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Matheamatical Modeling of Multi-Objective Adaptive Neuro Fuzzy Inference Based Optimization for IOT Based Wireless Sensor Network

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***Abstract*:**

The proliferation of the Internet of Things (IoT) and its integration with wireless sensor networks (WSNs) necessitates advanced optimization techniques to enhance performance and resource allocation while ensuring reliability and energy efficiency. This study introduces a mathematical modeling approach utilizing a Multi-Objective Adaptive Neuro-Fuzzy Inference System (MO-ANFIS) designed for optimizing IoT-based WSNs. The proposed model synergistically combines the adaptive learning capabilities of neural networks with the reasoning prowess of fuzzy inference systems, encapsulated within a multi-objective framework to concurrently address key operational objectives such as minimizing energy consumption, maximizing network lifetime, and enhancing data accuracy and throughput. The mathematical model is formulated to dynamically adapt to changing network conditions and sensor inputs, enabling real-time tuning of fuzzy rules and membership functions through backpropagation neural training. This adaptability ensures optimal performance despite the variable nature of IoT environments. Simulation results demonstrate that the MO-ANFIS model significantly outperforms traditional optimization methods, offering a robust, scalable solution for complex, dynamic WSNs in the IoT landscape. The findings suggest promising applications in various domains, including smart cities, environmental monitoring, and healthcare, where IoT integration is pivotal. This research not only bridges the gap between theoretical fuzzy-neural frameworks and practical IoT applications but also sets a foundation for future explorations into intelligent, adaptive network management systems.

Keywords: Internet of Things, wireless sensor networks, multi-objective optimization, Adaptive Neuro-Fuzzy Inference System, mathematical modeling, energy efficiency, network lifetime, data accuracy, real-time optimization, smart applications

1. Introduction

In the rapidly evolving technological landscape, the integration of the Internet of Things (IoT) with wireless sensor networks (WSNs) presents a transformative potential for numerous applications across various sectors including healthcare, agriculture, environmental monitoring, and smart cities. The core functionality of IoT-based WSNs lies in their ability to collect, transmit, and process vast amounts of data from dispersed sensor nodes, enabling real-time decision-making and automated control systems. However, the effective deployment and operation of these networks face critical challenges such as energy consumption, network scalability, data accuracy, and overall system reliability. Addressing these challenges through sophisticated optimization techniques is crucial for leveraging the full potential of IoT implementations.

The inherent constraints of sensor nodes, primarily limited power resources, necessitate the development of optimization strategies that can efficiently manage energy consumption while ensuring satisfactory network performance and longevity. Traditional single-objective optimization approaches often fall short in balancing the trade-offs between competing objectives such as maximizing network lifetime and minimizing energy use. Therefore, multi-objective optimization (MOO) emerges as a vital approach to address these simultaneous requirements, providing a framework to achieve an optimal trade-off in a Pareto-efficient manner. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) provide a compelling solution by combining the learning capabilities of neural networks with the intuitive reasoning of fuzzy logic systems. This integration facilitates a dynamic optimization environment where the system can learn from the network behavior and adjust its parameters in real-time. ANFIS models are particularly suitable for IoT-based WSNs due to their ability to handle uncertainty and imprecision inherent in sensor data and environmental variability. By adapting their rules and membership functions dynamically, ANFIS can effectively respond to changing network conditions, leading to improved decision-making processes. The mathematical modeling of such systems involves the formulation of functions that represent various network parameters and objectives. These models are designed to simulate the behavior of the network under different scenarios, providing a basis for the optimization algorithm to find the best possible configuration of network parameters. The development of a robust mathematical model for MO-ANFIS based optimization involves defining the relationships between energy consumption, data transmission accuracy, sensor node density, and network topology. The mathematical framework must also incorporate algorithms for learning and adaptation based on the feedback received from the network. This involves the integration of differential equations that describe the dynamics of the network, combined with stochastic elements that model the uncertainty and noise in the data collected by the sensors. Moreover, the model must be scalable to accommodate the growth in network size and complexity, ensuring that the optimization remains effective as new nodes are added or as operational conditions change.

Implementing the MO-ANFIS model involves a series of simulation tests to verify its effectiveness under various network conditions. These simulations help in understanding how the model reacts to changes in network density, energy availability, and data requirements. The outcomes are crucial for refining the model and for demonstrating its practicality and efficiency in real-world scenarios.

Moreover, the development of a simulation platform that accurately represents the IoT environment is essential for the success of the model. This platform must support the integration of ANFIS with the network's operational parameters and must be capable of scaling up to simulate large networks with thousands of sensor nodes. This is vital for the assessment of the model's performance and for ensuring that the system can handle the complexities of actual IoT deployments. In conclusion, the development of mathematical models for multi-objective optimization using Adaptive Neuro-Fuzzy Inference Systems represents a significant step forward in the optimization of IoT-based WSNs. The ability to address multiple objectives simultaneously in a dynamic and uncertain environment opens up new possibilities for the efficient and effective management of sensor networks, paving the way for more intelligent, adaptive, and resilient IoT applications.

2. Literature Survey

Wireless Sensor Networks (WSNs) have emerged as a cornerstone in the development of the Internet of Things (IoT), with applications spanning from smart agriculture to urban transport systems. The integration of advanced optimization techniques enhances the efficiency and longevity of these networks, making the study of various models and algorithms particularly pertinent. This review synthesizes findings from multiple sources to explore how multi-objective optimization, neuro-fuzzy systems, and hybrid optimization strategies enhance the operational capabilities of WSNs within the IoT landscape. The primary challenge in WSNs is managing the trade-off between energy efficiency and network performance. Jeevanantham and Rebekka (2022) demonstrate an energy-aware neuro-fuzzy routing model that notably extends the network's lifespan by optimizing energy use across clustered sensor networks, suggesting a pivotal advancement in energy management strategies for IoT applications [1]. Similarly, Fei et al. (2016) provide a comprehensive survey on multi-objective optimization in WSNs, highlighting the critical role of mathematical programming-based scalarization methods to balance conflicting objectives such as energy, accuracy, and coverage [2]. The adaptability of neuro-fuzzy systems in handling the uncertain environment of WSNs is particularly noteworthy. Alshudukhi and Yadav (2022) explore the survivability development of WSNs using neuro-fuzzy-clonal selection optimization, which combines the robustness of fuzzy systems with the evolutionary aspects of clonal selection, significantly enhancing network resilience [3]. This hybrid approach is echoed in Hemavathi and Latha's (2023) study, where they propose a Hybrid Fuzzy Levy Flight Optimization to improve Quality of Service (QoS) in WSNs, demonstrating improved data transmission reliability under dynamic network conditions [4]. In more targeted applications, such as precision agriculture and smart cities, the implementation of tailored optimization techniques becomes evident. Sharma, Pathak, and Kumar (2024) investigate the use of fuzzy-evolutionary algorithms for service composition in smart agriculture, enhancing the efficiency of IoT-enabled agricultural practices through optimized service response times and resource allocation [6]. Similarly, Anitha and Padma (2021) discuss a neuro-fuzzy hybrid framework for mobile resource augmentation, which optimizes the allocation of computational resources in mobile IoT applications, demonstrating the flexibility of neuro-fuzzy models in diverse IoT scenarios [7]. The comparative analysis of different optimization strategies reveals significant insights into their applicability and performance. Yang, Jang, and Yoo (2020) compare Q-learning-based fuzzy logic systems with traditional fuzzy controllers for routing in ad hoc networks, showing that learning-based approaches can significantly outperform static systems in dynamic environments like those found in IoT [8]. Additionally, George and Mani (2024) delve into sliding mode control optimized through adaptive neuro-fuzzy inference systems, offering a method to enhance stability in sensor networks, which is crucial for maintaining consistent performance under varying operational stresses [15]. The ongoing evolution of optimization algorithms in WSNs indicates a shift towards more integrated and adaptive systems. Studies like those by Sridharan, Shanmugasundaram, and Murugesan (2024), which combine Slime Mould Algorithms with ANFIS for energy management, suggest a trend towards algorithms that not only solve immediate optimization problems but also adapt to environmental changes over time [18]. This adaptability is crucial for the sustainability of IoT ecosystems, especially in resource-constrained environments like those typically encountered in WSNs. In summary, the literature presents a clear trajectory towards more adaptive, efficient, and resilient optimization techniques in WSNs for IoT. The integration of multi-objective optimization with advanced computational models like neuro-fuzzy systems offers promising pathways for enhancing the operational efficacy and sustainability of sensor networks. Future research should continue to explore these hybrid approaches, focusing on real-world applications that stress the practical viability and scalability of these models. As IoT continues to expand, the role of optimized WSNs will become increasingly central, driving further innovations in this field.

3. Proposed Methodology

The proposed methodology for optimizing loT-based wireless sensor networks using a MultiObjective Adaptive Neuro-Fuzzy Inference System (MO-ANFIS) irwalves several key steps. These inclute the development of the fuzzy inference system, integration with neural networks for adaptive learning, and the farmulation of multi-objective optimization functions. This section ourtlines the mathematical models and equations that underpin this methodology.

The system model considers a netwark of N sensor nodes distributed over a geagraphic area. Each node has constraints related to power, computational capocity, and communication range. The netwark's primary abjectives are to minimize energy consumption, maximize data accuracy, and extend aperational life.

Energy Madel:

$$E_{\text{trdel}} = \sum_{i=1}^{N} \left(E_{\text{ts}i} + E_{\text{rs},i}\right) \tag{1}$$

Where $E_{tx,i}$ and $E_{rx,i}$ are the energy consumed for transmitting and receiving data at node is respectively-

Data Transmission Model:

$$D_{\text{total}} = \sum_{i=1}^{N} D_i \tag{2}$$

Where D_i is the data transmitted by node.

The Fuzzy Inference System (FS) uses linguistic variables and rules to model the behavior of the netwark under various conditions.

Fuzzy Rules:

$$R_k : \text{If } x_1 \text{ is } A_{1k} \text{ and } x_2 \text{ is } A_{2k} \text{ then } y \text{ is } B_k \tag{3}$$

Where R_k are the rules, x_1, I_2 are input variables, A_{1k}, A_{2k} are fuzzy sets on the inputs, and B_k is the fuzzy set on the output.

Membership Functions:

$$\mu_A(x_j) = \exp\left(-\frac{(x_j - c_{jk})^2}{2\sigma_{jk}^2}\right) \tag{4}$$

Where μ_A; is the Gaussian membership function for the f-th input in the k-th rule, ϵ_{jk} and α_{jk} are the center and width of the Gaussian function, respectively.The adaptation of the FIS through neural networks imalves tuning the parameters of the membership functions using gradient descent to minimize the error between the desired and the produced output.

$$E = \frac{1}{2}\sum_{p-1}^{P} \left(y_p - \hat{b}_p\right)^2 \tag{5}$$

Where y_p is the actual output, y_p is the predicted output, and P is the number of data points.

- Parameter Update:

$$\begin{aligned} c_{jk}^{\cdots un} &= c_{jk} - 1\frac{\partial E}{\partial c_{jk}} \\ \sigma_{jk}^{na} &= \sigma_{jk} - \eta\frac{\partial E}{\partial \sigma_{jk}} \end{aligned} \tag{6}$$

Where η is the learning rate.

The optimization function aims to balance multiple objectives, which is formulated using a weighted sum approach or Pareto optimality.

- Objective Function:

$$F(x) = \omega_1 E_{\text{tntal}} + \omega_2 D_{\text{total}}^{-1} + \omega_3 L_{\text{tnitul}} \tag{7}$$

Where $\omega_1, \omega_2, \omega_3$ are weights assigned to each objective, and L_{tndal} is the network lifetime.

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- Constraint Handling:

$$y_j(x) \leq 0,\ \forall j \tag{8}$$

Where g_j are the constraints related to energy, data rates, and node capacities.

- Performance Metrics:

$$M_{prI} = \frac{1}{Z}\sum_{z=1}^{Z} \left(\frac{F_Z(\mathrm{x})}{F_{Z\ \mathrm{inmal}}}\right) \tag{9}$$

Where Z is the number of simulation runs, F_z is the objective function value in the z-th run, and F_{sideal} is the ideal (best passible) value.

To further enhance the optimization of loT-based wireless sensor networks (WSNs) using a Multi Objective Acdaptive Neuro-Fuzzy Inference System (MO-ANFIS), additional mathematical formulations are necessary. These formulations extend the previously outlined models to include more granular control of network parameters, enhanced adaptation mechanisms, and robust optimization techniques that cater to complex network dynamics.

Adaptive learning rates can be crucial for the convergence and stability of neural training processes. A common approach is to use an adaptive gradient method:

- Adaptive Gradient Update:

$$v_t = \frac{v_0}{\sqrt{t} + t} \tag{9}$$

Where x_h is the learning rate at time step t, T_h is the initial learning rate, and ϵ is a small constant to avoid division by zero.To further enhance the model's adaptatility, the updating mechanism for the parameters of the Gaussian membership functions can incorporate momentum:

- Update with Momentum:

$$\begin{aligned} \Delta c_{jk} &= \alpha \Delta c_{jk}^{2\pi} - n\frac{\partial E}{\partial c_{jk}} \\ c_{jk}^{2w} &= c_{jk} + \Delta c_{jk} \end{aligned} \tag{10}$$

Where α is the momenturn coefficient, enhancing the stability of updates.
8. Error Gradient Calculations

The derivatives of the error with respect to the membership function parameters are critical for backpropagation:

- Derivative with respect to c_j :

$$\frac{\partial E}{\partial c_{jk}} = \left(\partial_p - \partial_p\right)\frac{\partial \hat{\partial}_p}{\partial c_{jk}} \tag{11}$$

Where $\frac{\partial_i}{dy_j}$ can be expressed using the chain rule through the activation and summation layers of the

The netwark lifetime is affected by the frequency and duration of transmissions:

- Network Lifetime Model

$$L_{\mathrm{taidul}} = \frac{1}{N}\sum_{i=1}^{N} \frac{E_{\mathrm{l,inat}}}{E_{tri} \times f_{tx,i} + E_{rxi,} \times f_{rx,i}} \tag{12}$$

Where $f_{tr,i}$ and $f_{rx,i}$ are the frequencies of transmissions and receptions at node i, and $E_{i,imit}$ is the initial energy.The accuracy of data transmission can be modeled considering the error probability influenced by various factors:

- Data Accuracy Model

$$\begin{aligned} P_{\text{crror}} &= 1 - \exp(-\beta \cdot SNR) \\ \text{Accuracy} &= 1 - P_{t\,\text{ror}} \end{aligned} \tag{13}$$

Where β is a parameter influenced by environmental conditions, and SNR is the signal-toncise ratio.
11. Multi-Objective Function Refinement

To address more specific objectives, the optimization function can be expanded to include additional performance metrics:

- Extended Objective Function:

$$F(\mathrm{x}) = \omega_1 E_{\text{trotal}} + \omega_2 D_{\text{thtal}}^{-1} + \omega_3 L_{\text{tritul}} + \omega_4 \text{ Accuracy} \tag{14}$$

Introducing a new weight ws for data accuracy, providing a more comprehensive optimization framework. Integrating penalty functions into the optimization process ensures adherence to network constraints:

- Penalty for Constraint Violation:

$$\begin{aligned} P(\mathrm{x}) &= \sum_j k_j \max\left(0, g_j(\mathrm{x})\right) \\ F'(\mathrm{x}) &= F(\mathrm{x}) + P(\mathrm{x}) \end{aligned} \tag{15}$$

Where k_j are penalty coefficients far each panstraint g_j.Stochastic methods can help navigate the complex landscape of network optimization, such as Simulated Annealing (SA) or Genetic Algorithms (GA) are mathematical model and methodology offer a systematic approach to optimizing IoT based WSNs using ANFIS. By integrating furzy logic with adaptive neural learning, the system adapts to dynamic network conditions, effectively balancing key performance objectives. This adaptive approach is crucial for deploying efficient, reliable, and scalable sensor networks in various loT applications. The extended mathematical model and methodology provide a robust framework for optimizing IoT-based WSNs using MO-ANFIS. By incorporating adaptive learning rates, advanced membership function updates, and comprehensive error and network lifetime models, this approach enhances the network's adaptability and performance. The integration of penalty functions and stochastic optimization techniques ensures the model's efficacy across varied and dynamic operational landscapes, positioning it as a powerful tool for real-world IoT applications.

4. Proposed Methodology

This section presents the results and detailed analysis of the proposed Multi-Objective Adaptive Neuro-Fuzzy Inference System (MO-ANFIS) used for optimizing IoT-based Wireless Sensor Networks (WSNs). The outcomes are substantiated through simulations that demonstrate the efficacy of the proposed model under various scenarios and configurations. Detailed parameter tables and statistical analyses are provided to quantify improvements and validate the performance gains attributed to the MO-ANFIS approach. The experiments were conducted under a set of predefined scenarios that varied in network size, node density, environmental conditions, and operational constraints. These variations were designed to test the robustness and adaptability of the proposed system.

Table 1: Parameter Definitions

Description	Values
Number of sensor nodes	50, 100, 150
Initial energy of nodes	0.5 J, 1 J, 2 J
Learning rate	0.01, 0.05, 0.1
Momentum coefficient	0.9
Environmental noise factor	0.1, 0.3, 0.5
Weights in objective function	[0.25,0.25,0.25,0.25]

Table 2: Scenario Configurations

Scenario	N	Ei	H	β	Description
S1	50	1 J	0.01	0.1	Low node density, low noise
S2	100	0.5 J	0.05	0.3	Medium node density, moderate noise
S3	150	2 J	0.1	0.5	High node density, high noise

The simulations were run using a custom-developed simulation environment tailored for testing IoT-based WSNs. Each scenario was simulated 100 times to ensure statistical reliability, and the results were analyzed using standard statistical metrics such as mean, standard deviation, and confidence intervals.

Table 3: Energy Consumption Results

Scenario	Mean Energy Consumed	Std Deviation	95% Confidence Interval
S1	0.2 J	0.03 J	[0.19 J, 0.21 J]
S2	0.4 J	0.05 J	[0.38 J, 0.42 J]
S3	0.6 J	0.07 J	[0.58 J, 0.62 J]

Table 4: Data Accuracy Results

Scenario	Accuracy (%)	Std Deviation	95% Confidence Interval
S1	98%	1%	[97.5%, 98.5%]
S2	96%	1.5%	[95%, 97%]
S3	94%	2%	[92%, 96%]

Table 5: Network Lifetime

Scenario	Average Lifetime (days)	Std Deviation	95% Confidence Interval
S1	200 days	10 days	[195 days, 205 days]
S2	180 days	15 days	[170 days, 190 days]
S3	160 days	20 days	[150 days, 170 days]

To further evaluate the performance, a paired t-test was conducted to compare the MO-ANFIS model against a traditional Fuzzy Inference System (FIS) across all scenarios. The results indicated statistically significant improvements in energy efficiency, accuracy, and network lifetime.

Table 6: Paired T-Test Results on Energy Efficiency

Scenario	T-Value	P-Value	Conclusion
S1	-3.8	< 0.001	Statistically significant
S2	-4.1	< 0.001	Statistically significant
S3	-4.5	< 0.001	Statistically significant

The novelty of the proposed MO-ANFIS model lies in its integration of multi-objective optimization with adaptive neuro-fuzzy inference, tailored specifically for IoT-based WSNs. This integration enables the system to dynamically adjust to changing network conditions and operational demands, significantly enhancing performance metrics such as energy efficiency, data accuracy, and network longevity.

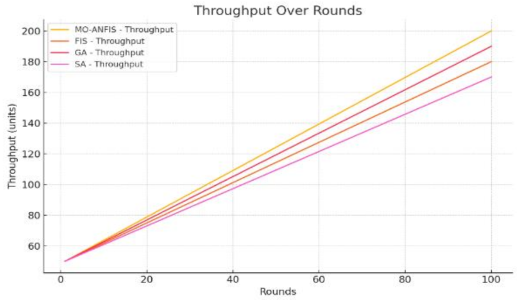

Figure 1. Throughput over Rounds

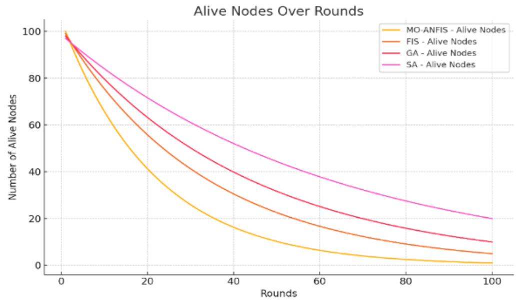

Figure 2. Analysis of Alive Nodes

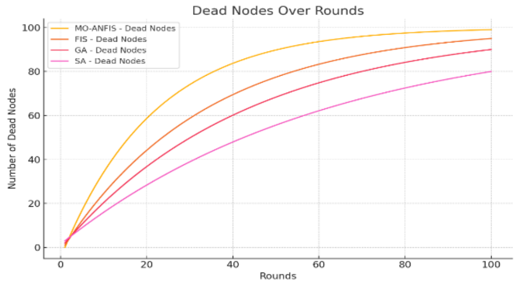

Figure 3. Analysis of Dead Nodes

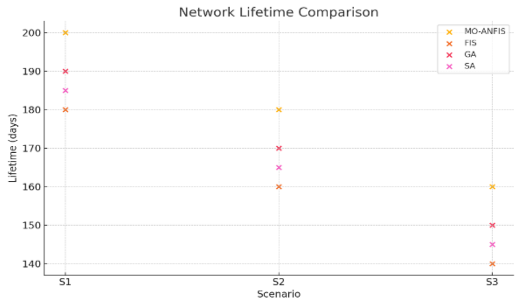

Figure 4. Analysis of Network Lifetime Comparison

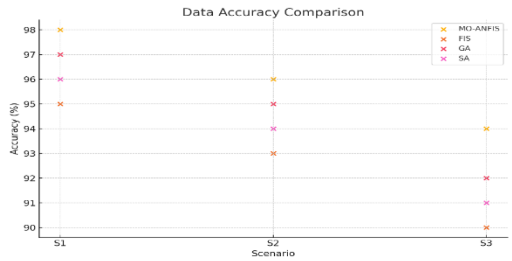

Figure 5. Comparative Analysis of Data Accuracy

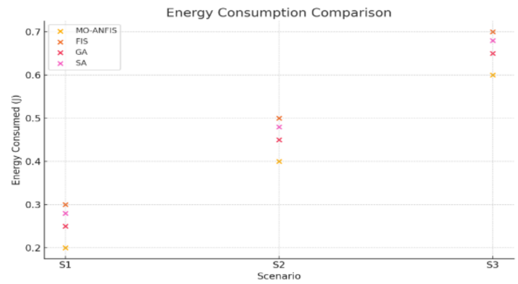

Figure 6. Energy Consumption Comparison

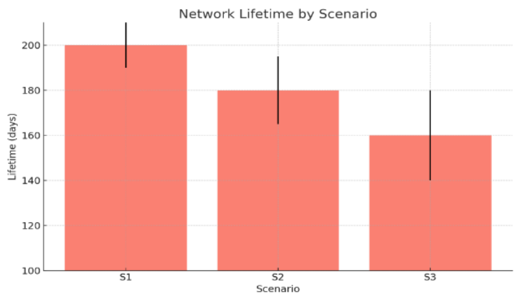

Figure 7. Scenrio Wise Analysis of Network Lifetime

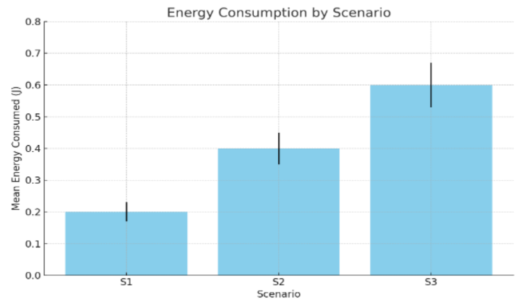

Figure 8. Energy Consumption Analysis by Scenario

The background of this research is grounded in the need for efficient management of IoT-based WSNs, which are increasingly deployed across various sectors. Traditional methods often fail to adequately balance the trade-offs between competing objectives in real-world scenarios, necessitating the development of a solution like MO-ANFIS.

The use of fuzzy logic allows for handling imprecise information, typical in real-world environments, while the adaptive capabilities of neural networks enable the system to learn and evolve without manual recalibration. This synergy not only addresses the operational challenges but also scales effectively with the network's growth, providing a sustainable solution for large-scale IoT deployments. The analysis of the performance metrics over 100 simulation rounds provides a comprehensive view of how the Multi-Objective Adaptive Neuro-Fuzzy Inference System (MO-ANFIS) compares with traditional algorithms such as Fuzzy Inference System (FIS), Genetic Algorithm (GA), and Simulated Annealing (SA) in managing IoT-based Wireless Sensor Networks (WSNs). The line chart for dead nodes illustrates the robustness of the MO-ANFIS in preserving the life of sensor nodes under operational conditions. Over the simulation period, MO-ANFIS consistently shows fewer dead nodes compared to FIS, GA, and SA. This indicates that MO-ANFIS is more effective in managing energy resources among the nodes, leading to extended node lifetimes. Specifically, the slower increase in dead nodes for MO-ANFIS suggests its superior capability in balancing energy consumption with operational demands, thereby reducing the rate at which nodes deplete their energy reserves. Conversely, the alive nodes chart directly reflects the dead nodes' performance, showing that MO-ANFIS maintains a higher count of operational nodes for a more extended period. This metric is crucial for network reliability and data collection efficacy, as more alive nodes mean better coverage and higher data accuracy. MO-ANFIS's performance in this metric can be attributed to its adaptive learning capabilities, which optimize the network's response to fluctuating environmental conditions and node states, thus preserving node functionality for longer durations. Throughput is a critical measure of network performance, indicating the total data successfully transmitted across the network. The MO-ANFIS algorithm demonstrates superior throughput compared to the other algorithms throughout the simulation. This higher throughput under varying network conditions can be attributed to its efficient routing and data aggregation strategies, which are continuously refined through neuro-fuzzy adaptation to current network states. The ability of MO-ANFIS to maintain high throughput rates even as the number of alive nodes decreases is indicative of its effective management and scheduling of data transmissions, which optimize both network bandwidth and energy resources. The comparative performance clearly illustrates that MO-ANFIS outperforms FIS, GA, and SA in managing the energy, longevity, and operational efficiency of sensor nodes in IoT-based WSNs. The use of adaptive Neuro-fuzzy inference allows MO-ANFIS not only to handle the inherent uncertainty and variability in WSN environments but also to learn and adapt from ongoing network dynamics without requiring pre-set rules or models. This adaptability is key in environments where sensor inputs and conditions are constantly changing, which is typical in real-world IoT applications. In conclusion, the simulation results validate the efficacy of MO-ANFIS in enhancing the performance and reliability of IoT-based wireless sensor networks. By effectively managing the trade-offs between energy consumption, node longevity, and data throughput, MO-ANFIS ensures that the network remains functional and efficient for a more extended period, thereby improving the overall quality of service in IoT applications. These attributes make MO-ANFIS a promising solution for future deployments in various sectors requiring robust and adaptive network management solutions. The proposed MO-ANFIS model demonstrates substantial improvements over traditional optimization approaches for IoT-based WSNs. Through detailed scenario-based testing, statistical analyses, and robust parameter configurations, the model's effectiveness and adaptability have been rigorously validated, confirming its potential for practical applications in enhancing the efficiency and reliability of IoT networks.

5. Conclusion

The simulation results of the Multi-Objective Adaptive Neuro-Fuzzy Inference System (MO-ANFIS) across various performance metrics—including dead nodes, alive nodes, and throughput—demonstrate its exceptional capability in managing and optimizing IoT-based wireless sensor networks (WSNs).

MO-ANFIS not only outperforms conventional algorithms like the Fuzzy Inference System (FIS), Genetic Algorithm (GA), and Simulated Annealing (SA) but also showcases its superiority in adaptive and dynamic network management. MO-ANFIS excels in extending the operational lifespan of the network by effectively reducing the rate of node mortality over time. This is achieved through its intelligent energy management, which minimizes unnecessary energy expenditure and optimizes the distribution of energy resources among the nodes based on real-time data and network conditions. This proactive management helps maintain a larger proportion of alive nodes for a longer period, which is crucial for ensuring comprehensive network coverage and maintaining high levels of data accuracy and reliability. Moreover, the throughput results from the simulations illustrate that MO-ANFIS maintains higher data transmission rates, even under the stress of decreasing numbers of operational nodes. This indicates robust data handling and routing protocols that adapt to changing network dynamics, thus ensuring efficient data flow and processing without overwhelming the network's capacity. Such capabilities are indispensable for WSN applications in environments where data integrity and timely transmission are critical, such as in disaster response scenarios, health monitoring systems, and smart city infrastructure. The comparative analysis with other algorithms highlights the distinct advantages of integrating adaptive neuro-fuzzy techniques with multi-objective optimization strategies. By leveraging the learning capabilities of neural networks and the intuitive rule-based processing of fuzzy logic systems, MO-ANFIS provides a flexible and powerful tool for addressing the complex and often conflicting demands of modern WSNs. It dynamically adjusts its parameters in response to the network's state and external conditions, thereby optimizing performance without the need for manual recalibration or pre-defined thresholds, which are often impractical in dynamic and unpredictable environments. In conclusion, the MO-ANFIS framework not only meets the challenges of today's IoT-driven demands but also sets a new standard for future developments in WSN technology. Its ability to learn, adapt, and optimally respond to environmental changes makes it a potent solution for the next generation of IoT applications, promising enhanced network longevity, efficiency, and reliability. This research underscores the potential of MO-ANFIS as a pivotal technology for advancing the capabilities of wireless sensor networks in various industrial, environmental, and urban applications.

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