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An Adaptive Federated Learning Model for Fault Detection and Node Reuse Using Deep Learning Mechanism in Wireless Sensor Networks

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Abstract: The growing complexity of Wireless Sensor Networks (WSNs) within Internet of Things (IoT) enabled applications presents significant challenges related to fault detection, energy efficiency, and network resilience. Node failures can cause severe disruptions, leading to increased energy consumption, data loss, and reduced network lifespan. Conventional fault detection methods lack flexibility when dealing with node relocations, while machine learning-based techniques often overlook energy efficiency considerations. This research proposes the Adaptive Federated Learning for Fault Detection and Node Reuse (AFL-FDNR) framework, which combines federated learning with Deep Q-Network (DQN) to provide an adaptive, energy-efficient solution for fault detection and node recovery. Federated learning ensures scalable, privacy-preserving model training across sensor nodes, while DQN optimizes node recovery decisions based on real-time network conditions. Simulation results demonstrate that AFL-FDNR achieves 96.01% fault detection accuracy, reduces energy consumption to 1910 J, and extends network lifetime to 11,452 hours. These metrics demonstrate the framework's ability to enhance the reliability, efficiency, and sustainability of large-scale WSNs, making it a robust solution for modern IoT applications.

Keywords – Internet of things, Wireless sensor Network, Fault Detection, Node Reuse, Auto Encoder, Deep Q-Network, AFL-FDNR, Adaptive Frame work, Federated Learning Coordinator, Global Model Aggregation.

I. INTRODUCTION

WSNs are integral to IoT-enabled applications, offering scalable and flexible solutions for continuous data collection and transmission in various environments, from industrial settings to environmental monitoring [1]. These networks consist of distributed sensor nodes that autonomously gather and relay data to a central base station, enabling real-time decision-making critical for automation and smart infrastructure. WSNs are particularly valuable in IoT for their ability to function in remote or challenging areas, although their performance is often limited by the energy constraints of sensor nodes, necessitating the development of energy-efficient and fault-tolerant mechanisms to ensure network sustainability and effectiveness[2]. Node failures in WSNs present serious challenges that significantly impact the network's performance, dependability, and energy consumption. When a node becomes non-functional whether due to hardware breakdowns, environmental conditions, or battery depletion it results in immediate data loss, creating voids in the continuous data flow essential for IoT systems [3]. Such failures also disturb established communication routes, necessitating the redirection of data through the remaining operational nodes. These rerouting increases the energy demands on these nodes, hastening their own potential failures and setting off a chain reaction that shortens the network's overall lifespan. As a result, the network's capacity to provide precise, real-time data is compromised, leading to decreased reliability, increased maintenance needs, and higher operational expenses. To counter these challenges, it is imperative to develop sophisticated fault detection systems and energy-efficient protocols that can quickly identify and address node failures, thereby maintaining network stability and extending its operational duration [4].

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The increasing complexity of modern networks necessitates the implementation of efficient fault detection and node reuse strategies to improve resilience and extend network lifetime, as node failures can severely disrupt communication, elevate latency, and compromise overall reliability. Employing advanced fault detection techniques, such as machine learning and deep learning algorithms, enables rapid identification and isolation of faulty nodes, ensuring swift corrective measures can be taken [5]. Simultaneously, strategic node reuse approaches ranging from redundancy and adaptive routing to energy-efficient protocols foster an agile network environment capable of dynamically adjusting to failures while conserving energy and maintaining performance [6-8]. Together, these strategies not only mitigate the adverse effects of node failures but also create robust networks that thrive under pressure, ultimately enhancing their longevity and operational effectiveness in an increasingly interconnected world. In this research, the proposed AFL-FDNR framework effectively addresses critical challenges in WSNs, particularly within IoT-enabled applications where network reliability, energy efficiency, and longevity are crucial. Traditional fault detection and recovery strategies often fall short in scalability and adaptability, especially in large, dynamic WSN environments prone to node failures from energy depletion, hardware issues, or environmental factors. The integration of federated learning in AFL-FDNR enables distributed model training across sensor nodes without the need to exchange raw data, preserving privacy and reducing communication overhead, which is vital in resource-constrained WSNs. This distributed approach enhances fault detection accuracy as the network scales. Additionally, DQN is employed to optimize the recovery strategies for faulty nodes, allowing the framework to learn and adapt to the network's dynamic conditions. DQN's continuous learning capability ensures that the framework efficiently manages energy consumption and node recovery, ultimately extending the network's operational life and improving overall performance. The key contributions of this research are as below.

1. **Efficient Fault Detection**: AFL-FDNR enhances fault detection accuracy through federated learning, which enables distributed model training across nodes, improving precision without compromising data privacy.
2. **Adaptive Node Recovery**: The framework optimizes node recovery with DQN, effectively reintegrating faulty nodes and significantly enhancing network resilience and operational longevity.

The rest of this paper is organized as follows. Section II presents a comprehensive review of related work in the field of fault detection and node reuse in WSNs. Section III presents the system model and design, including the problem formulation. The implementations of the proposed AFL-FDNR framework are discussed in Section IV. In Section V, the experimental setup and empirical evaluation of AFL-FDNR are presented, including empirical results and comparative analyses. The paper concludes in Section VI with a discussion of future research directions.

II. RELATED WORK

The growing complexity of WSNs in IoT applications has spurred research into improving reliability, energy efficiency, and fault tolerance. This review examines recent advancements, including deep learning, hybrid reasoning models, and autonomous systems, which address key challenges in fault detection and node recovery. These innovations have shaped the development of the AFL-FDNR framework, a scalable, adaptive solution designed to meet the evolving demands of modern WSNs.

Huang et al. [9] proposed a resilient routing mechanism for WSNs that utilizes deep learning to predict link reliability, enhancing the robustness of data transmission in dynamic environments. Their approach focuses on improving routing decisions based on predicted link quality, thereby mitigating the impact of node failures and ensuring more reliable communication. In a complementary study, Pang et al. [10] proposed a malicious node detection strategy for WSNs that combines a fuzzy trust model with the Artificial Bee Colony (ABC) algorithm. The fuzzy trust model evaluates node trustworthiness based on factors like energy consumption and packet delivery ratio, allowing for nuanced assessments. The ABC algorithm optimizes trust thresholds to minimize false positives and negatives in detecting malicious nodes. Simulation results show that their approach outperforms existing methods, achieving higher detection accuracy, particularly in networks with a greater number of malicious nodes, thus enhancing the effectiveness of detection in dynamic environments. The recent papers on deep learning-based fault detection in WSNs present a variety of approaches to enhance the identification and management of node failures. Regin et al. [11] introduced a fault detection model that employs a combination of a convex hull algorithm, Naïve Bayes classifier, and CNNs to detect faults in a fully distributed manner. Their findings indicate that the CNN outperforms traditional methods in identifying node faults, emphasizing the effectiveness of deep learning in this context. Kumar et al. [12] focused on malicious node detection and energy-efficient data transmission using an improved deep convolutional neural network, highlighting the dual challenges of maintaining security and efficiency in WSNs. Additionally, Sun et al. [13] proposed a fault diagnosis model based on a belief rule base with adaptive attribute weights, which enhances the accuracy of fault detection by incorporating expert knowledge and optimizing model parameters through advanced algorithms. Collectively, these studies illustrate the potential of deep learning and adaptive methodologies to significantly improve fault detection and management in wireless sensor networks, addressing critical issues of reliability and security. Prasad and Baghel [14] proposed a Deep Belief Network (DBN) based self-detection algorithm to enhance fault diagnosis in WSNs, addressing issues related to low detection accuracy and high false alarm rates in existing methods. Their approach demonstrates improved performance in terms of detection accuracy, false alarm rate, and energy consumption, making it suitable for large-scale networks. Shi et al. [15] introduced a fault diagnosis model that combines a Belief Rule Base with Adaptive Attribute Weights (BRB-AAW) to improve fault detection accuracy in WSN nodes. The model utilizes extracted numerical features from neighboring nodes and employs an optimization algorithm to enhance performance, showing significant improvements over conventional methods. Sun et al. [16] further developed a WSN node fault diagnosis model based on a belief rule base with a self-adaptive quality factor.

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This work emphasizes the importance of adapting to different environments while maintaining high accuracy in fault detection. Qiu et al.[17] discussed the challenges and prospects of deploying deep learning in WSNs, emphasizing the need for robust algorithms that can handle the unique constraints of these networks, such as limited computational resources and energy efficiency. They outlined potential applications and the importance of addressing data quality and model interpretability. In this context, Ye et al. [18] introduced a self-supervised learning-based method for anomalous node detection using an autoencoder, which aims to improve the detection of outliers without extensive labeled datasets. This method leverages the strengths of self-supervised learning to enhance the adaptability and effectiveness of anomaly detection in dynamic environments. In a recent study, Suresh et al. [19] introduced an innovative routing strategy leveraging Federated Deep Reinforcement Learning (FDRL) to optimize data routing in IoT-enabled wireless sensor networks (WSNs). This approach models the routing challenge as a Markov decision process and employs deep Q-learning to allow multiple IoT devices to collaboratively discover optimal routing strategies while maintaining data privacy. The strategy features adaptive routing that responds dynamically to real-time network conditions, ensures efficient resource management through load balancing, and minimizes energy usage by intelligently selecting the next hop. Simulation results reveal substantial enhancements in packet delivery ratio, reduced end-to-end delay, and extended network lifetime compared to conventional protocols, underscoring FDRL's potential in creating intelligent, adaptive routing mechanisms for WSNs. These works highlight various strategies to enhance the robustness and sustainability of WSNs, using deep learning for predictive fault detection, hybrid models for handling sparse data, and autonomous systems for self-recovery. These approaches provide a strong foundation for the AFL-FDNR framework, which combines federated learning for scalable, privacy-preserving model training and deep reinforcement learning (DQN) for optimized node recovery and reuse. This integration makes AFL-FDNR a comprehensive solution for addressing the challenges of fault detection, energy efficiency, and network resilience in WSNs.

III. SYSTEM MODEL AND DESIGN

A. Problem Definition

In this research, the fault detection and node reuse problem is formulated as the development of an energy-efficient and adaptive solution for identifying faulty nodes and enabling their recovery within IoT-enabled WSNs. This involves creating a robust mechanism that not only detects when a node becomes faulty but also determines the optimal conditions under which the node can be restored and reused as described below.

Fault Detection Problem: Let $\mathcal{N} = \{n_1, n_2, \dots, n_m\}$represent the set of sensor nodes in the WSN, where n_i denotes the i-th node in the network. Each node n_i is characterized by a state vector$\mathbf{x_i}$, containing features such as residual energy E_i, signal strength S_i, packet loss rate P_i, and other relevant metrics. The objective is to determine whether a node n_i is faulty based on its state vector$\mathbf{x_i}$. The fault detection problem can be formulated as a binary classification task as in (1), where $f(\cdot)$ is the decision function learned by the model.

$$f(\mathbf{x_i}) = \begin{cases} 1 \text{ if } n_i \text{ is faulty} \\ 0 \text{ if } n_i \text{ is normal} \end{cases} \quad (1)$$

Node Reuse Problem: Once a node $n_i$is detected as faulty($f(\mathbf{x_i}) = 1$), the goal is to assess whether the node can be recovered and reintegrated into the network. The node reuse problem involves determining the optimal recovery action a_i that maximizes the node's remaining operational life while minimizing energy consumption. The decision to reuse a node can be expressed as in (2), where $r(\cdot)$represents the recovery function, which is dependent on the current state $\mathbf{x_i}$ and the expected energy consumption.

$$r(\mathbf{x_i}) = \begin{cases} 1 \text{ if } n_i \text{ can be recovered and reused} \\ 0 \text{ if } n_i \text{ should be excluded} \end{cases} \quad (2)$$

Optimization Objective: The primary objective is to minimize the overall energy consumption $\mathcal{E}$ of the network while maximizing the network's operational lifetime$\mathcal{L}$. This can be formulated as a multi-objective optimization problem as in (3&4), where $\mathbf{w}$ represents the model parameters, and $\mathbb{I}(\cdot)$ is the indicator function that is 1 if the condition is true and 0 otherwise.

$$\min_{w} \mathcal{E}(w) = \sum_{i=1}^{m} E_i \cdot \mathbb{I}(r(x_i) = 1) \quad (3)$$

$$\max_{w} \mathcal{L}(\mathbf{w}) = \sum_{i=1}^{m} \mathbb{I}(f(x_i) = 0 \text{ OR } r(x_i) = 1) \quad (4)$$

The challenge is to develop a model $f(\mathbf{x_i})$and a recovery strategy $r(\mathbf{x_i})$ that balance the trade-off between energy consumption and network longevity, ensuring that the network remains functional with minimal resource depletion. The proposed AFL-FDNR model addresses this challenge by leveraging federated learning and deep reinforcement learning to provide an adaptive, distributed, and energy-efficient solution.

IV. PROPOSED AFL-FDNR

This section presents the AFL-FDNR framework, which is designed to enhance the reliability and lifespan of IoT-enabled WSNs through efficient fault detection and node reuse. The framework comprises key components including Sensor Nodes with Local Models, Auto encoder for Anomaly Detection, Deep Q-Networks (DQN) for Fault Classification, Recovery Decision Mechanisms, Adaptive Node Recovery Mechanisms, a Federated Learning Coordinator, and Global Model Aggregation.

1. Sensor Nodes with Local Models

Each sensor node in the WSN is equipped with a local model that processes operational data such as energy levels and signal strength. This decentralized approach allows nodes to independently detect anomalies and make decisions, reducing communication overhead and preserving data privacy. Each sensor node $n_i \in \mathcal{N}$ is equipped with a local model that processes operational data, represented by a state vector $x_i = [E_i, S_i, P_i, \dots]$,

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where E_i is the residual energy, S_i is the signal strength, and P_i is the packet delivery ratio. The local model is defined as a function $f_i(x_i, w_i)$, where w_i are the model parameters learned locally. The model outputs a decision d_i, which is used to determine if an anomaly is detected as in (5).

$$d_i = f_i(\boldsymbol{x}_i, \boldsymbol{w}_i) \quad (5)$$

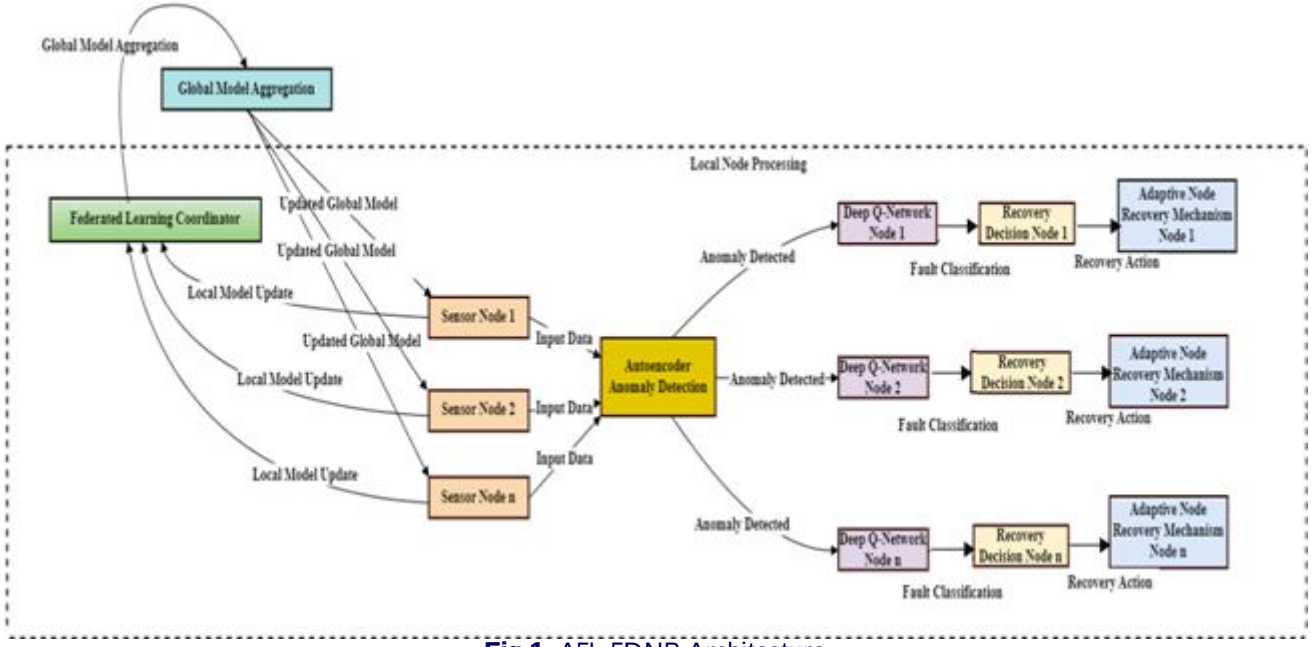


Fig.1. AFL-FDNR Architecture

2. Autoencoder for Anomaly Detection

The autoencoder is used to detect anomalies in the input data $\boldsymbol{x}_i$. The autoencoder consists of an encoder $\phi(\cdot)$ and a decoder $\psi(\cdot)$. The input data $\boldsymbol{x}_i$ is encoded into a latent representation $\boldsymbol{z}_i = \phi(\boldsymbol{x}_i)$ and then reconstructed as $\hat{\boldsymbol{x}}_i = \psi(\boldsymbol{z}_i)$. The reconstruction error ϵ_i is calculated as in (6). $\epsilon_i = \| \boldsymbol{x}_i - \hat{\boldsymbol{x}}_i \|$ (6)

If ϵ_i exceeds a predefined threshold ϵ_{th}, the node is flagged for potential fault as in (7).

$$\text{Anomaly Detected} \Leftrightarrow \epsilon_i > \epsilon_{\text{th}} \quad (7)$$

3. DQN for Fault Classification

Upon detecting an anomaly, the DQN evaluates the node's state $\boldsymbol{x}_i$and selects an action a_i from the action space $\mathcal{A}$ = {Normal,Faulty} that maximizes the expected reward. The state-action value function $Q(\boldsymbol{x}_i, a_i; \theta)$ is defined as in (8), where θ represents the DQN parameters, r_i is the reward, γ is the discount factor, and $\boldsymbol{x}_i'$ is the next state. The optimal action a_i^* is selected as in (9).

$$Q(\boldsymbol{x}_i, a_i; \theta) = \mathbb{E}[r_i + \gamma \max_{a'} Q(\boldsymbol{x}_i', a'; \theta') \mid \boldsymbol{x}_i, a_i] \quad (8)$$

$$a_i^* = arg \max_{a_i \in \mathcal{A}} Q(\boldsymbol{x}_i, a_i; \theta) \quad (9)$$

4. Recovery Decision Mechanism

If the DQN classifies the node as faulty, the recovery decision mechanism evaluates whether the node can be recovered. This decision is based on the expected recovery benefit R_i, calculated as in (10), where $U_i(t)$ is the utility of the node at time t, $C_i(t)$ is the cost of recovery, and T is the remaining operational time. The node is recovered ifR_i>R_{th}, where $R_{th}$is a predefined threshold.

$$R_i = \mathbb{E}[\sum_{t=0}^{T} \quad \gamma^t \cdot (U_i(t) - C_i(t))] \quad (10)$$

5. Adaptive Node Recovery Mechanism

This mechanism implements the selected recovery action a_i^* that minimizes the energy consumption $E_{i(t)}$ and maximizes the utility $U_i(t)$ over time. The new state $\mathbf{x}_i'$ after applying the action is updated as in (11), where$\Delta \mathbf{x}_i(a_i^*)$represents the change in the state vector due to the recovery action.

$$\mathbf{x}_i' = \mathbf{x}_i + \Delta \mathbf{x}_i(a_i^*) \quad (11)$$

6. Federated Learning Coordinator

This component aggregates local model updates $\Delta \mathbf{w}_i$ from each sensor node. The global model $\mathbf{w}^G$ is updated as in (12), where η is the learning rate and m is the number of nodes.

$$\mathbf{w}^G = \mathbf{w}^G + \eta \sum_{i=1}^{m} \quad \Delta \mathbf{w}_i \quad (12)$$

7. Global Model Aggregation

This process combines the local updates to produce a unified global model that is redistributed to all sensor nodes. Each node's local model is updated as in (13). This ensures that all nodes benefit from the collective learning, improving the accuracy and adaptability of fault detection and recovery across the network.

$$\mathbf{w}_i \leftarrow \mathbf{w}^G \quad (13)$$

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V. SIMULATION AND PERFORMANCE EVALUATION

This section presents the simulation setup and performance evaluation of the AFL-FDNR framework using the NS-3 simulator. The simulations replicate real-world IoT-enabled WSN conditions, focusing on fault detection accuracy, energy consumption, and network lifetime. Key details on network topology, traffic models, fault scenarios, and evaluation parameters are provided, offering insights into AFL-FDNR's effectiveness in improving WSN reliability and efficiency.

Simulation Setup

The performance of the AFL-FDNR framework was assessed using the NS-3 simulator in a realistic IoT-enabled WSN environment. The selection of hyperparameters for the AFL-FDNR framework was optimized using grid search, a methodical approach to explore a predefined set of hyperparameter values. Key parameters, including the DQN learning rate, discount factor γ, and batch size, were varied across a grid of possible values. The combination that yielded the best performance in terms of fault detection accuracy and energy efficiency during cross-validation was selected for the final model. The hyperparameters of the model are listed in Table 1. The network comprised 500 sensor nodes randomly deployed over a 500 × 500m^2 area, organized into clusters with designated cluster heads. Each node had an initial energy of 2J and a communication range of 100 meters. Communication was based on a TDMA protocol to minimize energy consumption and interference. Traffic was modeled with each node generating periodic data packets (512 bytes) at 1-second intervals, routed to a central sink node. The IEEE 802.15.4 standard governed wireless communication, accounting for free space and multi-path fading with a path loss exponent of 3.5. Random faults, including energy depletion and hardware malfunctions, were introduced to 20% of the nodes during the simulation. The DQN-based recovery mechanism evaluated these faults and attempted recovery actions such as adjusting duty cycles or transmission power. Federated learning was implemented with each node training its local model every 10 epochs. The Federated Learning Coordinator aggregated these updates using the FedAvg algorithm and redistributed the global model every 50 rounds. Model hyperparameters included a DQN learning rate of 0.01, a discount factor =0.95, and a batch size of 32.

Table 1. AFL-FDNR Hyperparameters

Parameter	Value
Network Area	500 × 500 m²
Number of Sensor Nodes	500
Initial Energy per Node	2 J
Communication Range	100 m
Traffic Model	Periodic, Inter-arrival time: 1 s
Packet Size	512 bytes
Communication Standard	IEEE 802.15.4
Path Loss Exponent	3.5
Fault Injection Rate	20% of nodes
Local Model Training Frequency	Every 10 epochs
Global Model Update Frequency	Every 50 rounds
DQN Learning Rate	0.01
DQN Discount Factor (γ)	0.95
DQN Batch Size	32

Performance Evaluation

The AFL-FDNR framework was evaluated using key performance metrics to assess its effectiveness in enhancing the reliability and efficiency of IoT-enabled Wireless Sensor Networks (WSNs). These metrics include Fault Detection Accuracy (FDA), Energy Consumption (EC), Network Lifetime (NL), and Recovery Success Rate (RSR). Each metric is defined below, emphasizing its significance and implications for WSN performance. FDA measures the percentage of correctly identified faulty nodes out of all actual faults introduced in the network as in (14). It is crucial for ensuring network reliability, as high accuracy reduces the risk of undetected faults that could lead to data loss and network disruptions. Accurate fault detection allows for timely and appropriate recovery actions, maintaining the overall performance of the WSN.

$$\text{FDA} = \frac{\text{Total number of actual faults}}{\text{Number of correctly detected faults}} \times 100\% \quad (14)$$

EC refers to the total energy used by all sensor nodes during network operation, including data transmission, processing, and recovery activities as in (15). Minimizing energy consumption is vital for extending the operational life of the network, especially in resource-constrained environments. The AFL-FDNR framework focuses on optimizing energy use by efficiently detecting and recovering faulty nodes, thereby reducing unnecessary energy expenditure.

$$\text{EC} = \sum_{\{i=1\}}^{m} E_{i(t)} \quad (15)$$

NLis the duration until a significant portion (e.g., 50%) of the network nodes are depleted of energy. It serves as an indicator of the network's sustainability and resource management. A longer network lifetime reflects the framework's ability to manage energy resources effectively, allowing the network to remain operational for a more extended period without requiring frequent node replacements.

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RSR represents the percentage of faulty nodes that are successfully recovered and reintegrated into the network as in (16). This metric highlights the effectiveness of the AFL-FDNR framework in restoring the functionality of nodes that would otherwise be lost. A high recovery success rate enhances network resilience and continuity, reducing the need for additional resources and maintaining consistent network performance.

$$RSR = \left(\frac{\text{Number of successfully recovered nodes}}{\text{Total number of detected faulty nodes}}\right) \times 100\% \quad (16)$$

Table 1 presents the performance metrics achieved by the AFL-FDNR. The evaluation of the AFL-FDNR framework shows significant improvements in IoT-enabled WSNs as network size increases from 100 to 500 nodes. Fault Detection Accuracy (FDA) rises from 91% to 96%, demonstrating the effectiveness of federated learning in refining model accuracy. Simultaneously, Energy Consumption (EC) decreases from 2487 J to 1910 J, highlighting efficient resource management. Network Lifetime (NL) extends from 8235 to 11452 hours, reflecting successful adaptive recovery strategies. The Recovery Success Rate (RSR) also improves from 82% to 93%, underscoring the robustness of the DQN model in reintegrating faulty nodes. These results affirm AFL-FDNR as a scalable and effective solution for enhancing WSN reliability, efficiency, and longevity. These metrics indicate that the AFL-FDNR framework significantly enhances the performance of IoT-enabled WSNs as network size increases. The framework improves FDA by leveraging FL, which refines model precision with more data. It also reduces EC through efficient resource management, extending NL by optimizing energy use and preventing premature node failures. Additionally, the improved RSR reflects the robustness of the DQN model in effectively recovering and reintegrating faulty nodes. Collectively, these improvements demonstrate that AFL-FDNR is a highly scalable and effective solution for maintaining the reliability, efficiency, and longevity of large-scale WSNs.

Table 2. AFL-FDNR Performance Metrics

Metric	No. of Nodes				
	100	200	300	400	500
FDA (%)	91.23	93.21	94.03	95.61	96.01
EC (J)	2487	2341	2198	2053	1910
NL (hours)	8235	9050	9883	10627	11452
RSR (%)	82.01	85.21	87.30	90.06	96.12

For a fair comparison, the performance of the AFL-FDNR is compared with the state-of-the-art models, evaluated on a network with 500 nodes in Table 3.The results in Table 3 demonstrate that the AFL-FDNR framework outperforms other state-of-the-art models across key metrics. With a FDA of 96.01%, AFL-FDNR surpasses BRB-AAW, Autoencoder, and FDRL models, highlighting its precision in fault detection. It also leads in energy efficiency, consuming only 1910 J, significantly less than the other models, due to its optimized resource management. AFL-FDNR extends network lifetime to 11452 hours, reflecting its effective adaptive recovery strategies. Additionally, its RSR of 96.12% indicates superior node reintegration capabilities. These results confirm AFL-FDNR's architectural strengths, making it a highly effective and sustainable solution for IoT-enabled WSNs.

Table 3. Comparison with State-of-the-art

Model	Metric			
	FDA (%)↑	EC (J)↓	NL (hours) ↑	RSR (%)↑
BRB-AAW [15] (2024)	86.47	5096	8509	87.01
Autoencoder [18] (2024)	89.65	4209	9870	88.23
FDRL [19] (2024)	91.21	2185	10387	94.01
AFL-FDNR (Proposed)	96.01	1910	11452	96.12

The AFL-FDNR framework surpasses state-of-the-art models by seamlessly integrating federated learning and DQN to deliver unparalleled fault detection, energy efficiency, and network resilience. Through federated learning, the framework achieves distributed model training that enhances accuracy and scalability, all while maintaining data privacy. The DQN element intelligently adapts to dynamic network conditions, optimizing the recovery and reintegration of faulty nodes, thus preventing cascading failures and significantly extending network lifespan. Furthermore, AFL-FDNR employs sophisticated resource management strategies that prioritize critical operations, reducing energy consumption and ensuring sustained network performance. This combination of cutting-edge technologies makes AFL-FDNR a powerful and adaptive solution, perfectly tailored to the demands of modern IoT-enabled WSNs. Figure 2 illustrates the recovery decision mechanism within the AFL-FDNR framework, highlighting the relationship between a node's utility, recovery cost, and the expected recovery benefit over time. As time progresses, the utility of the node decreases, reflecting its diminishing value, while the recovery cost increases, indicating the growing resources required restoring the node as its condition deteriorates. The expected recovery benefit, calculated as the discounted sum of utility minus cost, initially rises, reaches a peak, and then declines. The predefined recovery threshold serves as a benchmark to determine whether a node should be recovered. If the expected recovery benefit exceeds this threshold, it indicates that the node's recovery is advantageous, thereby justifying the allocation of resources to extend the node's operational life. This intelligent decision-making process, driven by the deep reinforcement learning component of AFL-FDNR, ensures that node recovery is both efficient and beneficial, contributing to the overall resilience and longevity of the network. By optimizing when and how nodes are recovered, AFL-FDNR effectively manages energy consumption and maintains network performance, making it a robust solution for fault management in IoT-enabled WSNs.

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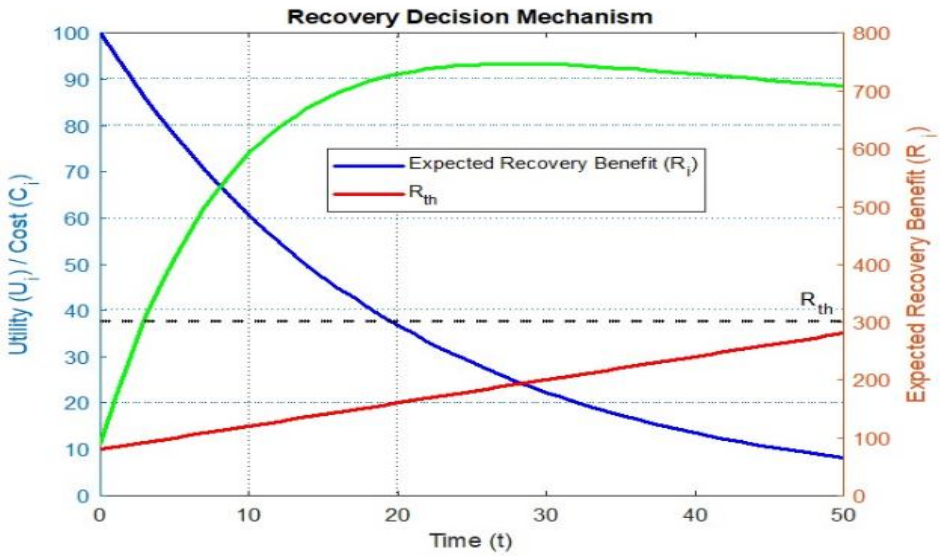


Fig. 2. Node Recovery Decision Analysis in AFL-FDNR

The AFL-FDNR framework delivers significant advancements in fault detection accuracy, energy efficiency, and network resilience, outperforming state-of-the-art models across key performance metrics. By integrating federated learning for distributed model training and deep reinforcement learning (DQN) for dynamic node recovery, the framework ensures that WSNs maintain operational longevity while minimizing energy consumption. The ability of AFL-FDNR to adapt to changing network conditions and optimize resource management makes it an essential solution for large-scale IoT-enabled WSN deployments. The findings from this evaluation underscore the potential of AFL-FDNR to enhance network sustainability, making it a promising approach for addressing the challenges faced by modern WSNs.

VI. CONCLUSION

This research presents the AFL-FDNR framework, addressing key challenges in WSNs by integrating federated learning and DQN. AFL-FDNR significantly improves fault detection accuracy, reduces energy consumption, and extends network lifetime, proving its effectiveness in enhancing network reliability and sustainability. The framework not only overcomes limitations of traditional strategies but also opens avenues for future research, including refining federated learning techniques and enhancing DQN for complex recovery scenarios. AFL-FDNR's adaptability makes it ideal for diverse IoT applications, such as smart cities and industrial automation, where real-time data accuracy and resilience are crucial.

AUTHOR CONTRIBUTION STATEMENT

Conceptualization: <Missing>
Literature Review and Methodology design: <Missing>
Software: <Missing>
Validation: <Missing>
Formal Analysis: <Missing>
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Writing original draft preparation: <Missing>
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