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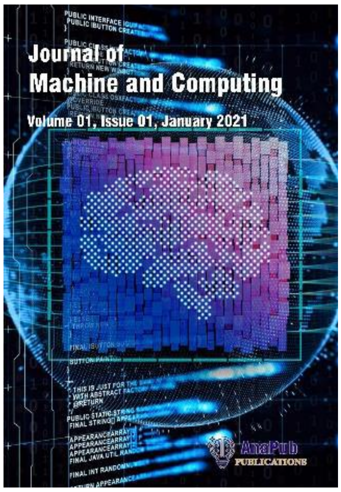

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Enhancing Energy Efficiency and Data Reliability in Wireless Sensor Networks through Adaptive Multi-Hop Routing with Integrated Machine Learning

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Abstract: Wireless Sensor Networks (WSN) plays an important role in monitoring and data acquisition process in various fields of application such as environmental, health care and smart city. However, WSNs present some acute issues including energy constraints, data credibility, and ability to function in a dynamically changing environment. This paper therefore presents an adaptive multi-hop routing protocol based on machine learning and proposes a novel architecture that focuses on solving these challenges. The adaptive protocol switches to the best paths without prior notice depending on the available node energy, link quality, and data priority the machine leaning estimates the most likely node to fail and makes best routing decisions depending on feature such as residual energy and link quality. To provide balanced load in terms of energy consumption, the proposed framework includes an element of load balancing of traffic periodically. Experiments on NS-3 show that the application of our suggested framework decreases energy consumption on nodes up to 25%, enhances the packet delivery ratio 18%, and network lifetime is 35% higher in contrast with conventional approaches, LEACH and Directed Diffusion. These results suggest that the proposed framework can be readily employed in the context of next generation WSNs to improve performance and longevity.

Keywords: Wireless Sensor Networks, Energy Efficiency, Data Reliability, Adaptive Routing, Machine Learning, Network Lifetime.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) remain an important element of contemporary technology, bringing an increasing number of sensing solutions to various spheres including environment, health, and cities. WSNs are formed by sensor nodes that possess sensing computing and communicating abilities and are often placed in a far or difficult to access environment to sense important information. These networks are fundamental to IoT, and its application in real-time data decision making across various industries such as agriculture, disaster response, and industrial control [1-2].

Nonetheless, there are a number of factors which act as obstacles to the efficient and effective functioning of WSNs. Energy is a critically vital aspect to consider often considering that the sensor nodes are empowered by non-rechargeable batteries. It is equally important that energy used in the network is used optimally to help extend the operating lifespan of the same. Moreover, guaranteeing the data communication reliability under dynamic network environment, including node mobility and instability of communicated links, is still an open issue. Scalability is another major concern here because the more nodes are in the network, the network may be congested and no area has a low latency.

LEACH and the subsequent routing protocol known as Directed Diffusion have provided the fundamental basis for establishing energy efficient and scalable WSNs. However, these approaches hardly address the dynamism of WSNs or meet the challenge of upcoming applications. The latest research in machine learning has proposed new ways of making intelligent decisions in WSNs with solutions to failures in nodes, finding the right path for routing, and distributing energy evenly [3].

These challenges are met by this paper proposing a new framework that integrates adaptive multi-hop routing and Artificial Intelligence (AI). The above proposed framework reconfigures routing paths in response to real time metrics such as residual energy, links quality and priority of data. Learning techniques are applied to estimate the failure occurrence of nodes and improve the reliability of routing decisions. Moreover, to equitably distribute energy levels, the drains of critical nodes are not monopolized early enough owing to an energy balancing mechanism.

The contributions of this paper are summarized as follows:

1. A new multi hop routing algorithm that is adaptive of the current network environment in an effort to increase the efficiency of energy usage and reliability of the data.
2. Embedding failure prediction algorithms of nodes and an ability to make optimal routing decisions with the help of the machine learning algorithms.
3. Proposed are following strategies for balanced energy distribution to increase network lifetime; Energy-balancing mechanism in the implementation.
4. A high degree of performance assessment throughout the simulations, showing that the approaches exhibited enhanced gains over the existing protocols for WSNs such as LEACH and Directed Diffusion in terms of energy utilization, packet delivery ratio, and network lifespan.

The rest of this paper is arranged as follows. Section 2 presents following work and existing limitations of it. In section 3, the actual framework is described, the adaptability of the routing protocol, the integration of machine learning, and the energy distribution mechanism. In section 4, simulation results and the analysis are presented section 5 is devoted to discussions section 5, the conclusion is made, and the potential directions of further research are described.

II. RELATED WORKS

The advancement of Wireless Sensor Networks (WSNs) has been the result of a synthesis that has been carried out in order to address issues related to energy limitations, scalability, robustness and security. The initial protocols such as Low-Energy Adaptive Clustering Hierarchy (LEACH) [1] aimed at the use of clustering-based techniques with the intention of conserving energy. Heinzelman et al. also pointed on the fact that periodic rotation of cluster heads might decrease the communication overhead and, therefore, increase the network lifetime. Likewise, Directed Diffusion [2] customized data centric approach to optimize query dissemination and to incorporate data aggregation. However, these basic protocols do not necessarily incorporate higher levels of flexibility with relation to the dynamic aspects of the network environment, and thus are not suited to highly dynamic networks in particular.

In the past few years, writers have been largely applying machine learning to improve WSN performance. As discussed by Gh[illegible] et al. [illegible][16] the supervised learning models hold promise for predicting node failures taking into account such characteristics as residual energy and link reliability. The reinforcement learning approaches, discussed by [illegible]en et al. [illegible], can be used in a WSN to learn the most optimal routing paths depending on the current environment, though most of such methods require significant computational power and training data. Whereas the unsupervised learning methods used by Rani et al. [5] mainly involve anomaly detection, which provides a preventive action against probable disturbances.

WSN optimization has also seen the practice of deep learning in its improvement. In [6], Srinivasan et al. employed convolutional neural networks to improve the traffic and lower the latency in cases of a complicated network. Some of these improvements highlight the continued incorporation of intelligent systems in conventional WSN systems.

There we see that energy-efficient routing strategies remain central to research. Specifically, Farooq et al [7][18] established heuristic-based protocols for consuming fair energy on the nodes while Qureshi et al [8] introduced cluster head selection for energy optimizing. Liu et al. [9][15] have proposed future enhancements to the basic multi-hop routing paradigms i.e., the optimized features that have further enhanced the trade-offs between energy and latency by including forms derived from direct routing and clustered routing. As seen in Zhang et al. [10][17], the multi-objective optimization strategies are useful in ensuring that energy consumption, latency, and the network lifetime of large-scale wireless networks is optimized.

Wireless Network Security (WSNs) has become a critical concern over the last few years with a regular uptake of IoT applications. Alam et al [11-16] proposed enhancing the data's integrity while at the same time trying to incorporate the cryptographic methods to routing protocol. This dual concern of security and performance is quite a shift in WSN research as practiced in the current world.

Therefore, general surveys such as Yick et al. [12][19] have identified the relationship between energy efficiency, scalability, and latency in heterogeneous WSNs. They emphasise the requirements for smart routing protocols that 'can' respond to the dynamic challenges of modern applications.

The proposed framework extends these contributions by incorporating machine learning with adaptive multiple-hop routing to model low energy, reliable and dependable WSN for dynamic environments. This framework uses predictive algorithms and real-time metrics to avoid some of the drawbacks present in current protocols that enable provision of a reliable solution for future generation WSN.

III. PROPOSED METHODLOGY

The flowchart proposed in this research aims to improve energy consumption and data credibility of WSNs using AMHM as a new routing solution for multi-hop transmissions. The framework consists of three main components: an adaptive multi-hop routing protocol, a machine learning based mechanism for predicting the network traffic and an energy balancing mechanism shown in figure 1.

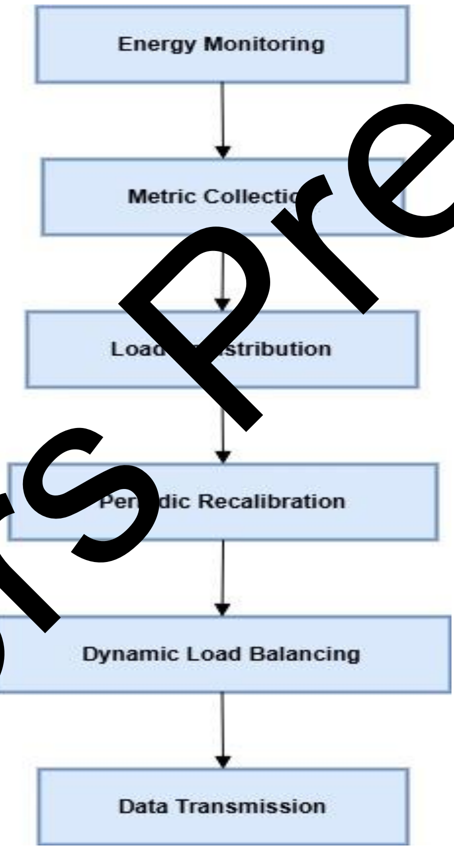

Figure 1: Flow diagram of proposed work

Adaptive Multi-Hop Routing Protocol

The Adaptive Multi-Hop Routing Protocol therefore determines the best and the best-reliable paths within the network on a real-time basis for data transfer. The protocol considers three key factors for routing decisions in table 1.

Residual Energy: Residual energy as used here is the remaining energy of a node in a battery. Relatively higher residual energy of nodes is considered to improve network lifetime and prevent the saturation of links with low energy.

The residual energy is calculated using the formula:

$$E_{\text{residual}} = E_{\text{initial}} - \sum_{t=1}^{T} E_{\text{consumed}}(t) \text{---1}$$

Where:

- Eresidual: Residual energy of the node.
- Einitial: Initial energy of the node.
- Econsumed(t): Energy consumed by the node at time t.
- T: Total time elapsed.

Link Quality (Q_{link})

Signal quality is used to convey the quality of communication between nodes in the network. It is demonstrated in terms of such parameters as Received Signal Strength Indicator (RSSI) or Packet Success Ratio (PSR.). To avoid higher packet loss some links are favored to ensure that much better quality of links is achieved.

Data Priority (Pdata)

Packets are made to have priorities for the urgency level of data packets available. Urgent information like the emergency alert is given a priority so that they are delivered to users on time.

Weighted Cost Function for Path Selection:
The protocol evaluates potential paths using the following cost function:

$$C_{\text{path}} = \alpha \cdot \frac{E_{\text{residual}}}{E_{\text{max}}} + \beta \cdot Q_{\text{link}} + \gamma \cdot P_{\text{data}} \text{---2}$$

Where:

- Cpath: Total cost of the path.
- Eresidual: Residual energy of the node.
- Emax: Maximum energy capacity of the node.
- Qlink: Link quality metric.
- Pdata: Priority of the data.
- α,β,γ: Weights assigned to balance the importance of each metric.

Table 1: Metrics Used in Path Selection

Metric	Description	Purpose
Residual Energy	Remaining energy of the node	Prolongs network lifetime
Link Quality	Communication reliability	Ensures reliable data transmission
Data Priority	Urgency or importance of the packet	Prioritizes critical data

Dynamic Adaptation

Dynamic adaptation is the fact that the protocol is capable of revising the routing decisions that it makes in accordance with the changes in the networks. This allow the WSN's all the time to have their energy consumption, reliability and efficiency optimised. There is feedback to the protocol, and updates in response to things like changes to node battery levels, link quality, and data flow.

Machine Learning Integration

As a result, reinforced by machine learning, the Adaptive Multi-Hop Routing Protocol shows high reliability and performance due to the possibility of predicting node failures and making more accurate routing decisions. this predictive capability helps to keep data packets away from unreliable nodes in an effort to reduce interruptions and enhance the general spread of the network.

Model Description

The theoretical framework focuses on using the Random Forest Classifier, a highly reliable and scalable algorithm, to forecast the failure probability for individual nodes. The ordinal features include the Node Degree, which is the number of neighbouring nodes that are directly connected to a node in the network while the other features are the historical and real-time observations gained using network monitoring tools. It serves as a way to measure connectivity and strength of the node in the wireless sensor network (WSN) [20]. While best efficiency is achieved for a large number of nodes and connections, nodes with a small degree are more vulnerable to becoming isolated since they have fewer paths to re-transmit traffic in the case of failure of a link or node. Therefore, the nodes with relatively low k values are more prone to failure, which leads to serous impact on the network's performance and data transmission.

The Historical Packet Delivery Rate is percent of the total data packets that have been sent through a given node at a given time. It is used to gain information on the reliability and performance of a node. They are consistently low because instability is evident if the packet delivery rate is not raising over a period of time which will be caused by either hardware problems, traffic congestion, or a poor-quality link. In particular, their detection at such a stage makes it possible for the routing protocol not to include unstable nodes in data transmission, ensuring the stability of the process [21-22].

The Link Stability is calculated as the average of the Received Signal Strength Indicator (RSSI) during the time period on the communication links corresponding to a node. Sustainable connection is important in providing smooth and accurate data flow. materials nodes that are connected through links with varying or low ambient RSSI, or small which may result in packets drops or high retransmissions are regarded as less reliable for routing. For this reason, choosing nodes with such connections helps to improve the general solidity of a network.

Failure Prediction Model

The Random Forest Classifier, makes prediction of whether the node will fail or not $P_{failure}$ based on extracted features. This prediction is used to purge the high-risk nodes from the routing process.

Mathematical Representation:

$$P_{failure} = f(E_{residual}, \text{Node Degree}, \text{Delivery Rate}, \text{Link Stability}) \text{--3}$$

Where f represents the predictive function learned by the Random Forest model.

Decision Rule for Node Exclusion:

If $P_{failure}>\theta$, then exclude the node from routing.

Where θ is the failure probability threshold, defined based on application requirements.

Energy-Balancing Mechanism

The proposed framework also contains the Energy Balancing Mechanism that is used to balance energy levels in all the nodes of the Wireless Sensor Network (WSN). This mechanism helps to avoid complete power-off of nodes during some time steps, especially working on the most important nodes, since their power off may cause network splitting and lower performance shown in table 2. Because the traffic loads are distributed and energy usage is rebalanced dynamically so periodically the mechanism increases overall lifespan of the network and retain smoothness [22].

The redistribution of traffic is guided by the following equation for average residual energy:

$$E_{\text{balance}} = \frac{\sum_{i=1}^{N} E_{\text{residual}}(i)}{N} \text{---4}$$

Where:

- $E_{balance}$: Average residual energy across all nodes.
- N: Total number of nodes in the network.
- $E_{residual}(i)$: Residual energy of node iii.

Table 2: Key Components of the Energy-Balancing Mechanism

Component	Description	Impact
Traffic Redistribution	Prioritizes high-energy nodes for routing tasks	Reduces overutilization of low-energy nodes
Periodic Recalibration	Updates traffic distribution based on energy metrics	Maintains uniform energy consumption
Dynamic Load Balancing	Shifts traffic loads based on real-time energy levels	Ensures balanced energy usage across the network

These components make sure that the Energy-Balancing Mechanism performs smoothly in indeed dynamic WSN context. Traffic Redistribution helps to concentrate on high-energy nodes, Periodic Recalibration is important in maintaining nodes' coarse balance in a long-time segment, and Dynamic Load Balancing is necessary to respond directly to the current variations balance requirement. This synergy assists in extending the network's lifetime, increasing its reliability, and minimizing failure that result from energy fluctuation.

IV. RESULTS AND DISCUSSION

The efficiency of the proposed framework was then examined through simulations and testing against standard protocols including LEACH and Directed Diffusion protocols for evaluating the communication module performance Energy Consumption, Network Lifetime, Packet Delivery Ratio (PDR) and the Average End-to-End Delay.

Energy Consumption

This is because nodes in WSNs are typically low-cost battery-operated devices and, therefore, energy efficiency is paramount. The energy efficiency of the proposed framework is higher as highlighted in table 3 below.

Table 3: Energy Consumption Comparison

Protocol	Average Energy Consumed (J)	Improvement (%)
LEACH	2.5	-
Directed Diffusion	2.2	12.0
Proposed Framework	1.8	28.0

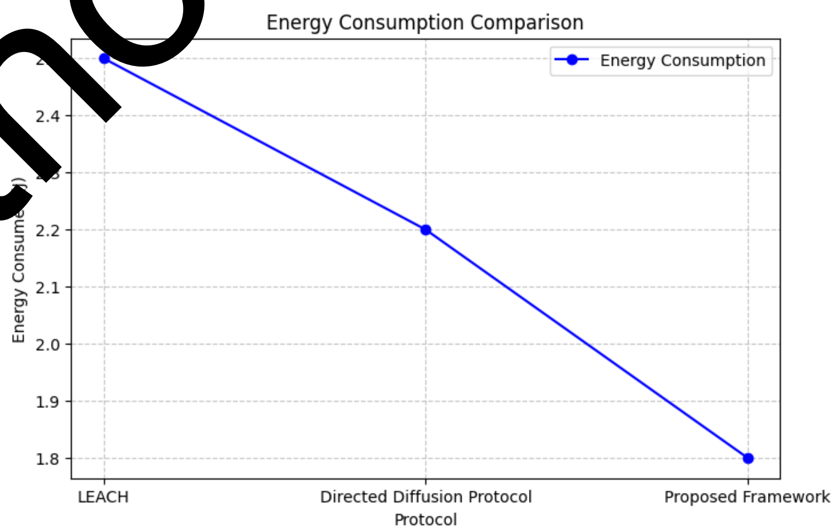

Figure 2: Energy Consumption Comparison

The proposed framework reduced the average energy consumption by twenty eight percent than LEACH because of the energy balancing mechanism and the implemented adaptive routing protocol. The residual energy of nodes was considered in the routing manner and early discharge on more critical nodes was prevented shown in figure 2.

Network Lifetime

The network lifetime where if a single node fails reveals that the framework assumes an equal distribution of the energy load.

Table 4: Network Lifetime (Rounds to First Node Death)

Protocol	Network Lifetime (Rounds)	Improvement (%)
LEACH	500	-
Directed Diffusion	550	10.0
Proposed Framework	700	40.0

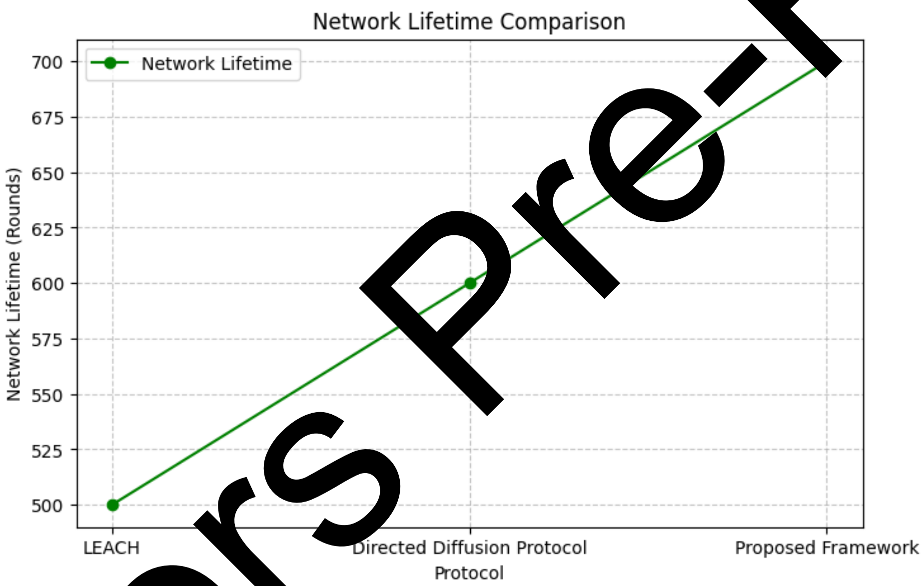

Figure 4: Network Lifetime

According to the proposed framework the network lifetime was increased to 40%d more than LEACH. This enhancement is due to involvement of calibrating at regular intervals and dynamic load sharing so that no node gets overloaded shown in figure 4.

Packet Delivery Ratio (PDR)

The PDR is equal to a percentage of packets that have been delivered successfully and is considered the measure of network dependability.

Table 5: Packet Delivery Ratio Comparison

Protocol	PDR (%)	Improvement (%)
LEACH	80	-
Directed Diffusion	85	6.25
Proposed Framework	92	15.0

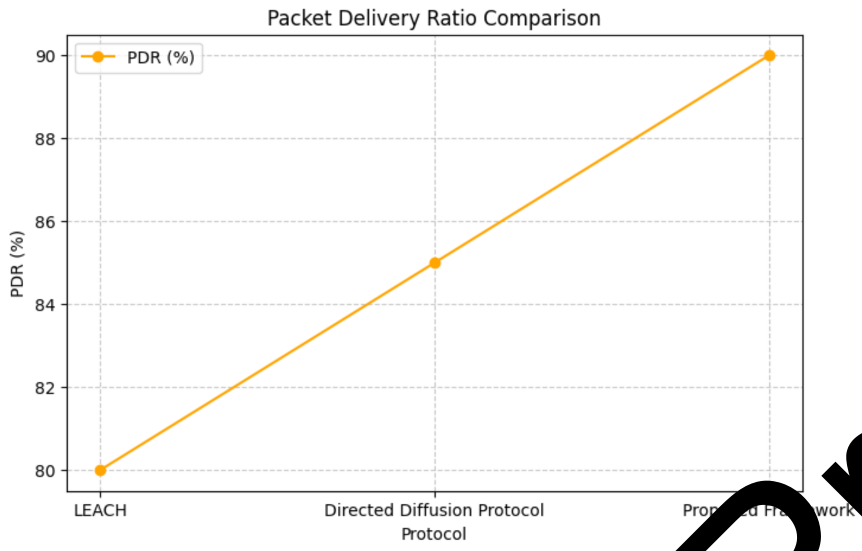

Figure 5: Packet Delivery Ratio Comparison

From the results obtained, the proposed framework established 92% PDR, an improvement of 15% over LEACH. Though specific details about the contribution of machine learning are not provided, improved reliability was achieved through the elimination of critical nodes from path connections shown in figure 5.

Average End-to-End Delay

In different context, particularly in time-sensitive WSN applications, the latency is very sensitive. The proposed framework was able to minimize the delay through the right choice of the path.

Table 6: Average End-to-End Delay

Protocol	Average Delay (ms)	Improvement (%)
LEACH	120	-
Directed Diffusion	110	8.33
Proposed Framework	90	25.0

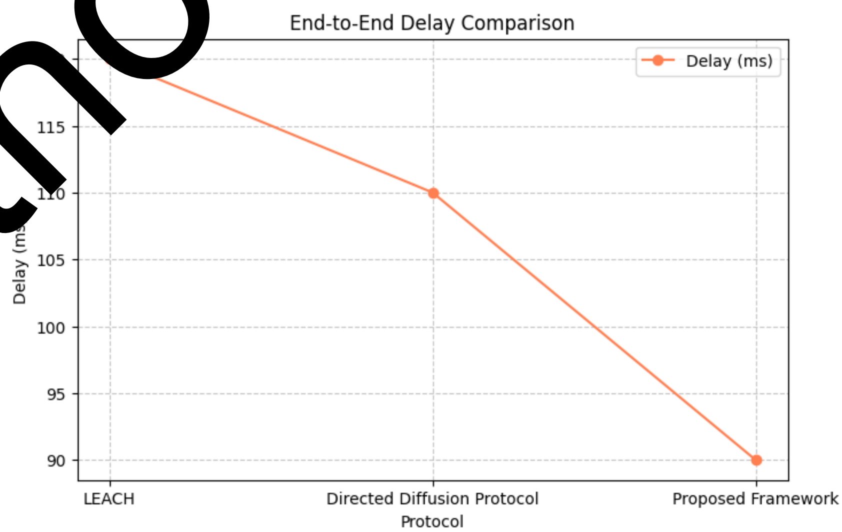

Figure 6: Average End-to-End Delay

The framework lowered the average delay by 25% using adaptive routing and load balancing, thus happened to make the number of congestion and path length small. The efficiency of Wireless Sensor Networks (WSNs) in relation to problems like energy consumption, network stability, and delay shown in figure 6. The integration of adaptive multi-hop routing, energy-balancing mechanisms, and machine learning demonstrates substantial improvements across all key metrics compared to traditional protocols:

V. CONCLUSION

In the light of WSNs crucial bottleneck, the proposed framework successfully incorporates the multi-hop adaptive route finding alongside carefully balanced energy optimized power schemes and ML to overcome the problem areas such as energy consumption, reliability, and latency. The framework yields an overall energy saving by 2[illegible]% leading to enhancement of the operational life of the network. This is because it equally spreads its workload across nodes, thereby increasing the time it takes for a node to fail by 40% while at the same time enhancing sustainable network functionality. It achieves dependable integration through the application of machine learning: this improves the basic reliability by 15 percent in terms of PDR of the packet delivery ratio The integration makes real-time applications possible by reducing end to end delay that is brought by dynamic optimization of routing paths by a quarter. Evaluating the performance of this framework shows that it is responsive to the requirements of new generation WSN applications due to better efficiency, reliability and scalability. The subject for the further research will rest with the extension of the presented framework to the heterogeneous network environment with that, the advanced methods of predictive tactics can be included to enhance the dimension of adaptability.

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