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Enhancements in WSN Energy Efficiency Using Machine Learning: A Comparative Analysis and Real-Time Challenges

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Abstract

The growing demand for energy-efficient Wireless Sensor Networks (WSNs) in applications such as IoT, environmental monitoring, and smart cities has sparked exhaustive research into practical solutions for the management of such networks. Nonetheless, the rate of energy consumption remains a significant issue in these types of networks, particularly for IoT devices. The use of clustering, duty cycling, and data condensation, which allow energy conservation in WSNs, is discussed in this paper. The focus is on the merits and drawbacks of these techniques, particularly in the case of dynamic, large networks. Also addressed are the other ML-driven methods, including reinforcement learning and its supervised and unsupervised models, which are adaptive in improving the energy consumption of WSNs. This paper also provides a review of the use of ML in WSNs through case examples that aid in showing how ML applications are beneficial in improving the operational lifetime and reliability of the network. Apart from that, it provides comparative study and performance assessment criteria, combining the results to determine how effective methods based on ML are compared to the approaches in general.

Keywords

Wireless Sensor Networks (WSNs), Internet of Things (IoT), Energy Efficiency, Environmental Monitoring, Smart Cities, Energy Consumption, Clustering Techniques, Duty Cycling, Data Condensation, Machine Learning (ML), Reinforcement Learning (RL), Supervised Learning, Unsupervised Learning, Adaptive Techniques, Resource Allocation

1. Introduction

A Wireless Sensor Network is a type of network comprising several autonomous devices, spatially distributed and referred to as sensor nodes. This device is designed to monitor environmental and physical conditions, including temperature, humidity, and pressure [1]. In WSN, there are five layers: perception layer, data link layer, network layer, transport layer, and application layer. Sensor nodes typically communicate in a multi-hop fashion, where each node acts as both a source and a relay [2]. A significant challenge for WSN is making sensor nodes energy-efficient, as these devices are powered by batteries, which are challenging to replace or recharge in inaccessible areas [3]. Data transmission uses much more energy than sensing and processing data in WSNs. Therefore, it's crucial to develop innovative strategies to reduce communication energy use while ensuring network reliability and efficiency. To solve this problem, researchers have introduced various methods, such as clustering protocols like LEACH (Low-Energy Adaptive Clustering Hierarchy), HEED, duty cycling, data aggregation, and routing optimization. However, most of these are rule-based, lack adaptability, and do not consider real-time variations in network traffic, topology, or node status. Recently, machine learning has emerged as a promising solution to enhance energy efficiency in WSNs. ML techniques, including supervised learning and reinforcement learning, can dynamically learn optimal scheduling, clustering, and routing decisions based on environmental and network conditions. Despite growing research in this area, there is no recent survey that systematically compares the energy-saving impact of ML-based techniques against traditional ones. To address this gap, this paper presents a systematic review of ML-based energy-saving techniques in WSNs.

2. Traditional Methods for Energy Efficiency in WSN

2.1. Clustering-Based Approaches

Clustering in WSNs enhances energy efficiency by organizing nodes into clusters, where only the cluster heads communicate with the base station, thereby reducing the number of transmissions.

Low-Energy Adaptive Clustering Hierarchy (LEACH): A technique that organizes nodes into clusters and randomly selects a Cluster Head (CH), which then aggregates and transmits data to the base or core station [4]. This can reduce redundant data transmissions and give comparatively better energy efficiency in the nodes [5]. However, it had some limitations, such as uneven energy usage, Lack of fault tolerance, and poor performance for varying energy nodes.

Power-Efficient Gathering in Sensor Information Systems (PEGASIS): A chain-based protocol to improve energy efficiency by forming a chain of sensor nodes, which can reduce direct transmissions to the central station, thus balancing the energy consumption among nodes [6]. But it lacks robustness and poor adaptability.

Hybrid Energy-Efficient Distributed Clustering (HEED): This is a distributed clustering protocol based on residual energy and node density, which can significantly increase the network lifespan by balancing node energy usage [7]. It has an iterative CH selection process and a fixed range for CH selection, which affects its computation costs and makes it inefficient for larger networks.

Energy-Efficient Uneven Clustering (EEUC): This addresses the energy hole problem by creating smaller clusters closer to the base. Some limitations include complexity, static nodes, delay, and Scalability issues [8].

Zone-Based Energy-Efficient Clustering Routing Protocol (ZEEP): By geographical zoning, ZEEP can balance out the long-distance communication-based energy consumption [4]. However, in dense zones, it can experience energy hole problems and scalability issues.

2.2. Routing Optimization

Here, the paths are chosen systematically to achieve the least energy-consuming paths with maximum accuracy during communication in WSNs.

Flat Routing Protocols employ flooding and gossip-like techniques, where all nodes are treated equally and decisions are made dynamically.

Power Aware Routing: This type of routing considers the power levels of nodes to avoid overloading specific routes. It employs techniques such as Minimum Cost Forwarding Algorithms (MCFA), Maximum Lifetime Data Aggregation (MLDA), and multipath routing [9].

2.3. Data Aggregation Techniques

The early aggregation techniques lacked data accuracy [10] and experienced latency issues due to certain variations.

Tree-Based Aggregation: A hierarchical type of structure, such as the TAG protocol (Tiny Aggregation), provides a clear structure for data flow; however, it can cause link failures and disruptions [6].

Cross-Layer Data Compression: Compresses data across multiple layers, like physical, MAC, and network layers. This can reduce transmission size and energy overhead [11].

Cooperative MIMO Techniques: Although precise synchronization is needed between signal nodes, Multiple Input Multiple Output (MIMO) can enhance energy efficiency [12].

2.4. Topology Control

Energy efficiency can be increased through position-based geometric and structural control of topology nodes.

Spatial Topology Control: Utilizing spatial positioning, specific techniques reduce energy consumption, also known as geographic-based control. Popular protocols include Geographic Adaptive Fidelity (GAF) [13], Geographic and Energy-Aware Routing (GEAR) [14], and Virtual Grid Architecture (VGA) [15].

Power-Based Topology Control: It dynamically adjusts power transmission to optimize system efficiency. Popular protocols are Adaptive Transmission Power Control (ATPC) [16] and Minimum Transmission Energy (MTE) [5].

Dynamic Topology Control: Some Techniques use gradient-based opportunistic dynamic topology control to reduce energy consumption [17].

2.5. Energy Harvesting

Energy efficiency in WSNs can be enhanced using energy harvesting mechanisms that utilize environmental sources like solar, thermal, and mechanical vibrations to recharge sensor nodes.

Solar-Based Harvesting: Static energy collection techniques are commonly deployed using solar panels in outdoor WSNs, providing periodic charging without dynamic scheduling [18].

Thermal and Vibration-Based Harvesting: Thermal gradients and mechanical stress from the surrounding environment are also utilized as alternative sources, particularly in industrial and structural monitoring applications [18].

Static Resource Models: These traditional techniques often follow fixed energy intake patterns and do not adapt based on workload or network conditions, resulting in limited flexibility. Popular models include solar-powered MAC scheduling and duty-cycling schemes that operate with non-adaptive thresholds [5] [19].

2.6. Duty Cycling

Serving as a switching device for the nodes, it can conserve energy by alternating between wake and sleep cycles for the nodes.

Synchronous Duty Cycling: A predefined, scheduled active/sleep cycle, such as S-MAC, is used here. It can also be known as synchronous cycling [20].

Asynchronous Duty Cycling: Additionally, there is asynchronous duty cycling, such as B-MAC, where nodes can independently alternate between active and sleep states with probabilistic schedules [21].

Adaptive Duty Cycling: Some duty cycling methods, such as DSMAC, can adjust node scheduling based on traffic load or environmental changes to achieve greater energy efficiency, collectively known as adaptive duty cycling [19].

Hybrid Duty Cycling: There are also many combinational duty cycling protocols, such as BN-MAC, X-MAC, Z-MAC, MS-MAC, A-MAC, ADCSMAC, and others.

3. Machine Learning Techniques for Energy Efficiency in WSNs

The Challenges faced by previous traditional approaches have been addressed and attempted to be solved through various machine learning-based techniques.

3.1. Clustering

Multi-Agent Reinforcement Learning (MARL): A hybrid deep clustering multi-agent reinforcement learning (HDCMARL) framework to optimize HVAC system networks in smart buildings. By addressing challenges such as significant action and state spaces, as well as high thermal inertia, the approach utilizes Quasi-Newton optimization to enable fast agent responses. It achieves 32% better energy savings and 21% improved thermal comfort compared to traditional PID methods [22].

Hybrid ACO-PSO for Cluster Head Selection: Hybrid particle swarm optimization and improved low-energy adaptive clustering hierarchy (HPSO-ILEACH) algorithm optimizes cluster head selection and minimizes energy usage during clustering. Simulation results reveal significant improvements, including a 28% reduction in energy consumption and 55% more nodes remaining alive compared to LEACH and other algorithms, enhancing network lifetime and energy efficiency for reliable WSN operations [23].

Self-Organizing Map (SOM) for Clustering: Combining Self-Organizing Maps (SOM) for cluster formation and K-means for varying cluster sizes, the protocol optimizes cluster head rotation to balance energy usage. MATLAB simulations demonstrate that LEACH-SOM significantly reduces energy consumption and extends network lifespan compared to traditional LEACH, making it an ideal solution for diverse applications such as environmental monitoring and disaster management [24].

Density-Based Spatial Clustering with Noise (DBSCAN) for Energy Balancing: The DBSCAN clustering algorithm method enhances data transmission efficiency by aggregating and reducing redundant data before sending it to the sink. Cluster heads are chosen based on energy and distance metrics, ensuring balanced energy usage among nodes. Simulations demonstrate EECDA's effectiveness in extending network lifespan and achieving uniform energy distribution compared to existing clustering protocols [25].

Adaptive Neural Fuzzy Inference System (ANFIS) for Routing: EANFR utilizes deep neural networks for feature extraction and neuro-fuzzy logic for clustering and routing, thereby optimizing energy usage and extending network lifespan. Simulation results show that EANFR significantly outperforms existing methods in terms of energy efficiency and quality of service, improving clustering by 89.23% and enhancing network lifetime for IoT applications [26].

3.2. Routing Optimization

Q-Learning for Energy-Efficient Routing: By analyzing sensor type-dependent aggregation, communication energy, and node residual energy, the method optimizes routing pathways. Compared to current energy-aware protocols, simulations demonstrate that this approach reduces data transmission, eliminates energy-depleted nodes, and increases the lifetime of WSNs [27].

Deep Q-Network (DQN) Routing: Deep Q-learning models resolve the traditional static connectivity problems by reducing the routing path through DRL-based path planning and fuzzy-defined gateways in WSNs. Additionally, it can optimize the energy consumption of high-speed networks using DQN [28].

Hierarchical Reinforcement Learning for Multi-Hop Routing: Hierarchical Reinforcement Learning for Multi-Hop Routing: Static Cluster Head (CH) and EAMMH protocols often result in inefficient CH selection and shorter network lifespan, which leads to greater energy consumption in the nodes with dying nodes and low throughput. Using SAC-D (Soft Actor Critic for Discrete action space) with K-Means clustering, Hierarchical RL improves the energy efficiency [29].

Distributed Q-Learning for Decentralized Power Management: The FQLDEM method balances energy harvesting and consumption for continuous operation by changing duty cycles using fuzzy inference and Q-learning. Experimental results show improved battery management and service quality in terms of energy tolerance and efficiency, compared with dynamic duty cycle adaptation and reinforcement learning methods [30].

Monte Carlo Tree Search (MCTS) for Route Optimization: To find energy-efficient routes, MCTS has been used for route optimization in WSNs to balance exploration and exploitation. This method lowers energy usage and packet delays in dynamic real-time situations [31].

Hybrid PSO-GA for Optimal Path Selection: PSOGA, a hybrid approach for optimum routing that combines GA with Particle Swarm Optimization (PSO). Cluster heads are chosen using a trust-based methodology to ensure effective communication. It is effective for Internet of Things applications because simulations show notable gains in energy efficiency, throughput, packet delivery rate, and residual energy when compared to LEACH and PSO [32].

Ant Colony Optimization (ACO) for Route Optimization: The Butterfly Optimization Algorithm (BOA) for cluster head selection and Ant Colony Optimization (ACO) for routing can be combined to present an energy-efficient routing protocol for wireless sensor networks (WSNs). Cluster heads are chosen based on node degree, closeness, and residual energy. In comparison to LEACH, DEEC, and other approaches, simulations demonstrate increased data delivery, decreased energy consumption, and improved network lifespan [33].

Proximal Policy Optimization (PPO) for Adaptive Duty Scheduling: PPO optimizes node activity plans to save energy usage without sacrificing data accuracy when used with adaptive duty scheduling in WSNs. Real-time adaptability is provided by the continually updated method [34].

Energy-Efficient Routing using Neural Networks: ERFN optimizes cluster head selection by integrating fuzzy logic and neural networks, distributing energy consumption among nodes, and thereby extending the network lifetime. Simulations ensure effective, sustainable operations by outperforming conventional techniques in terms of residual energy, alive nodes, and energy decay [35].

3.3. Data Aggregation

Deep Belief Networks (DBN) for Data Aggregation: Utilizing Recurrent Neural Networks (RNN) with Long Short-Term Memory (LSTM), DL-GMA improves cluster formation, Cluster Head (CH) selection, and maintenance. Achieving metrics like 88.7% energy efficiency and 93.4% Quality of Service (quality of service), the model extends network lifespan, reduces congestion, and enhances data transmission efficiency, representing a significant advancement in WSN energy optimization [36].

RBM and CAO for Intrusion Detection and Energy Optimization in WSNs: Traditional security measures, such as intrusion detection systems, often fail to ensure the reliability and energy efficiency of wireless sensor networks (WSNs) due to the evolving nature of threats and dynamic conditions. This study introduces a Restricted Boltzmann Machine (RBM) framework enhanced by Chaotic Ant Optimization (CAO), which optimizes sensor node confidence levels and addresses both intrusion detection and energy efficiency [37].

Data Fusion for Wireless Sensor Nodes Using Belief Structures: Traditional data collection in wireless sensor networks suffers from high redundancy and increased costs, resulting in inefficiency in data transmission and processing. This study introduces a data fusion method based on belief structure within multi-granulation rough sets to optimize attribute reduction. By integrating belief structures, the technique enhances granular computing, enabling three reductions: positive region reduction, belief reduction, and plausibility reduction [38].

Deep Autoencoders for Data Compression: Ensuring security in Wireless Sensor Networks (WSNs) is challenging due to limited resources and hostile deployment environments. This review explores Secure Data Aggregation (SDA) as a solution, discussing its goals, challenges, and various network topologies. SDA protocols are categorized based on security mechanisms, goals, and topologies, highlighting their applicability and security levels [39].

Sparse Coding for Efficient Data Collection: Wireless Sensor Networks (WSNs) face significant challenges in ensuring security due to limited resources and deployment in hostile environments. Secure Data Aggregation (SDA) provides a practical solution that combines data aggregation with security mechanisms to mitigate resource constraints while maintaining optimal performance. This review categorizes SDA protocols based on security goals, mechanisms, and network topologies, highlighting their applications and security levels [40].

3.4. Topology Control

Adaptive Power Adjustment: Conventional topology-based energy-saving methods for WSNs often neglect node-specific energy optimization, limiting their efficiency. The N1-energy saving phase utilizes a hybrid filter-wrapper feature selection approach to minimize the number of active sensor nodes while maintaining network performance. The N2-energy saving phase uses Simulated Annealing (SA) to optimize sampling rates and transmission intervals, reducing node-level energy consumption while maintaining quality of service [41].

Distance-Based Power Adjustment: Certain distance-based power adjustments, such as Power-Net, can offer effective power regulation. It utilizes GLI to bypass channel estimation and combines convolutional layers for interference pattern learning with a deep learning-based technique that leverages geographical location information (GLI) to eliminate channel estimation and achieve effective power regulation [38].

Residual Energy-Aware Cooperative Transmission: Traditional cooperative transmission systems in wireless networks often utilize all relay nodes for communication, leading to inefficient energy consumption and a reduced network lifetime. The Residual Energy-Aware Cooperative Transmission (REACT) algorithm selects an optimal subset of relay nodes based on their residual energy to maximize network lifetime. The algorithm guarantees effective packet transport with a limited energy supply [42].

Genetic Algorithm-Based Deployment for Energy-Efficient WSNs: Random placement of sensor nodes in WSNs results in uncovered areas, redundant data, and significant energy waste. Genetic Algorithm (GA)-based methodology for self-organized WSN deployment optimizes node placement to improve connection and coverage while reducing energy consumption.GA determines the best sensor node placements, resulting in efficient network performance [43].

GNN and RL-Based Sink Movement Planning for WSN Lifetime Maximization: Traditional sink movement planning methods in wireless networks are inefficient because they rely on mathematical programming, which suffers from high computational costs and dependencies on human expertise. Graph Neural Networks (GNN) and Deep Reinforcement Learning (DRL) automatically optimize the sink's moving pattern for maximum lifetime [44].

3.5. Energy Harvesting

Federated Learning: Federated Learning (FL) in energy-harvesting wireless networks faces challenges from interference and energy constraints, which limit user participation and engagement. Joint energy management and user scheduling problem to optimize FL training by minimizing training loss. The proposed algorithm analyzes the convergence rates of FL to optimize transmit power, user scheduling, and user association [45].

Heterogeneous Ultra-Dense Networks (HUDN): This method faces challenges due to the unpredictable and random nature of harvested energy, as well as the complexity of controlling small-cell base stations. The Wolpertinger Deep Deterministic Policy Gradient (W-DDPG) algorithm addresses these challenges by optimizing energy harvesting and data transmission in HUDNs [46].

Price-Anticipating Kelly Mechanism (PAKM): This mechanism is used for resource allocation, but it faces difficulties when misbehaving users attempt to degrade the utilities of benign users through strategic payments. A study shows a noncooperative game involving a misbehaving user and multiple users to evaluate PAKM's robustness [47].

Deep Learning for Energy Prediction: Traditional approaches, which utilize probability models and classical machine learning, struggle with achieving high prediction accuracy. A study presents three deep learning-based energy prediction methods that can reduce packet loss and transmission delay, ultimately aligning with the energy efficiency goal [48].

3.6. Duty Cycling

Deep Reinforcement Learning Duty Cycling: Traditional power allocation approaches in multicarrier wireless systems overlook the critical role of experience replay parameters in dynamic learning models. This study examines the impact of replay buffer and mini-batch sizes on multi-agent cooperative deep reinforcement learning for dynamic power allocation. The research highlights their impact on system performance and proposes optimized configurations [49].

Decision Tree-Based Duty Cycling: Intelligent Duty Cycle (IDCSC) adopted a decision-based algorithm to enhance energy-efficient quality of service in multi-hop wireless sensor networks (WSNs). Combining SCA-Lévy clustering for optimal cluster head selection with a Forecast-based Duty-Cycle Adaptation (FDCA) using RNN, the algorithm reduces energy consumption and delays in cluster communication [50].

Adaptive Low-Power Listening (ALPL): Wireless Sensor Networks (WSNs) face challenges like packet loss and inefficiency due to energy and bandwidth constraints. Mission-critical surveillance system leveraging a decision tree algorithm on a centralized server to predict wireless channel quality. The adaptive duty cycle mechanism enables sensor nodes to respond proactively to mobility, interference, and hidden terminals, thereby improving performance in industrial settings [51].

Time Series Analysis with LSTM for Node Energy Prediction: The uncertain availability of environmental energy introduces challenges in energy management for rechargeable wireless sensor nodes. Integrated approach combining adaptive duty cycling with machine learning-based solar irradiance prediction and dynamic programming optimization to maximize node performance while efficiently utilizing harvested energy [35].

4. Energy Trade-Offs in ML-Based WSN Optimization

While machine learning (ML)-based techniques significantly reduce communication overhead and improve network longevity in Wireless Sensor Networks (WSNs), they introduce additional energy consumption at the computational layer. Complex models such as Deep Q-Networks (DQNs) and Proximal Policy Optimization (PPO) require considerable processing power for forward passes and Q-value computation, which may not be suitable for deployment on low-power sensor nodes. For example, [28] shows that although DQN-based routing optimizes energy efficiency by reducing path length and delay, the model's inference cost becomes a bottleneck when executed locally.

Moreover, continuous model updates in dynamic networks, particularly for reinforcement learning agents, lead to frequent memory access and CPU cycles, thereby increasing the energy burden [46]. These factors create a practical trade-off: the energy saved through intelligent routing or clustering must outweigh the processing energy spent during ML inference.

Lightweight models, such as Q-learning with discrete states or fuzzy-neural hybrids [35], offer a better balance for deployment in real-time embedded systems. In contrast, heavier models such as GNNs, PPO, or LSTMs are more suited for offloading to edge devices or base stations with higher computational capabilities.

To ensure net energy gain, future WSN deployments should benchmark ML models not only for routing or aggregation performance but also for their processing energy per inference, model size, and inference latency. A holistic energy profile is essential for validating the benefits of ML in WSNs under constrained environments.

5. Real-Time Challenges in ML-Based WSN Energy Optimization

Despite the promising potential of machine learning (ML) in improving energy efficiency for Wireless Sensor Networks (WSNs), real-time deployment introduces several critical challenges that must be addressed to ensure practical viability.

5.1. Computational and Memory Constraints

Sensor nodes are typically resource-constrained, operating on microcontrollers with limited CPU frequency, RAM, and storage. Executing complex ML models such as Deep Q-Networks (DQNs), LSTMs, or GNNs on these models can cause processing delays and battery drain, offsetting energy savings. Model compression techniques (e.g., pruning, quantization) or shallow models are necessary for device execution [28] [35].

5.2. Adaptability to Dynamic Topologies

WSNs often operate in environments with changing node density, mobility, or failures. Static ML models trained offline may fail to adapt in real time to these changes, leading to suboptimal decisions. Online learning or lightweight transfer learning methods are needed to maintain accuracy in dynamic conditions [46].

5.3. Latency-Sensitive Applications

Many WSN use-cases, such as industrial automation, emergency alerts, or healthcare, have strict latency requirements. Delays from model inference or large-scale feature processing can compromise real-time responsiveness. Models must be optimized for both inference speed and communication scheduling.

5.4. Energy VS. Intelligence Trade-Off

While ML can reduce communication energy by optimizing routing or aggregation, executing the model itself consumes energy. The balance between energy saved and energy spent must be carefully analyzed.

Lightweight heuristic models or hybrid rule-ML frameworks can offer a better trade-off.

Addressing these real-time challenges is essential for transitioning ML-based WSN energy optimization from simulation to real-world deployment.

6. Comparative Performance Analysis

A Systematic Literature Review (SLR) was conducted based on key performance metrics, which was then organized in a comparison table for a clear understanding of the comparison between the traditional and ML-driven methods. There can be different primary key parameters to evaluate a network's feasibility and viability for any system, particularly in terms of its energy-efficient data transfer. However, five primary metrics were chosen for this analysis to understand the network's condition and enable us to decide whether the ML-based approach is beneficial for the system or not. Reputed databases, such as IEEE Xplore, ScienceDirect, and SpringerLink, were used to collect structured results with quantitative metrics on EC, PDR, NL, and latency.

Key parameters to evaluate the performance of any WSNs based on energy efficiency are,

Energy Consumption (EC): This directly affects the energy efficiency of any network as it is related to the average energy usage of nodes in action. Joules (J) and Milliwatts (mW) are the standard units for this.

Network Lifetime (NL): This metric measures the duration for which a node can operate without exhausting its energy level. It is measured by cycles, units, or hours.

Packet Delivery Ratio (PDR): This metric measures the accuracy of data delivered to the receiver and is typically expressed as a percentage of successfully delivered data.

Latency (L): It is the median time required to communicate from a source node to the base station. The unit used for this is in milliseconds (ms).

Scalability (S): The Last major parameter for WSNs in terms of energy efficiency is the scalability factor, which indicates the network's performance in dense traffic and node conditions. It is quantized as nodes per unit.

The results were synthesized into a comparison table that included the five different energy efficiency techniques, as well as a side-by-side comparison of traditional methods and ML-based methods (Table 1). Each method section will have its subsections and comments on the specifics, along with related literature.

Table 1. Comparative Analysis between Traditional and ML-based approaches for energy efficiency in WSNs.

Techniques	Traditional Method		ML-Based Method	
Clustering	LEACH [4]	Uneven (EC), poor (S), low (NL)	LEACH-SOM [24]	25% better (NL)
	PEGASIS [6]	Large (EC), Low (PDR)	ACO-PSO [23]	28% reduced (EC)

Continued

	HEED [7]	Low (S), medium (EC)	MARL [22]	32% better (EC)
	EEUC [8]	Low (S), good (PDR)	DBSCAN [25]	20% longer (NL)
	ZEEP [4]	Low (S), medium (EC)	ANFIS [26]	89% efficiency
Routing Optimization	Static Power Aware Protocols [9]	High (EC), Poor (NL), Low (PDR)	DQN [17], PSO-GA [32], ACO [33], MCTS [31]	30% better (NL), 35% reduced latency, 20% reduced (EC)
Data Aggregation	Tree-Based [6]	High (L), Medium (EC)	DBN, DAE [36]	88.7% better (EC), 93% QoS
	Cross Layer [11]	Large (EC)	RBM, CAO [37]	40% better (EC)
	MIMO [12]	Complex (S)	EECDA [25]	20% better (NL)
Topology Control	Spatial, Grid-Based [13]-[15]	High (EC), High (L)	Power-Net. VGA [15] [38]	20% better (EC), 18% reduced (L)
Energy Harvesting	Static, resource picking models [5] [19]	Inefficient resource utilization, poor (EC)	FL, HUDN, PAKM, JDSRA [45]-[48]	28% higher resource allocation
Duty Cycling	S-MAC, T-MAC [20] [21]	Periodic (EC), High Latency	PPO, IDCSC [34] [50]	20% - 30% reduced (EC), Low Latency

7. Conclusions

This paper presents a comprehensive comparison between traditional and machine learning (ML)-based techniques for improving energy efficiency in Wireless Sensor Networks (WSNs). Through detailed categorization and performance analysis, it is evident that ML approaches, including reinforcement learning, neural models, and hybrid optimization algorithms, can significantly enhance energy saving, network lifetime, and scalability. However, the performance gain often comes at the cost of increased computational complexity, memory usage, and latency.

Our analysis shows that clustering and duty cycling benefit most from ML integration, with measurable improvements in energy reduction and packet delivery ratio. Routing optimization using RL and evolutionary methods also demonstrates promising results. Despite these advancements, practical deployment remains limited due to hardware constraints and a lack of adaptive protocols. These findings underscore the need for targeted research on model efficiency and real-time adaptability.

8. Future Work

To close the implementation gap, future research should prioritize the development of lightweight and hardware-friendly ML models that can operate efficiently on microcontroller-based sensor nodes. Techniques such as model pruning, quantization, and knowledge distillation can reduce inference cost without sacrificing accuracy.

Another critical direction is exploring federated learning for WSNs, which allows decentralized model training without requiring raw data transmission, thereby preserving privacy and conserving communication energy. Additionally, transfer learning and online learning mechanisms should be investigated to enable model adaptability in dynamic topologies and varying workloads.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Heinzelman, W.B. (2000) Application-Specific Protocol Architectures for Wireless Networks.

[2] Biswas, S. and Morris, R. (2005) Opportunistic Multi-Hop Routing for Wireless Networks. *Proceedings of the* 2005 *Conference on Applications*, *Technologies*, *Architectures*, *and Protocols for Computer Communications*, Philadelphia, 22-26 August 2005, 133-144.

[3] Zhang, H. and Hou, J. (2005) Maintaining Sensing Coverage and Connectivity in Large Sensor Networks. In: *Handbook on Theoretical and Algorithmic Aspects of Sensor*, *Ad Hoc Wireless*, *and Peer-to-Peer Networks*, Auerbach Publications, 89-124. https://doi.org/10.1201/9780203323687.ch28

[4] Tyagi, S. and Kumar, N. (2013) A Systematic Review on Clustering and Routing Techniques Based Upon LEACH Protocol for Wireless Sensor Networks. *Journal of Network and Computer Applications*, **36**, 623-645. https://doi.org/10.1016/j.jnca.2012.12.001

[5] Bagci, F. (2016) Energy-Efficient Communication Protocol for Wireless Sensor Networks. *Ad-Hoc & Sensor Wireless Networks*, **30**, 301-322.

[6] Madden, S.F. (2002) A Tiny Aggregation Service for Ad-Hoc Sensor Networks. *ACM SIGOPS Operating Systems Review*, **36**, 131-146.

[7] Younis, O. and Fahmy, S. (2004) HEED: A Hybrid, Energy-Efficient, Distributed Clustering Approach for Ad Hoc Sensor Networks. *IEEE Transactions on Mobile Computing*, **3**, 366-379. https://doi.org/10.1109/tmc.2004.41

[8] Joon, R., Tomar, P., Kumar, G., Balusamy, B. and Nayyar, A. (2024) Unequal Clustering Energy Hole Avoidance (UCEHA) Algorithm in Cognitive Radio Wireless Sensor Networks (CRWSNs). *Wireless Networks*, **31**, 735-757. https://doi.org/10.1007/s11276-024-03801-6

[9] Anandrao, D.T. and Parthiban, L. (2024) A Review of Different Techniques Used for Routing in Wireless Sensor Networks. *International Journal of Advanced Intelligence Paradigms*, **28**, 316-326. https://doi.org/10.1504/ijaip.2024.140093

[10] Fasolo, E., Rossi, M., Widmer, J. and Zorzi, M. (2007) In-Network Aggregation Techniques for Wireless Sensor Networks: A Survey. *IEEE Wireless Communications*, **14**, 70-87. https://doi.org/10.1109/mwc.2007.358967

[11] Krishnamachari, L., Estrin, D. and Wicker, S. (2002) The Impact of Data Aggregation in Wireless Sensor Networks. *Proceedings* 22*nd International Conference on Distributed Computing Systems Workshops*, Vienna, 2-5 July 2002, 575-578. https://doi.org/10.1109/icdcsw.2002.1030829

[12] Islam, M.R. and Kim, J. (2008) Energy Efficient Cooperative MIMO in Wireless Sensor Network. 2008 *International Conference on Intelligent Sensors*, *Sensor Networks and Information Processing*, Sydney, 15-18 December 2008, 505-510.

https://doi.org/10.1109/issnip.2008.4762039

[13] Roychowdhury, S. and Patra, C. (2010) Geographic Adaptive Fidelity and Geographic Energy Aware Routing in Ad Hoc Routing. *International Journal of Computer and Communication Technology*, **1**, 91-95. https://doi.org/10.47893/ijcct.2011.1077

[14] Yu, Y.G. (2001) Geographical and Energy Aware Routing: A Recursive Data Dissemination Protocol for Wireless Sensor Networks. UCLA Computer Science Department Technical Report.

[15] Nakas, C., Kandris, D. and Visvardis, G. (2020) Energy Efficient Routing in Wireless Sensor Networks: A Comprehensive Survey. *Algorithms*, **13**, Article 72. https://doi.org/10.3390/a13030072

[16] Akbari Torkestani, J. (2015) An Energy-Efficient Topology Control Mechanism for Wireless Sensor Networks Based on Transmit Power Adjustment. *Wireless Personal Communications*, **82**, 2537-2556. https://doi.org/10.1007/s11277-015-2363-9

[17] Luo, J., Hu, J.Y., Wu, D. and Li, R.F. (2014) Opportunistic Routing Algorithm for Relay Node Selection in Wireless Sensor Networks. *IEEE Transactions on Industrial Informatics*, **11**, 112-121. https://doi.org/10.1109/tii.2014.2374071

[18] Vullers, R.J.M., Schaijk, R.V., Visser, H. J., Penders, J. and Hoof, C. V. (2010) Energy Harvesting for Autonomous Wireless Sensor Networks. *IEEE Solid-State Circuits Magazine*, **2**, 29-38,

[19] Al-Karaki, J.N. and Kamal, A.E. (2004) Routing Techniques in Wireless Sensor Networks: A Survey. *IEEE Wireless Communications*, **11**, 6-28. https://doi.org/10.1109/mwc.2004.1368893

[20] Ye, W.H. (2002) An Energy-Efficient MAC Protocol for Wireless Sensor Networks. *Proceedings of the IEEE INFOCOM* 2002, New York, 23-26 June 2002, 1567-1576.

[21] Polastre, J., Hill, J. and Culler, D. (2004) Versatile Low Power Media Access for Wireless Sensor Networks. *Proceedings of the 2nd International Conference on Embedded Networked Sensor Systems*, Baltimore, 3-5 November 2004, 95-107. https://doi.org/10.1145/1031495.1031508

[22] Homod, R.Z., Togun, H., Kadhim Hussein, A., Noraldeen Al-Mousawi, F., Yaseen, Z.M., Al-Kouz, W., *et al.* (2022) Dynamics Analysis of a Novel Hybrid Deep Clustering for Unsupervised Learning by Reinforcement of Multi-Agent to Energy Saving in Intelligent Buildings. *Applied Energy*, **313**, Article 118863. https://doi.org/10.1016/j.apenergy.2022.118863

[23] Sharmin, S., Ahmedy, I. and Md Noor, R. (2023) An Energy-Efficient Data Aggregation Clustering Algorithm for Wireless Sensor Networks Using Hybrid PSO. *Energies*, **16**, Article 2487. https://doi.org/10.3390/en16052487

[24] Nayak, P., Swetha, G., Kaushal, P. and Padhan, D.G. (2022) Cluster Formation Algorithm in WSNs to Optimize the Energy Consumption Using Self-Organizing Map. In: *Lecture Notes in Networks and Systems*, Springer, 11-22. https://doi.org/10.1007/978-981-16-2919-8_2

[25] Singh, J. (2022) Energy Efficient Data Aggregation and Density-Based Spatial Clustering of Applications with Noise for Activity Monitoring in Wireless Sensor Networks. *Engineered Science*, **19**, 144-153.

[26] Jeevanantham, S. and Rebekka, B. (2022) Energy-Aware Neuro-Fuzzy Routing Model for WSN Based-IoT. *Telecommunication Systems*, **81**, 441-459. https://doi.org/10.1007/s11235-022-00955-6

[27] Yun, W. and Yoo, S. (2021) Q-Learning-Based Data-Aggregation-Aware Energy-Efficient Routing Protocol for Wireless Sensor Networks. *IEEE Access*, **9**, 10737-10750.

https://doi.org/10.1109/access.2021.3051360

[28] Zhang, X., Xiong, K., Chen, W., Fan, P., Ai, B. and Ben Letaief, K. (2024) Minimizing AoI in High-Speed Railway Mobile Networks: DQN-Based Methods. *IEEE Transactions on Intelligent Transportation Systems*, **25**, 20137-20150. https://doi.org/10.1109/tits.2024.3472033

[29] Fofana, A.H.R. and Lei, J. (2023) Reinforcement Learning Based Cluster Formation Algorithm in Wireless Sensor Networks. *Proceedings of the 2nd International Conference on Signal Processing*, *Computer Networks and Communications*, Xiamen, 8-10 December 2023, 367-371. https://doi.org/10.1145/3654446.3654512

[30] Hsu, R.C., Lin, T. and Su, P. (2022) Dynamic Energy Management for Perpetual Operation of Energy Harvesting Wireless Sensor Node Using Fuzzy Q-Learning. *Energies*, **15**, Article 3117. https://doi.org/10.3390/en15093117

[31] Wang, Q. and Hao, Y. (2023) Routing Optimization with Monte Carlo Tree Search-Based Multi-Agent Reinforcement Learning. *Applied Intelligence*, **53**, 25881-25896. https://doi.org/10.1007/s10489-023-04881-1

[32] Mishra, M., Gupta, G.S. and Gui, X. (2021) Network Lifetime Improvement through Energy-Efficient Hybrid Routing Protocol for IoT Applications. *Sensors*, **21**, Article 7439. https://doi.org/10.3390/s21227439

[33] Maheshwari, P., Sharma, A.K. and Verma, K. (2021) Energy Efficient Cluster Based Routing Protocol for WSN Using Butterfly Optimization Algorithm and Ant Colony Optimization. *Ad Hoc Networks*, **110**, Article 102317. https://doi.org/10.1016/j.adhoc.2020.102317

[34] Li, R.X. (2023) Proximal Policy Optimization (PPO)-Based Resource Allocation for Energy Harvesting Industrial Wireless Sensor Networks. *IEEE Transactions on Industrial Informatics*, 1-25.

[35] Varun, R.K., Gangwar, R.C., Kaiwartya, O. and Aggarwal, G. (2021) Energy-Efficient Routing Using Fuzzy Neural Network in Wireless Sensor Networks. *Wireless Communications and Mobile Computing*, **2021**, Article 5113591. https://doi.org/10.1155/2021/5113591

[36] Surenther, I., Sridhar, K.P. and Kingston Roberts, M. (2023) Maximizing Energy Efficiency in Wireless Sensor Networks for Data Transmission: A Deep Learning-Based Grouping Model Approach. *Alexandria Engineering Journal*, **83**, 53-65. https://doi.org/10.1016/j.aej.2023.10.016

[37] Srivastava, J. and Prakash, J. (2024) Deep Learning-Enabled Energy Optimization and Intrusion Detection for Wireless Sensor Networks. *OPSEARCH*, **62**, 368-405. https://doi.org/10.1007/s12597-024-00791-z

[38] Long, C.L. (2021) A Data Fusion Method in Wireless Sensor Network Based on Belief Structure. *EURASIP Journal on Wireless Communications and Networking*, **2021**, 1-22.

[39] Cui, J. (2016) Data Aggregation in Wireless Sensor Networks. Doctoral Dissertation, National Institute of Applied Sciences of Lyon.

[40] Liu, X., Yu, J., Li, F., Lv, W., Wang, Y. and Cheng, X. (2019) Data Aggregation in Wireless Sensor Networks: From the Perspective of Security. *IEEE Internet of Things Journal*, **7**, 6495-6513. https://doi.org/10.1109/jiot.2019.2957396

[41] Kang, J., Kim, J., Kim, M. and Sohn, M. (2020) Machine Learning-Based Energy-Saving Framework for Environmental States—Adaptive Wireless Sensor Network. *IEEE Access*, **8**, 69359-69367. https://doi.org/10.1109/access.2020.2986507

[42] Liu, E., Zhang, Q.Q. and Leung, K.K. (2010) Residual Energy-Aware Cooperative

Transmission (REACT) in Wireless Networks. *The* 19*th Annual Wireless and Optical Communications Conference* (*WOCC* 2010), Shanghai, 14-15 May 2010, 1-6.

[43] Aissa, Y.B., Bouaziz, W., Mohammedi, A., *et al.* (2022) Genetic Algorithm-Based Optimal Wireless Sensor Network Deployment. 2022 *International Symposium on Innovative Informatics of Biskra* (*ISNIB*), Biskra, 7-8 December 2022, 1-6. https://doi.org/10.1109/isnib57382.2022.10075689

[44] Han, X., Mu, X. and Zhong, J. (2024) HGFF: A Deep Reinforcement Learning Framework for Lifetime Maximization in Wireless Sensor Networks. *IEEE Transactions on Artificial Intelligence*, **6**, 859-873. https://doi.org/10.1109/tai.2024.3497926

[45] Hamdi, R., Chen, M., Said, A.B., Qaraqe, M. and Poor, H.V. (2021) Federated Learning over Energy Harvesting Wireless Networks. *IEEE Internet of Things Journal*, **9**, 92-103. https://doi.org/10.1109/jiot.2021.3089054

[46] Ye, J. and Gharavi, H. (2020) Deep Reinforcement Learning-Assisted Energy Harvesting Wireless Networks. *IEEE Transactions on Green Communications and Networking*, **5**, 990-1002. https://doi.org/10.1109/tgcn.2020.3045075

[47] Chaoming Hsu, R., Liu, C. and Lee, W. (2009) Reinforcement Learning-Based Dynamic Power Management for Energy Harvesting Wireless Sensor Network. In: *Lecture Notes in Computer Science*, Springer, 399-408. https://doi.org/10.1007/978-3-642-02568-6_41

[48] Zazoua, E., Ajib, W. and Boukadoum, M. (2023) Deep Learning-Based Receiver Energy Prediction in Energy Harvesting Wireless Sensor Network. 2023 *IEEE* 14*th Latin America Symposium on Circuits and Systems* (*LASCAS*), Quito, 28 February-3 March 2023, 1-5. https://doi.org/10.1109/lascas56464.2023.10108110

[49] Khan, A.A., Jamal, M.S. and Siddiqui, S. (2017) Dynamic Duty-Cycle Control for Wireless Sensor Networks Using Artificial Neural Network (ANN). 2017 *International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery* (*CyberC*), Nanjing, 12-14 October 2017, 420-424. https://doi.org/10.1109/cyberc.2017.93

[50] Aravinthan, N. and Geetha, K. (2024) An Intelligent Duty Cycle Forecasting and Optimized Clustering Algorithm for Improving Energy Efficiency in Multi-Hop WSNs.

[51] Sharma, A. and Kakkar, A. (2019) Machine Learning Based Optimal Renewable Energy Allocation in Sustained Wireless Sensor Networks. *Wireless Networks*, **25**, 3953-3981. https://doi.org/10.1007/s11276-018-01929-w