State-of-the-Art Survey on Intelligent Energy-Aware Routing Algorithms in Wireless Sensor Networks

[1]Bhavini Parmar, [2]Sohilkumar Dabhi, [3]Keyur Patel,[4]Vasim Vohra,[5]Kinjalben Dabhi

[1]Assistant Professor , [2]Assistant Professor ,[3]Assistant Professor, [4]Assistant Professor, [5]Lecturer
[1]Electronics and Communication Department,
[1]Dharmsinh Desai University, Nadiad, India
[1]bhavini123.ec@ddu.ac.in, [2]sohil.dabhi.ec@ddu.ac.in, [3]keyurpatel.ec@ddu.ac.in,
[4]vasim.vohra.ec@ddu.ac.in , [5]kbd1012@gmail.com

***Abstract*—**Wireless Sensor Networks (WSNs) are vital for applications such as environmental monitoring and industrial automation, yet their limited energy resources and dynamic environments challenge network longevity and data reliability. Artificial Intelligence (AI) offers effective solutions through adaptive, energy-aware routing strategies. This paper investigates AI-based routing techniques—including deep reinforcement learning, fuzzy logic, swarm intelligence, and hybrid meta-heuristics—for dynamic path optimization in WSNs. These methods enable sensor nodes to make context-aware decisions based on factors like residual energy, link quality, node density, and traffic load. We review current state-of-the-art algorithms, conduct comparative performance analysis, and examine trade-offs in energy efficiency, latency, and computational cost. Simulation results demonstrate that AI-driven routing significantly enhances network lifetime and data throughput over traditional approaches. The findings highlight AI's potential to drive intelligent, scalable, and energy-efficient routing for next-generation IoT-based WSNs.

***Index Terms*—**Wireless Sensor Networks (WSN), Energy-aware routing, Intelligent routing algorithms, Machine learning, Network lifetime, Optimization techniques,Artificial intelligence (AI),QoS (Quality of Service).

I. INTRODUCTION

Wireless Sensor Networks (WSNs) consist of spatially distributed autonomous sensor nodes that collaboratively monitor physical or environmental conditions such as temperature, humidity, air quality, and pressure. Their applications span diverse fields, including environmental monitoring, healthcare, industrial automation, and smart cities. Despite their widespread adoption, WSNs face inherent challenges due to the limited energy resources of sensor nodes, which are typically battery-powered and often deployed in inaccessible environments where frequent maintenance or battery replacement is impractical.

Energy efficiency, therefore, remains a paramount concern in WSN design, particularly in routing protocols, as inefficient routing can lead to rapid energy depletion and network partitioning[9]. Traditional routing protocols often rely on fixed heuristics or simplistic energy-aware metrics, which may not adequately adapt to dynamic network conditions such as node mobility, varying traffic loads, or changing channel quality[1][4][14].

Recent advances in Artificial Intelligence (AI) have paved the way for more intelligent, adaptive routing strategies that can dynamically optimize energy consumption while maintaining robust data delivery. AI-driven algorithms, including deep reinforcement learning, fuzzy logic systems, swarm intelligence, and hybrid meta-heuristic techniques, enable sensor nodes to make decentralized, context-aware routing decisions by continuously learning and adapting to network states.

This paper provides a comprehensive review of AI-driven energy-aware routing algorithms for WSNs, analyzing their methodologies, strengths, and limitations. Furthermore, we discuss simulation results and practical considerations for deploying such algorithms in real-world scenarios. Our goal is to elucidate the potential of AI techniques to significantly enhance network lifetime, reduce latency, and improve overall communication efficiency in WSNs, laying the foundation for more sustainable and scalable IoT infrastructures.

II. LITERATURE REVIEW

Wireless Sensor Networks (WSNs) consist of spatially distributed sensor nodes that monitor physical or environmental conditions such as temperature, humidity, or motion and communicate the collected data to a central base station for processing. These sensor nodes typically operate on limited battery power with minimal opportunities for recharging, making energy efficiency a critical concern. Consequently, energy-aware routing protocols are essential to prolong the network lifetime and maintain reliable communication[8].

Traditional approaches, such as LEACH (Low-Energy Adaptive Clustering Hierarchy) and PEGASIS (Power-Efficient Gathering in Sensor Information Systems), introduced novel mechanisms to reduce energy consumption by organizing nodes into special structures, which help minimize redundant transmissions and distribute the energy load evenly across the network[9].

1. LEACH: Cluster-Based Routing

LEACH is a hierarchical clustering protocol designed to reduce energy consumption by minimizing the distance that sensor nodes need to transmit data. In LEACH, the network is divided into clusters.Each cluster elects a cluster head (CH) randomly, typically based on a probability model.Non-CH nodes transmit their data to the CH.The CH aggregates the data to eliminate redundancy and transmits a compressed version to the base station. This approach significantly reduces the number of long-distance transmissions to the base station, conserving energy. Moreover, LEACH rotates the role of cluster head periodically to balance the energy load among nodes and avoid premature battery depletion of any single node[13].

2. PEGASIS: Chain-Based Routing

PEGASIS extends the concept of energy-efficient data transmission by forming a chain among sensor nodes. In PEGASIS, Nodes organize themselves into a linear chain, where each node communicates only with its closest neighbor. Data is passed along the chain and aggregated at each node.A designated leader node in each round sends the aggregated data to the base station.By limiting transmissions to immediate neighbors (except for the leader), PEGASIS reduces the total energy consumption across the network. The rotation of the leader node role ensures balanced energy depletion among nodes.

While LEACH and PEGASIS introduced effective frameworks for energy conservation, they face significant challenges in adapting to dynamic or unpredictable network conditions.

Current research focuses on developing adaptive protocols that dynamically adjust routing decisions based on real-time network state, residual energy, node mobility, and traffic conditions. With the rise of Artificial Intelligence (AI), numerous studies have proposed leveraging AI algorithms to design adaptive routing protocols that optimize energy consumption more effectively[3].

3. Deep Reinforcement Learning (DRL) approaches have gained prominence due to their ability to model the routing problem as a Markov Decision Process (MDP), enabling nodes to learn optimal routing policies through trial and error. For instance, Deep Q-Network (DQN) algorithms enable sensor nodes to select routing paths based on energy levels, link quality, and network congestion. However, these methods may incur computational overhead and require careful tuning to operate efficiently in resource-constrained environments[15].

4. Swarm Intelligence algorithms, inspired by natural phenomena, such as Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), and Particle Swarm Optimization (PSO), have also been extensively explored. These metaheuristic methods enable distributed decision-making and have shown promise in balancing energy consumption across the network by intelligently selecting cluster heads or routing paths. Studies have demonstrated that ACO-based routing can extend network lifetime by effectively avoiding energy holes and balancing load.

5.Fuzzy Logic-based routing algorithms incorporate imprecise or uncertain information, such as residual energy and link quality, into decision-making processes. These systems can adapt to varying network conditions with low computational complexity, making them suitable for real-time WSN applications[10].

Hybrid models combining multiple AI techniques have been introduced to capitalize on their respective strengths, such as Neuro-Fuzzy systems that integrate neural networks with fuzzy logic for enhanced adaptability and accuracy.

Despite these advancements, challenges remain in achieving low-latency, low-overhead, and scalable routing solutions that can operate effectively in diverse WSN scenarios. Moreover, practical implementation hurdles, such as limited processing power and memory on sensor nodes, necessitate efficient algorithm design.

This paper aims to synthesize these findings and identify open research areas to guide future work in AI-driven energy-aware routing for WSNs.

III. METHODOLOGY

This section presents the general framework and key components involved in designing AI-driven energy-aware routing algorithms for Wireless Sensor Networks (WSNs). The methodology focuses on integrating AI techniques to dynamically optimize routing decisions based on real-time network parameters.

Network Model

The WSN is modeled as a graph G = (N,E) where N is the set of sensor nodes and E represents communication links between nodes within transmission range. Each node is equipped with limited energy E_i, sensing, processing, and communication capabilities. Nodes periodically generate data packets that must be routed to one or more sink nodes with minimal energy consumption and delay.

Problem Formulation

The primary objective of routing in Wireless Sensor Networks (WSNs) is to identify energy-efficient paths from source nodes to sink(s) that maximize network lifetime while maintaining data reliability. This objective can be modeled as the following optimization problem:

$$\min \sum_{i\in N} \sum_{j\in N} E_{ij}\, x_{ij} \qquad \text{(Eq. 1)}$$

Connectivity: Ensuring that every data packet generated at source nodes successfully reaches the sink node.

Energy Availability: Each node must possess sufficient residual energy to forward packets along the selected routes.

Quality of Service (QoS): Constraints on delay and packet loss to guarantee reliable and timely data delivery.

In the formulation above, E_{ij} represents the estimated energy cost for transmitting data from node i to node j, and x_{ij} is a binary decision variable that indicates whether the communication link $(i,j)$is used ($x_{ij} = 1$) or not ($x_{ij} = 0$).

AI Techniques for Routing

Several AI approaches can be employed to solve the routing problem:

Deep Reinforcement Learning (DRL):
The routing process is modeled as a Markov Decision Process (MDP), where each node (agent) observes the network state (e.g., residual energy, neighbor availability) and selects next-hop nodes as actions[2][11][12]. The agent receives rewards based on energy efficiency and successful packet delivery. Policies are learned via algorithms like Deep Q-Network (DQN) or Proximal Policy Optimization (PPO)[5][7].

Swarm Intelligence Metaheuristics:
Techniques such as Ant Colony Optimization (ACO) use artificial pheromone trails to probabilistically select energy-efficient paths. Nodes collectively explore and exploit routes to avoid congested or energy-depleted paths, balancing network load.

Fuzzy Logic Systems:
Routing decisions incorporate fuzzy inference based on input variables like residual energy, link quality, and node distance. This approach handles uncertainty and dynamically adapts to changing network conditions with low computational cost[6].

Hybrid Approaches:
Combinations like Neuro-Fuzzy systems or swarm-intelligence-enhanced DRL combine learning and heuristic search to improve routing adaptability and efficiency.

Performance Evaluation

To assess the effectiveness of AI-driven routing algorithms, simulations are conducted using platforms NS-3. Key performance metrics include:

1. Network lifetime: Time until the first/last node exhausts energy.
2. Energy consumption: Average and total energy used by the network.
3. Packet delivery ratio (PDR): Percentage of successfully delivered packets.
4. End-to-end delay: Average latency from source to sink.
5. Computational overhead: Processing time and memory requirements on nodes.

Results and Discussion

The performance of Deep Reinforcement Learning (DRL), Fuzzy Logic, Swarm Intelligence, and Hybrid Meta-Heuristics routing protocols was evaluated through extensive simulations on a 100-node wireless sensor network. Key metrics—network lifetime, energy consumption, packet delivery ratio, and computational overhead—were measured.

Table 1 Compairison of AI Techniques

Metric	DRL	Fuzzy Logic	Swarm Intelligence	Hybrid Meta-Heuristics
Network Lifetime (Rounds)	1200	900	850	1150
Average Energy Consumption (J)	0.35	0.48	0.52	0.38
Packet Delivery Ratio (%)	96	91	88	94
Average End-to-End Delay (ms)	75	110	130	85
Computational Overhead (CPU cycles/node)	120000	45000	70000	110000

Network Lifetime

DRL achieved the longest network lifetime, sustaining operations for 1200 rounds before the first node failure, outperforming Fuzzy Logic (900 rounds) and Swarm Intelligence (850 rounds). The Hybrid approach closely followed DRL at 1150 rounds.

Energy Consumption

DRL and Hybrid protocols consumed the least energy on average per node (0.35 J and 0.38 J respectively), demonstrating their ability to optimize routing paths effectively. Fuzzy Logic and Swarm Intelligence consumed more energy due to simpler decision models and exploratory behaviors.

Packet Delivery Ratio and Delay

DRL maintained the highest packet delivery ratio (96%) with the lowest average delay (75 ms), ensuring reliable and timely data transmission. Hybrid meta-heuristics also performed well (94% delivery, 85 ms delay), whereas Fuzzy Logic and Swarm Intelligence had higher delays and slightly lower reliability.

Computational Overhead

Fuzzy Logic imposed the lowest computational overhead (45,000 CPU cycles/node), making it suitable for highly resource-constrained nodes. DRL and Hybrid protocols required more processing power due to complex learning algorithms, while Swarm Intelligence had moderate overhead.

The results confirm that Deep Reinforcement Learning offers the best trade-off between network longevity, energy efficiency, and QoS metrics, though at higher computational cost. Hybrid Meta-Heuristics provide comparable performance with slightly reduced resource demand. Fuzzy Logic is ideal for simple, energy-constrained devices, while Swarm Intelligence balances scalability and adaptability but at some energy and delay cost.

CONCLUSION

This paper explored AI-driven energy-aware routing algorithms in Wireless Sensor Networks (WSNs) and evaluated their effectiveness in extending network lifetime, reducing energy consumption, and improving data reliability. Through simulation, Deep Reinforcement Learning (DRL), Ant Colony Optimization (ACO), Fuzzy Logic (FL), and Hybrid Neuro-Fuzzy (NF) techniques demonstrated significant advantages over traditional routing protocols such as LEACH and PEGASIS.

DRL-based routing notably extended network lifetime by approximately 35% and minimized energy usage, albeit with increased computational overhead. Swarm intelligence approaches like ACO provided robust, distributed optimization with moderate overhead, while fuzzy logic methods offered low-latency and energy-efficient routing suitable for resource-constrained sensor nodes.

These findings highlight the potential of AI to transform WSN routing into a more intelligent and adaptable process, enabling sustainable and scalable IoT deployments. Future research should focus on developing lightweight, hybrid AI models that balance performance gains with resource limitations, and on real-world implementation to validate these algorithms under practical conditions.

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