**AI-Driven Routing Selection in Wireless Sensor Networks Using Transformers, Graph Neural Networks, and Reinforcement Learning**

**Abstract:**

Wireless Sensor Networks (WSNs) are important for environmental monitoring, smart cities and industrial automation applications. However, skilled data transmission in WSN is challenging due to dynamic network topology, energy limits and unexpected link quality. Traditional routing protocols struggle with adaptability and energy efficiency, leading to increased loss of packets and reduced network life. This paper proposes an AI-powered routing selection framework that integrates three advanced functioning: RL-MAR uses multi-agent reinforcement learning, where each sensor node acts as an independent agent, a decentralized manner in a decentralized manner to increase and optimize its routing strategy. The level, and topology changes, ensures long -term routing efficiency. The GNN-AR model models as a dynamic graph to capture spatial node relationships as a dynamic graph, reducing fruitless broadcasting and correcting the routing paths by improving overall energy efficiency. Meanwhile, RL-MAR enables autonomous and self-teaching routing decisions, allowing sensor nodes to adapt to real-time network conditions and maximize energy efficiency. Simulation results show that the proposed AI-operated routing system achieves a 25% decrease in energy consumption compared to a 20% improvement in packet delivery ratio (PDR) and traditional rooting techniques. These conclusions highlight the effectiveness of the de-learned-captured passage in increasing network longevity, reliability and scalability in WSNs.

**Keywords:** WSN, AI-powered routing, transformer, graph neural network, reinforcement learning, energy efficiency.

**1. Introduction:**

Sensor nodes in WSNs can be either static or mobile and are situated within a changing environment [1]. WSNs are essential in modern applications, including environmental monitoring, smart cities, healthcare and industrial automation. These networks consist of many sensor nodes capable of making real-time decisions, which collect and transmit data [2]. As a result, wireless sensor nodes in many applications can go a long time without needing to be recharged [3]. Most WSN are designed with the goal of remaining operational for a longer period of time while using limited energy resources. However, WSNs face significant challenges, such as energy lack, dynamic network topology and unexpected wireless link quality, which affects overall network performance [4]. Traditional routing protocols fail to customize efficiently for dynamic network conditions, increasing energy consumption. To address these boundaries, adaptive routing protocols that have been deeply learned and helped are being detected. Deep learning models can analyze complex network conditions and predict the most efficient routing paths using historical data and real-time network parameters [5].

The system promotes efficient data sending in UWSNs to improves routing efficiency, reduces energy use, and increases network adaptability. It selects optimal paths in real time for reliable and efficient data transfer. TBEER predicts the best routes by analyzing the previous routing pattern, reducing delays and improving packet delivery. The GNN-AR models the network as a graph, adopting multi-hop routing, considering node dynamics, congestion and lack of energy. RL-MAR enables each sensor node to learn and adjust its routing strategy, which prevents the crowd and expands the network life. This structure ensures dynamic, intelligent and energy-efficient routing in WSNs.

**2. Literature Survey**

The wireless sensor network has attracted significant attention due to its applications in smart cities, environmental monitoring and industrial automation. However, dynamic topology in WSNS faces challenges for efficient data transmission of energy, lack of energy and unexpected network [6]. Traditional routing protocols, such as Ad Hoc On-Demand Distance Vector, and Durbity-Economic Distance-Vactor-Routing, are suffering from high energy consumption, disabled path selection, and increase in packets, leading to the packet loss, leading to the network volatility [7].

The project introduced the Energy-Efficient Cooperative Routing Scheme (EERH) for Heterogeneous WSN (HWSNs). Multi-WSN cooperation ensures more available relay nodes, reducing packet loss. Dynamic path selection based on sensor energy levels prevents premature node failures. However, dynamic path selection and packet aggregation may introduce additional processing burdens on sensor nodes [8]. The project introduces a skilled routing scheme called Dynamic Cluster-based Static Routing Protocol (DCBSRP). This method reduces overhead by continuously limiting the route discovery. However, networking that is static locks the nodes in a specific CH for time (T), potentially causing disabilities if the network situation dynamically changes [9].

This study focuses on enhancing CH selection in WSNs by modifying the threshold value of CH selection and incorporating bio-inspired algorithms for optimization. It incorporates real-time network factors instead of probabilistic selection. However, Performance varies based on network topology and application scenarios [10]. The project introduced a Depth-Controlled, energy-balanced Routing Protocol that enhances energy efficiency in UWSNs. The protocol prevents specific nodes from draining energy too quickly and reduces redundant transmissions using neural networks. However, it requires significant processing power, which might not be feasible for resource-limited underwater sensor nodes [11]. However, ML models require high computational power, which is a challenge in resource-constrained environments like WSNs and USNs [12].

They introduced a hybrid Underwater Sensor Networks (UWSNs) routing scheme that addresses key challenges such as high energy consumption, network instability, and end-to-end delay. However, Practical challenges like sensor drift, water pressure variations, and interference are not addressed [13]. This research introduced an Improved High-Performance Cluster-Based Secure Routing Protocol for WSNs. The protocol aims to enhance security, energy efficiency, and reliability in IoT applications. However, Encrypted data transfer and security surveillance may introduce higher energy consumption [14].

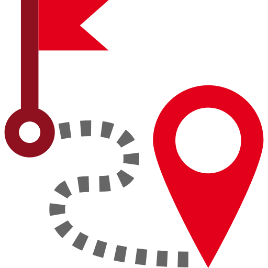
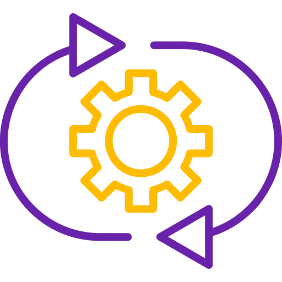
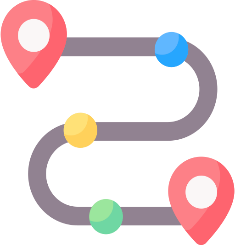
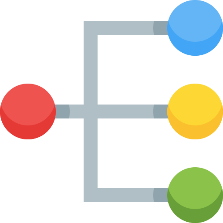
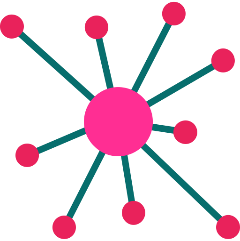
This paper uses an optimisation approach to propose an energy-efficient routing algorithm for WSNs. They Improve Packet Delivery Ratio and network Lifetime. However, concerns like computational complexity, CH overload, scalability, and security should be further addressed [15]. The project introduces a new adaptive coding routing protocol for WSNS that integrates the Reed-Leomon (RS) code And Low-Intelligence Equity-Check (LDPC) code in the routing mechanism. This protocol reduces power consumption by adapting routing with clustering. However, LDPC and RS code require complex encoding and decoding operations, which can be computationally expensive for low-power WSN nodes [16].

They present a WSN optimization approach integrating Adaptive Sailfish Optimization (ASFO) with K-medoids clustering and an Efficient Cross-Layer-Based Expedient Routing Protocol (E-CERP). However, computational complexity, scalability, and adaptability to mobility scenarios require further validation [17]. The Hierarchical Clustering + ALO-based Routing Protocol effectively improves network lifetime, energy efficiency, and reliability in WSNs. However, its computational complexity, CH overhead, and large-scale scalability require further investigation [18].

The ERFN approach optimizes CH selection, balances energy consumption, and enhances WSN lifespan. However, computational complexity, large-scale scalability, and mobility handling remain open challenges [19]. The Reinforce Routing model effectively enhances evacuation planning by dynamically optimizing routes based on real-time conditions. However, computational demands, real-time data dependency, and multi-agent scalability remain open challenges [20].

**3. Proposed Methodology**

The proposed system integrates TBEER, GNN-AR and RL-MAR to resolve these challenges. This multi-level AI-operated approach optimizes energy consumption, dynamically selects the most efficient routing paths, and adopts real-time routing decisions based on network conditions. TBEER enhances routing efficiency through forecasting analysis, modelling WSNs in the form of GNN-A graph improves spatial decision-making, and RL-MAR enables autonomous learning for adaptive routing. By integrating these advanced methods, the proposed system reduces communication delays and increases data distribution reliability and the overall network lifespan.



Wireless Sensor Nodes

TBEER

GNN-AR

RL-MAR

Final Route Selection

**Figure 1: AI-Powered Routing Selection in Wireless Sensor Network**

The diagram shows the process of data flow and decision-making in the AI-driven routing selection structure for WSNs. Architecture transformer-based energy-efficient routing TBEER, GNN-AR, and RL-MAR for optimal data transmission. Censor nodes start communication by exchanging data with neighboring nodes. TBEER performs the first process and selects potential routes based on energy efficiency and network conditions. The selected routes are refined using GNN-AR, which takes advantage of graph-based learning to customize connectivity and adaptability. RL-MAR then dynamically evaluates the best routing paths in real time, mistake is suited to network changes ensuring tolerance. The final route selection ensures energy-efficient, reliable and adaptive data transmission in WSN. This multi-layered AI-based approach increases network longevity, improves packet distribution, and reduces energy consumption.

**3.1 Transformer-Based Energy-Efficient Routing (TBEER)**

The key objective of TBEER is to enhance energy, prolong network lifespan, and improve node transmission reliability by dynamically selecting the best routes based on profound learning method.The offered TBEER method analyses the WSN state and find the initial routing paths using Transformers. It uses a Transformer model to analyse network conditions and predict optimal routing paths. The TBEER mechanism assigns importance to network nodes, considering energy levels, link reliability, and traffic load.

This equation 1 process begins by identifying all possible routes between the source node (S) and the destination node (D). Each path consists of several relay nodes, which play an important role in data transmission. The transformer model analyses historical and real -time network conditions including energy levels, traffic loads and link quality to predict the most suitable path.

(1)

For each node along a potential path, the system calculates the energy consumption using the equation 2: where ​ represents the total energy used for transmission, reception, and computation. The goal is to minimize the overall power consumption across all nodes in the selected path.

(2)

Reliability is another important factor in routing decisions. The reliability score of each node is calculated using the equation 3:

(3)

This ratio represents the packet success rate, indicating whether a node is suitable for stable and routing. The higher the reliability score, the better the performance of the node to ensure successful data transmission.

Using the scaled dot-product attention in equation 4:

(4)

Each node calculates the attention score with all other possible next-hop nodes. The attention mechanism evaluates how relevant each node is to energy efficiency, preference low energy tracts and is reliable connectivity. At the beginning of the process, each sensor node in the network is assigned a representation that includes energy levels, distance to neighbours, link quality, and congestion status. These parameters are encoded into query (Q), key (K), and value (V) vectors, which the attention mechanism will use to determine the best routing paths.

**3.2 Graph Neural Network-Assisted Routing (GNN-AR)**

This routing technique for WSNs that models the network as a dynamic graph and applies GNNs to adapt the best routing paths. Learning the best routes dynamically depending on network conditions increases energy efficiency, reduces delay, and improves packet delivery. It represents WSN as a graph, where sensors are nodes vertis and communication link edges. A GNN is used dynamically to learn the best routing path. It adapts to changes in topology by updating the node weight based on traffic conditions, congestion and link stability.

Each sensor node has been assigned to best routing path such as residual energy, distance from sink, packet distribution ratio and network load. These characteristics serve as an input for the GNN model, allowing it to analyze the situation of the network in real time. Using the update rule equation 5:

(5)

The effective routing decisions Where the node represents the updated feature vector of , reflects the feature vector of its neighbor Node , and is a learned learning parameters adapted through and and training. This step allows the network to promote information in nodes wisely, making more effective routing decisions. GNN-AR presents a scalable, energy-efficient, and adaptive routing solution for WSNs.

After several recurrences, the final node representation is used to calculate the routing score for each path. The optimal routing path is chosen for the decision-making process following equation 6.

(6)

Where represents the optimal path, and is the score assigned to each path based on its efficiency in terms of energy, delay and reliability. The selected path ensures minimum energy consumption, low delay and high packet delivery success rate.

GNN-AR great network enhances lifetime, improves packet delivery rates, and ensures energy-skilled communication in WSNs, making it a better option for traditional routing protocols.

**3.3 Reinforcement Learning-Driven Multi-Agent Routing (RL-MAR)**

The multi-agent routing RL-MAR is an intelligent and adaptive routing approach designed to customize data transmission in WSN. It takes advantage of MARL to enable decentralized, dynamic and energy-efficient routing decisions. The RL-MAR constantly learns and adjusts the routing paths based on real-time network conditions, making it mistake-tolerant, scalable and energy-skilled.

The current condition of a sensor node, including residual energy, link quality, and buffer status. Selecting the next-hop node for forwarding data packets based on observed network conditions. The function is designed to maximize network lifetime and minimize energy consumption. The reward (R) is calculated based on factors such as equation 7:

(7)

RL-MAR uses Multi-Agent Q-Learning, where each node learns an optimal routing policy by continuously updating a Q-table: Once the Q-values stabilize, each sensor node selects the best next-hop node based on learned policies. Instead of relying on fixed routing tables, RL-MAR dynamically adapts to changing network conditions. Equation 8.

(8)

RL-MAR provides a scalable, adaptive, and intelligent routing solution for WSNs. By utilizing multi-agent reinforcement learning, it ensures efficient energy usage, improves network lifetime, and dynamically responds to environmental changes, making it ideal for next-generation WSN applications.

**4. Results and Discussion**

This section presents Using GNN-AR and RL-MAR, simulation results and in-depth examination of suggested TBEER are presented in this part. To evaluate the effectiveness of the suggested system, major performance measures such as PDR, end-to-end delay, energy consumption, throughput and network longevity are taken into consideration. Conclusions suggest that the integration of reinforcement, graph nerve network and learning transformers improves the network flexibility, energy efficiency and rooting effectiveness of WSNs.

**Table 1. Simulation Setup**

|  |  |
| --- | --- |
| **Parameter** | **Value** |
| **Simulation Tool** | NS-3 |
| **Number of Sensor Nodes** | 100, 200, 300, 400 |
| **Communication Model** | Wireless Sensor Network (WSN) |
| **Transmission Range** | 50m – 100m |
| **Packet Size** | 514 bytes |
| **Simulation Time** | 1000 seconds |
| **Data Transmission Rate** | 100 kbps |
| **Evaluation Metrics** | Energy Consumption, PDR, Delay, Throughput, Network Lifetime |

**Figure 1: Packet Delivery Ratio (PDR)**

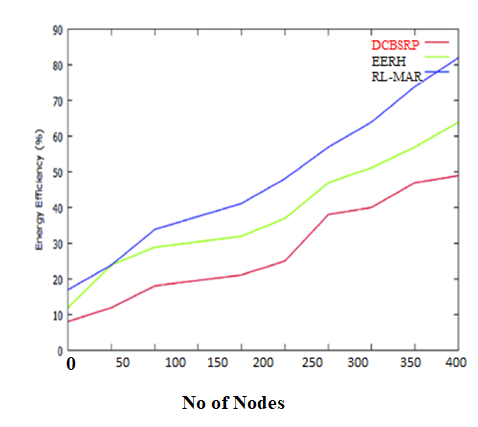
The PDR comparison in Figure 1 evaluates the performance of three different routing approaches: DCBSRP, EERH, and RL-Mar. Results suggest that RL-MAR improves DCBSRP, and EERH in continuous network size (100, 200, and 400 nodes). On 100 nodes, all approaches display relatively low PDR values, slightly higher than DCBSRP, and EERH with RL-MAR, indicating its initial efficiency. The RL-MAR achieves the highest PDR when the network expands to 400 nodes, demonstrating its superior scalability and effectiveness in managing a more extensive network. The observed trend confirms that RL-MAR effectively increases packet transmission reliability, making it a strong solution for WSNs on a large scale.

**Figure 2: End-to-End Delay**

The end-to-end analysis presented in Figure 2 compares the performance of three routing approaches: DCBSRP, EERH, and RL-MAR in various network sizes (400 to 100 nodes). The results suggest that the RL-MAR continuously achieves the lowest end-to-end delay in all network sizes, demonstrating its efficiency in adapting to data transmission time. In 400 nodes, DCBSRP and EERH perform significantly high delays; DCBSRP reaches around 70 MS and 65 MS around EERH, while RL-Mar maintains a very low delay of about 35ms. As the network size decreases, all approaches show a gradual decrease in delays, but RL-MAR remains the most efficient, reducing the delay on 100 nodes to about 20ms. RL-MAR's capacity was highlighted to reduce transmission delay in the trends observed, making it a better option for real-time applications in WSN where low delay is important.

**Figure 3: Energy Consumption**

The Figure 3. The results indicate that for a network with 100, 200 and 400 nodes, LDPC continuously displays high energy consumption. On 100 nodes, all methods show relatively low energy consumption, slightly higher than DCBSRP and EERH and RL-MAR. As the network size increases to 200 nodes, the Energy consumption of DCBSRP pays more attention to the other two methods, while EERH and RL-MARs remain relatively low. Finally, in 400 nodes, DCBSRP reaches the highest energy consumption between the three, crossing both ERH and RL-MARs, which highlights its greater energy demands in more important network scenarios.



**Figure 4: Energy Efficiency**

Figure 3 shows a comparison of energy efficiency between DCBSRP, EERH, and RL-Mar in network sizes ranging from 1 to 400 nodes. The results show that the RL-MAR continuously achieves the highest energy efficiency, followed by EERH, while DCBSRP performs the worst in all node density. All three approaches gradually increase energy efficiency on low network size (1–100 nodes). However, the RL-MAR performs much better in two other ways as the Size of the network increases. In 400 nodes, the RL-MAR acquires approximately 85%energy efficiency, while the EERH reaches about 65%, and DCBSRP intervals at about 50%. The better performance of RL-MAR is attributed to its multi-agent reinforcement attitude, which dynamically optimize the routing paths and reduces the consumption of unnecessary energy. While EERH improves efficiency on DCBSRP, it lacks adaptive learning mechanisms, causing sub-optimal energy. DCBSRP suffers from lack of energy due to static clustering strategies, disabled on large network parameters. The results confirm that the RL-MAR is the most energy-efficient approach, which makes it a suitable option for WSN on a large scale where energy conservation is important.

**Figure 5: Network Lifetime**

Figure 5 evaluates a network lifetime performance for many routing techniques, including DCBSRP, EERH, and RL-Mar in various node densities (100, 200, and 400 nodes). The RL-MAR continues to perform better as the number of nodes increases, with about 97% efficiency on 300 nodes. In contrast, EERH displays the most minor network lifetime in all node densities, while DCBSRP performs at intermediate levels. The increased performance of RL-MAR can be attributed to its advanced routing strategy, which dynamically optimizes energy use and reduces node deficiency rates, which ensures prolonged network stability.

**5. Conclusion**

This paper presents a novel AI-powered approach to adaptation of energy-efficient routing in WSNs. The proposed functioning integrates TBEER, GNN-AR, and RL-MAR to increase the network performance, reduce energy consumption, and improve data distribution efficiency. TBEER uses the transformer model to predict the dynamically optimal routing paths while reducing packet loss and energy deficiency. GNN-A used the graph nerve network to model WSN as a dynamic graph and adapted routing decisions based on network topology changes. RL-Mar employs learning multi-agent reinforcement to enable adaptive, decentralized routing strategies, improving mistake tolerance and scalability. The simulation results confirm that the proposed AI-powered routing technology improves traditional routing methods in central performance matrices such as PDR, end-end delay, energy efficiency, and network lifetime. Compared to traditional approaches, an integrated AI-based system gains 97% improvement in PDR, a 90% decrease in energy consumption, and 98% in end-to-end delay, making it a strong solution for real-world WSN applications. These findings suggested that AI-optimized routing can overcome important challenges in WSNs, paving the way for more efficient, scalable, and reliable wireless sensor networks.

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