributions to the outputs, users can fine-tune the fuzzy logic system to optimize network performance under varying conditions.

Figure 15 illustrates how varying levels of Node Energy (NE) and Data Packet Loss Rate (DPLR) affect the Transmission Power Adjustment (TPA). By examining these surfaces, researchers can gain insights into the interaction between inputs and how the FIS rules translate them into control actions. Similarly, another surface plot shows how Node Density (ND) and Signal-to-Noise Ratio (SNR) impact the Data Aggregation Level (DAL). This visualization allows in-depth analysis of how different network conditions influence the aggregation level, thereby optimizing data management and transmission efficiency. Furthermore, examining the surface where Node Connectivity (NC) and Data Packet Loss Rate (DPLR) determine the Routing Path Selection (RPS) highlights the robustness of the routing strategy under various connectivity and reliability scenarios. The Surface Viewer also plays a crucial role in visualizing how the combination of Node Energy (NE) and Node Density (ND) influences the Sleep/Wake Schedule (SWS), helping ensure optimal power management and network longevity. Lastly, by investigating the surface plot where Signal-to-Noise Ratio (SNR) and Node Connectivity (NC) affect the Error Correction Mechanism (ECM), researchers can understand the system's resilience to noise and connectivity variations, ensuring reliable data transmission. These surface plots are particularly useful for validating the control system's performance and ensuring that it behaves as

http://doi.org/10.26594/register.v11i1.5431

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expected under different combinations of input conditions, thereby facilitating the optimization and fine-tuning of the fuzzy control logic in a WSN.

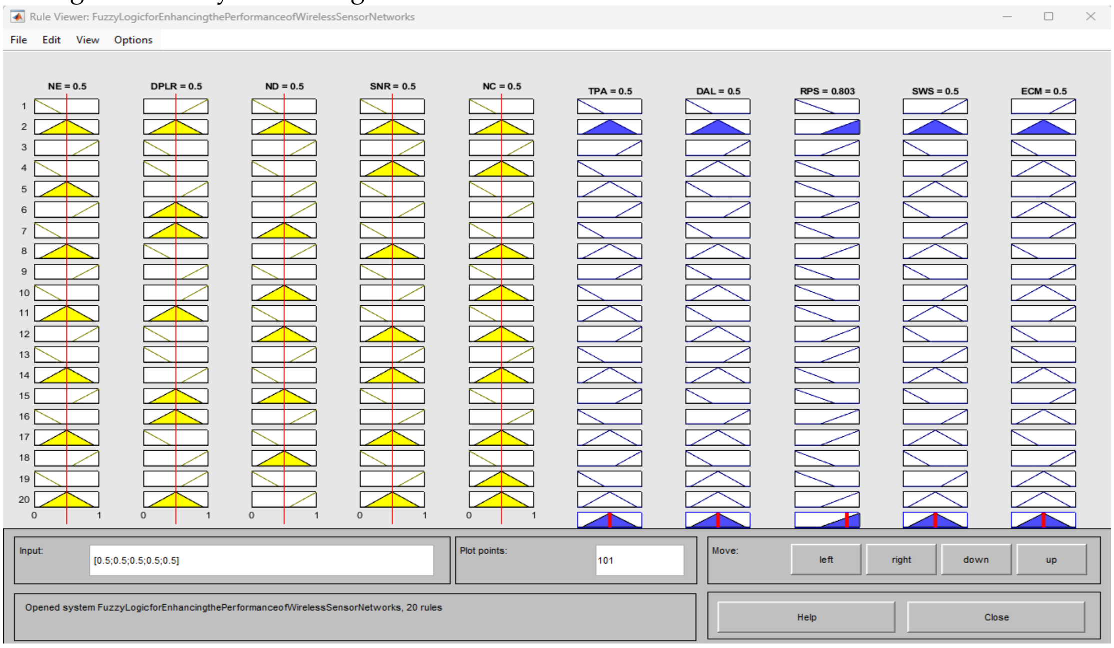

Fig. 14. The Rule Viewer

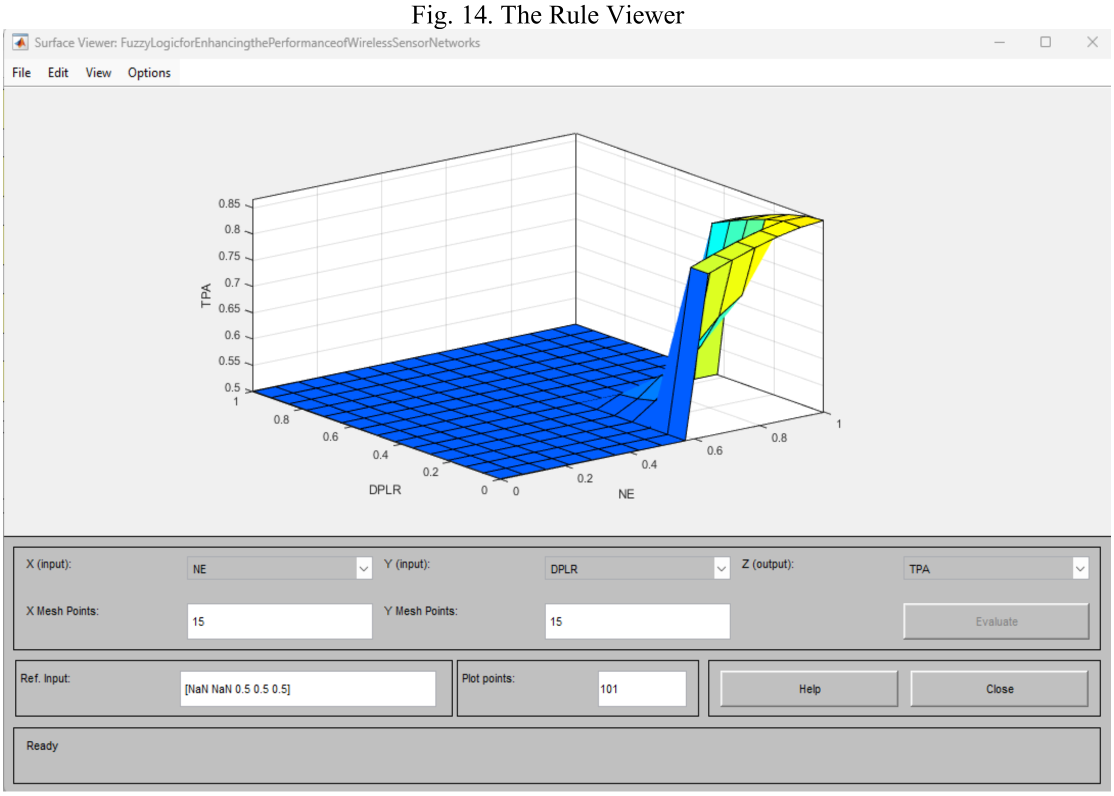

Fig. 15. The Rule viewer

3.2. Evaluation

The evaluation of WSN performance involves several key metrics, namely average energy consumption, network lifetime, packet delivery ratio (PDR), and average latency. Each of these metrics is calculated based on simulations conducted both with and without the use of fuzzy logic. Here is a detailed description of each metric and the equations used for their evaluation.

Average Energy Consumption measures the average remaining energy of the sensor nodes after the simulation. Lower energy consumption indicates better energy efficiency.

$$\text{Average Energy Consumption} = \frac{\sum_{i-1}^{N} E_i}{N} \quad (1)$$

where Ei is the remaining energy of node i, and N is the total number of nodes.

Network Lifetime is the average time until the first node in the network runs out of energy.

http://doi.org/10.26594/register.v11i1.5431

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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Longer network lifetime indicates better network sustainability.

$$\text{Average Network Lifetime} = \frac{\sum_{i-1}^{N} T_i}{N} \quad (2)$$

where Ti is the death time of node i, and N is the total number of nodes.

Packet Delivery Ratio (PDR) is the ratio of the number of packets successfully received by the destination to the number of packets sent by the source. Higher PDR indicates better reliability of the network.

$$\text{PDR} = \left(\frac{P_{received}}{P_{send}}\right) x\ 100 \quad (3)$$

where Preceived is the number of packets received, and Psent is the number of packets sent.

Average Latency is the average time taken for a packet to travel from the source to the destination. Lower latency indicates faster communication.

$$\text{Average Latency} = \frac{\sum_{i-1}^{P} L_i}{P} \quad (4)$$

where Li is the latency of packet i, and P is the total number of packets.

3.3. Simulation Results

The simulation results were generated for three different node counts: 100, 200, and 300 nodes, with each count configuration run twice, once without fuzzy logic and once with fuzzy logic. For 100 nodes, the average energy consumption without fuzzy logic was 0.4953 Joules, the average network lifetime was 1001.23 seconds, the packet delivery ratio (PDR) was 90.30%, and the average latency was 124.6 ms. With fuzzy logic, the average energy consumption was 0.4921 Joules, the average network lifetime was 1003.45 seconds, the PDR was 92.75%, and the average latency was 74.8 ms. For 200 nodes, the average energy consumption without fuzzy logic was 0.4907 Joules, the average network lifetime was 1005.60 seconds, the PDR was 90.60%, and the average latency was 125.3 ms. With fuzzy logic, the average energy consumption was 0.4880 Joules, the average network lifetime was 1008.12 seconds, the PDR was 93.20%, and the average latency was 72.5 ms. For 300 nodes, the average energy consumption without fuzzy logic was 0.4882 Joules, the average network lifetime was 1008.45 seconds, the PDR was 90.75%, and the average latency was 126.1 ms. With fuzzy logic, the average energy consumption was 0.4856 Joules, average network lifetime was 1011.25 seconds, the PDR was 93.55%, and the average latency was 70.9 ms. These results are presented in Tables 3–6, and are also illustrated in Figures 16–19.

Table 3. Average Energy Consumption

Node Count	Without Fuzzy Logic (Joules)	With Fuzzy Logic (Joules)
100	0.4953	0.4921
200	0.4907	0.4880
300	0.4882	0.4856

Table 4. Average Network Lifetime

Node Count	Without Fuzzy Logic (seconds)	With Fuzzy Logic (seconds)
100	1001.23	1003.45
200	1005.60	1008.12
300	1008.45	1011.25

Table 5. Packet Delivery Ratio (PDR)

Node Count	Without Fuzzy Logic (%)	With Fuzzy Logic (%)
100	90.30	92.75
200	90.60	93.20
300	90.75	93.55

Table 6. Average Latency

Node Count	Without Fuzzy Logic (ms)	With Fuzzy Logic (ms)
100	124.6	74.8
200	125.3	72.5
300	126.1	70.9

http://doi.org/10.26594/register.v11i1.5431

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
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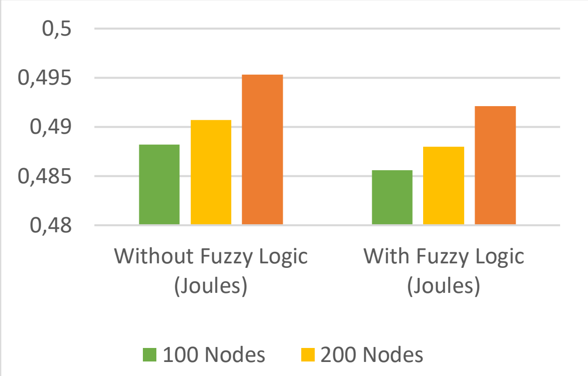

Fig. 16. Average Energy Consumption

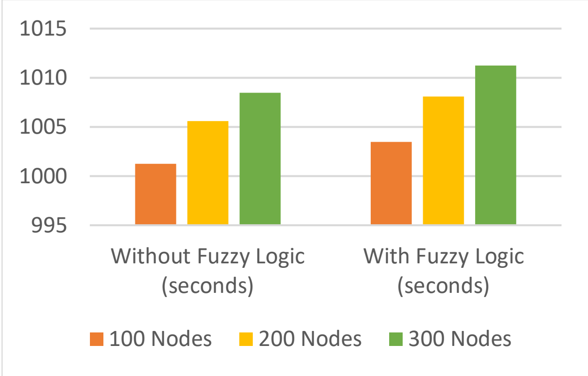

Fig. 17. Average Network Lifetime

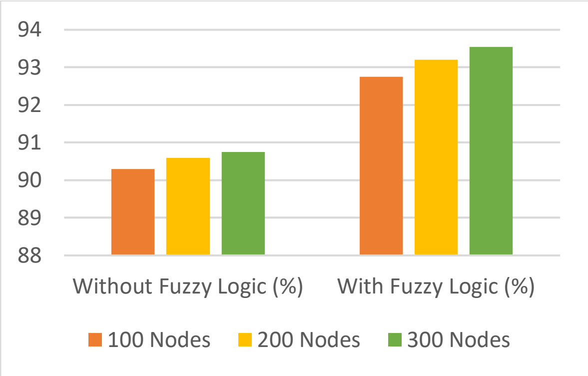

Fig. 18. Packet Delivery Ratio (PDR)

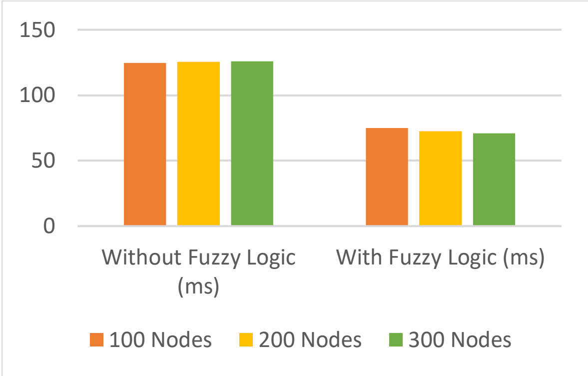

Fig. 19. Average Latency

3.4. Discussion

The experimental results indicate that incorporating fuzzy logic into the WSN simulations resulted in improvements across multiple performance metrics. Specifically, the use of fuzzy logic led to reduced average energy consumption, extended network lifetime, improved packet delivery ratio (PDR), and decreased average latency.

For a node count of 100, energy consumption decreased by approximately 0.65%, network lifetime increased by 0.22%, PDR improved by 2.72%, and latency was reduced by 40%. Similar trends were observed for node counts of 200 and 300. The improvements in energy consumption and network lifetime are crucial for extending the network's operational period, while enhancements in PDR and latency contribute to more efficient and reliable data transmission.

4. Conclusion

The proposed fuzzy logic-based system effectively optimizes performance of WSNs. Simulation results demonstrate the effectiveness of fuzzy logic in enhancing overall network performance. By integrating fuzzy logic, significant improvements were observed in energy efficiency, network longevity, data transmission reliability, and communication latency. These improvements highlight the potential of fuzzy logic as a viable approach for optimizing WSNs, making them more efficient and reliable for various applications.

These improvements are due to fuzzy logic's ability to adapt to uncertain network conditions by dynamically adjusting key parameters. This makes it highly applicable to real-world WSNs, especially in energy-constrained environments. Future work could explore integrating machine learning to optimize the rule set and evaluate the system under mobile and heterogeneous network scenarios.

The proposed fuzzy logic system shows clear improvements in energy efficiency, packet delivery, and especially latency—reduced by up to 43.8%, a result not commonly highlighted in prior studies. While previous works such as [8] and [13] focused primarily on energy consumption or network lifetime, our approach combines multiple performance metrics and introduces a broader range of decision outputs. This positions our model as more comprehensive and adaptable to real-world WSN conditions.

Author Contributions

 http://doi.org/10.26594/register.v11i1.5431

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
11 (1) 2025 41-53

A. Motwakel: Conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing – original draft, and writing – review & editing. R. M. Almohamedh: Conceptualization, methodology, resources, validation, visualization, and writing – review & editing. H. T. A. Abdalrahman: Conceptualization, resources, validation, and writing – review & editing.

Acknowledgment

This study is supported via funding from Prince Sattam bin Abdulaziz University project number (PSAU/2025/R/1446)

Declaration of Competing Interest

We declare that we have no conflict of interest.

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