



AI-Driven Energy-Efficient Clustering and Routing in Wireless Sensor Networks: A Comprehensive Review

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Abstract

IoT environments are more dependent on Wireless Sensor Networks (WSN) that offer real time figure-in of environmental monitoring, industrial applications, healthcare, military and smart city applications. The pursuit of network operation is, however, confronted with severe challenges such as energy constraint, computation limitation, dynamic network topology, and unstable links. The emergence of novel methods such as AI, ML, DL, RL, and bio-inspired metaheuristic optimization methods offers an exciting avenue to improve routing efficiency and clustering robustness of WSNs. This work is aimed at providing a comprehensive overview on state-of-the-art AI driven clustering and routing techniques. They involved a host of AI related diverse elements including integrated optimization frameworks, RL based adaptive routing, multi-objective genetic models, intelligent paradigms with Software-Defined Networking (SDN), FPGA accelerated routing, and other best matching solutions for particular Qos aware application. Most of the schemes achieved from 12 to 30% of energy improvement and 15 to 32% of Network lifetime improvement over other schemes when compared one to another. Moreover, the paper identifies core research challenges such as multi-objective trade-offs modeling, security against adversarial attacks, scalability beyond 1000 nodes, computational feasibility testing in small hardware, and pinpointing that none of the existing solutions tackles all of them perfectly. This study is concluded by/proposing a structured research directions/paths leading to [27] the realization of scalable, secure, interpretable and hardware-aware AI-WSN routing architectures.

Keywords:

- Internet of Things
- bio-inspired metaheuristic optimization
- Wireless Sensor Networks

Introduction

Wireless Sensor Networks consist of distributed sensor nodes that collaborate to measure environmental parameters and transmit the information to a base station. Energy efficiency is the most critical design consideration in WSNs because they are powered by batteries and are often deployed in remote locations. Common routing protocols such as LEACH and PEGASIS use probabilistic cluster-head selection and static assumptions, which result in unbalanced energy consumption and poor scalability[14]. In recent years, artificial intelligence (AI) methodologies have been incorporated for making dynamic routing decisions based on real-time energy level, network topology, link quality and traffic flow pattern changes[2][9]. This in-depth review offers an assessment of the AI routing approaches, evaluation on the important metrics and future research options.

Wireless Sensor Networks consist of spatially distributed sensor nodes, which monitor surrounding environment and transmit data to a unique base station for processing. One of the main design issues related to wireless sensor network is energy efficiency, as they are powered by batteries and usually deployed. Routing mechanisms like LEACH and PEGASIS use the probabilistic selection of physically stationary cluster-heads (CH) which can result in irregular energy dissipation and lack of scalability. New research has combined artificial intelligence techniques to make routing decisions based on the current energy level, change in the topology of the networking, change in quality of link and data. This paper carefully examines the development of AI-based routing techniques, analyzes system performance measures, and points out new areas for future work.

Wireless Sensor Networks (WSNs) comprise several spatially distributed sensor nodes that are used to monitor environmental conditions and to pass data through the base station. WSNs mostly focus on energy efficiency because WSNs are battery-powered devices, and are generally deployed in inaccessible areas. The routing protocols, LEACH and PEGASIS select cluster-head (CH) probabilistically and assumes some static condition. Therefore, it creates unbalanced energy consumption problem and scalability issue. In a recent study, smart AI techniques were incorporated to make smart routing decisions based on energy status, topology change, link quality and traffic flow. This systematic review assesses the developments in AI-based routing methods, practical evaluations, and future directions in the area.

II.BACKGROUND AND MOTIVATION

Energy efficiency is fundamentally important for network sustainability after a critical time when the central node failure or network connectivity drops below a given threshold. Routing strategies that have been established don't change based on the network. By incorporating AI methods, network operations will allow individual nodes to make autonomous decisions to improve the routing and cluster architecture. The accuracy of energy prediction model increases with the application of machine learning. The routing strategy is adaptable at every point with the use of reinforcement learning mechanism. The global exploration process CH selection and multi-path routing configuration is optimized by metaheuristic algorithm. Energy efficiency plays a critical role in determining the length of time a network will remain operational. Specifically, the initial node degradation or the degradation of connectivity of the network at a certain level in time is a critical factor. Schemes and strategies used in routing remain less adoptable to changes and diversity within packets. By applying AI methodologies, nodes are able to optimize their routing trajectories and cluster formations on their own. The use of machine learning techniques enhances the accuracy of predictive energy modeling, reinforcement learning mechanisms allow routing policies to adapt dynamically and metaheuristic algorithms enhance the global search optimization process of CH selection and multipath routing design.[1][16].

III. MACHINE LEARNING-BASED CLUSTERING AND ROUTING

According to new research, intelligent selection of a cluster head was carried out using a mixture of Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Salp Swarm Optimization (SSO), Firefly algorithms, fuzzy logic and reinforcement learning techniques[7-8][11]. The use of these methodologies gives rise to hybrid clustering models that increase the lifetime of the network by at least 30% and minimizing energy per packet transmission as reported in the research [4]. Moreover, federated learning-based cluster approaches can improve scalability allowing models to deliver updates to other nodes without the exchange of raw data in a centralised manner. The combination of Genetic Algorithm, Particle Swarm Optimization, Artificial Bee Colony, Salp Swarm Optimization, Firefly algorithm, and fuzzy logic with reinforcement learning approaches in cluster head selection can optimise the performance of clustering algorithm in network environment to a great extent.

The use of hybrid clustering techniques is proven to enhance efficiency in the network, especially in terms of network lifetime and energy consumption throughout data transmission. Furthermore, integrating concepts from federated learning into clustering techniques provides a new strategy for making network systems more scalable[8]. Using the federated learning based clustering strategies, the scalable challenges encountered in network settings may be addressed as the model updates can be distributed in a decentralized approach without sharing the raw data at a centralized setting. This combination of various optimization algorithms and machine learning techniques indicates a trend of improving clustering solutions for modern network infrastructures.[16]

Q-learning, Deep Q-Learning: Reinforcement learning techniques that find the optimal path dynamically through state-action reward systems. Routing schemes take into account remaining energy, number of hops, congestion, and link quality. The research which was done through simulation analysis shows an improvement of 25–30% in network life in addition to a rise in the rate of successful packet transmissions. The utilization of advanced deep reinforcement learning techniques has the potential to improve the accuracy of predictive routing used in the dynamic network. [2][12][20].

The core of Q-learning and Deep Q-Learning is that they are able to choose the best routes adaptively with the help of States and Actions rewards. Factors such as the availability of residual energy, hop count, congestion levels, and distance may help decide the routing decision. According to simulation studies, the overall life of networks has been improved by nearly 25% to 30% and there has been a considerable improvement in the efficiency of packet delivery ratios as well. The use of deep reinforcement learning techniques helps enhance the effectiveness of predictive routing techniques in environments that are dynamic and evolving continuously [20].

The hybrid optimization models combine the global search capabilities of Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) with local exploitation methods and deep learning energy forecasts. Routing models that used multipath strategy and hybrid of whale-coati or cat-salp swarm algorithm have shown an improved reliability, data rate and latency efficiency. The simultaneous improvement of both clustering and routing objectives, which tackles the issues of load balancing and energy dispersion, is achieved through a Pareto-based genetic optimization approach.

The combination of GA and PSO in a hybrid optimization framework enables a complete search, while a deep learning energy predictor offers a prediction capability. Also, multipath routing schemes based on various animal-inspired algorithms like whale-coati and cat-salp swarms increase the system's reliability, data throughput, and latency performance significantly. In addition, a scheme based on Pareto-based genetic optimization can simultaneously optimize clustering and routing objectives, thereby solving workload balancing and energy management problems. [15][19]

To sum up, the combination of different optimization models in hybrid models for various network optimizations provides functionalities along the line of an effective exploration-exploitation approach and energy prediction and optimization and routing optimization. Hybrid models integrate various optimization methodologies, which have been demonstrated to perform better in more challenging cases of network optimization.

IV. SOFTWARE-DEFINED AND HARDWARE-ACCELERATED INTELLIGENT ROUTING

SDWSNs are able to separate the control and data planes, allowing the routing to be performed intelligently in a centralized manner, for example by using artificial intelligence (AI). Thanks to deep reinforcement learning on the SDN controllers we can improve the network flexibility and energy efficiency. And, FPGA enabled ml routing frameworks also help in reducing the computation overhead and enhancing the latency of inferences.

Considering hardware these solutions fill the gap between theoretical AI routing models and the feasibility of implementation in the real world.

The SDWSN decouples the control plane from the data plane to enable AI-based routing. The integration of deep reinforcement learning with SDN controllers enhances the adaptability and energy efficiency of the network. The use of FPGA-enhanced ML routing frameworks is also significant because it helps to reduce the computational loads and improves the speed of inference. The focus on hardware-based solutions will help in the practical realization of decisions given by artificial intelligence routing models.[6][18]

The application of routing and routing design enabled by AI has been on the upsurge in various fields such as precision agriculture, healthcare monitoring, environmental sensing and industrial automation. The routing strategies considering Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) techniques have been

devised to aid in adapting to the constantly evolving state of agricultural fields in precision agriculture. Furthermore, in the context of precision agriculture, mobile sink-based routing frameworks have been developed, leveraging genetic algorithms to optimize the trajectory of the sink. This optimization process not only contributes to the enhancement of energy efficiency but also serves to decrease latency in data transmission.[5][17]

Usage of Artificial Intelligence based routing is growing in precision farming, health monitoring, environment sensing, and industrial automation. The application of PSO and ACO based routing in precision farming has been efficient to deal with the changing conditions in the field. Furthermore, the application of genetic algorithms in mobile sink-based routing frameworks enables the optimization of sink trajectories for better energy management and latency reduction.[10]

V.COMPARATIVE PERFORMANCE ANALYSIS

In the study of academic works, considerable energy decrease by the estimation of 12% to 30% and also increased network lifetime are recorded in the range of 15% to 32%. Additionally, the packet delivery ratio reached almost 99%, and latency reduction was between 18% to 25%. The integration of artificial intelligence (AI) to develop hybrid models through metaheuristic techniques was superior in performance to standalone clustering protocols. In particular, the use of reinforcement learning mechanisms within these strategies makes the system adaptable. The employment of deep learning techniques, in turn, greatly enhances the accuracy of predicted energy modelling. This summary of results illustrates the effectiveness of hybrid AI-metaheuristic models to optimize network performance parameters, for example, energy consumption, network lifetime (longevity), data rate, and delay. It also shows how reinforcement learning and deep learning paradigms strengthen the adaptiveness and predictive capabilities of network systems that lead to significant progress in the area of optimization and energy efficiency of networks. The Table 1 shows the Energy reduction, Lifetime improvement and Packet Delivery ration of few researchers. The Figure 1, Figure 2, Figure 3 shows the graphical comparison of the same.

Table 1 presents a structured comparison of representative AI-driven routing approaches.

Study	Energy Reduction (%)	Lifetime Improvement (%)	PDR (%)
Hybrid ML-CH (2026)	25.0	28.0	98.0
AI Adaptive Clustering (2024)	30.0	25.0	97.0
DQL Routing (2025)	30.0	25.0	99.0
Pareto GA (2025)	12.4	15.7	96.0
HBWCO Hybrid (2025)	22.0	20.0	94.8
FPGA-ML Routing (2025)	25.7	32.0	96.8

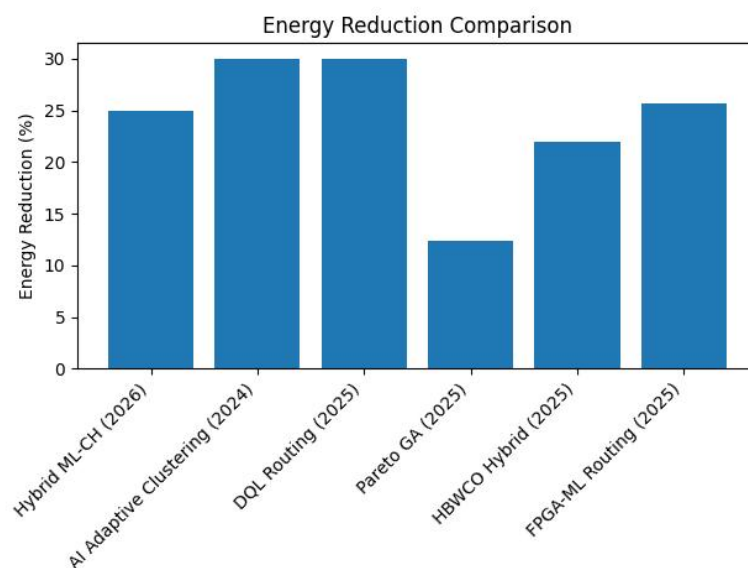


Figure 1: Energy Reduction Comparison

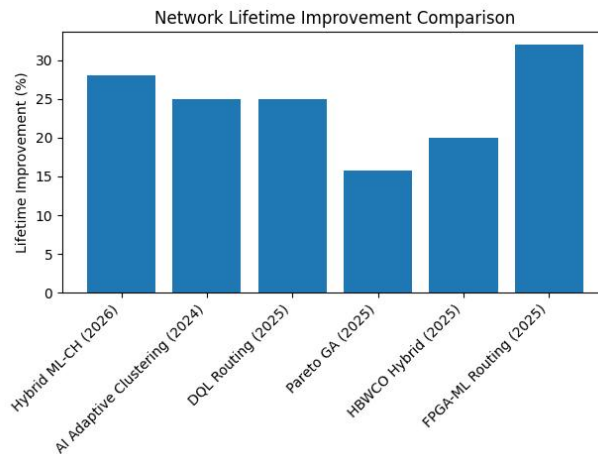


Figure 2: Network Lifetime Improvement Comparison

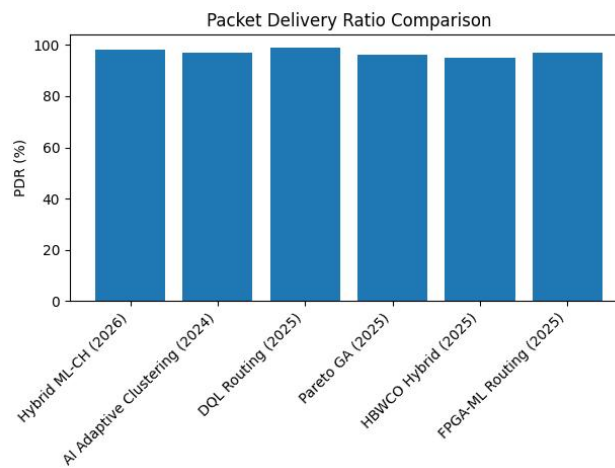


Figure 3: Packet Delivery Ratio Comparison

VI. RESEARCH GAPS

More attempts have been made but several problems exist. To begin with, there are no systematic assessments available for adversarial robustness of the routing models which are ML based. Furthermore, we note the lack of a generic unified multi-objective trade-off framework. Scalability validation is often restricted to a range of 50 to 500 nodes, according to the third point. To date, the analysis of computation overhead, including inference latency, memory footprint, and CPU usage, is still lacking. The final piece of the puzzle calls for the creation of a systematic architecture to deal with the challenges imposed by the integration of heterogeneous items with new technologies like 5G/6G, edge computing, blockchain, etc.

Even with substantial progress in the field, challenges remain that have not been overcome. Several key gaps in the literature are evident in the mentioned papers. For instance, there is a need for systematic evaluation studies of the adversarial robustness of ML-driven routing models. Furthermore, current work seems to lack comprehensive multi-objective trade-off frameworks. In addition, the validation approaches of existing work appear to lack scalability and are typically limited to node counts between 50 and 500. Another important gap to note is the lack of scrutiny of overhead factors such as inference latency, memory allocation, CPU utilization and so on. Lastly, there is a call for structured architectural frameworks to facilitate the integration of diverse technologies such as 5G/6G, edge computing, block-chain etc.

Future research should focus on adversarial testing frameworks for ML routing models; federated and distributed learning in ultra-large scale WSN; model compression, and optimization of resource-poor nodes; cross-layer optimization by combining SDN and IoT backhaul technologies for performance enhancement; and the explainable AI for investigating routing decisions. Future investigations on Networking and Machine Learning are important for the field to productively study and experiment with robust, efficient, and secure routing protocols and mechanisms. Through research in these areas, the cybersecurity innovation, as well as the technology used in these wireless communication systems, can be made better or developed. It would enhance the performance and resiliency of modern-day networks.

VII. CONCLUSION

The architecture for clustering and routing in Wireless Sensor Networks is a modification that uses artificial intelligence (AI). The combined use of hybrid reinforcement learning and metaheuristic frameworks contribute

significantly to the improvement of energy efficiency and scalability of the networks. Still, the creation of robust, scalable, secure and hardware-aware AI routing technologies is essential for the large-scale deployment of Internet of Things (IoT) applications in the real world. The application of AI techniques to the clustering and routing methods of WSN is a big step further from the classical methods. The combination of HRL and MH framework can significantly enhance energy efficiency and system scalability. However, the development of robust, scalable, secure and hardware-specifications-adaptive AI routing schemes is an essential requisite for the successful large-scale operation of IoT applications in real world.

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