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Energy-Efficient Routing in Wireless Sensor Networks: A Comprehensive Review of Machine Learning, Optimization, Clustering, and Duty Cycling Techniques

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Abstract. Wireless Sensor Networks (WSNs) are widely used in various applications, yet they remain limited by the energy constraints of sensor nodes. This review paper explores and compares recent advancements in energy-efficient routing strategies across four major categories: Q-Learning-based routing, traditional optimization algorithms, clustering-based protocols, and sleep scheduling techniques. Each approach is analyzed in terms of its methodology, simulation environment, performance metrics, and limitations. Q-Learning techniques provide adaptive and intelligent routing decisions but often lack real-world deployment. Traditional algorithms such as Ant Colony Optimization (ACO) and Whale Optimization Algorithm (WOA) offer reliable clustering but adapt poorly to dynamic environments. Clustering-based protocols, especially those integrating fuzzy logic or quantum methods, show strong results in simulations but assume static and homogeneous nodes. Sleep scheduling and duty cycling protocols significantly reduce idle energy waste, yet are rarely integrated with routing layers. The review identifies that most current protocols are evaluated only through simulations and face challenges such as congestion near sinks, lack of cross-layer integration, and scalability under heterogeneous conditions. Future research should focus on building lightweight, real-time learning frameworks that jointly optimize routing, clustering, and sleep scheduling in practical deployments.

Keywords: Wireless Sensor Networks; Energy Efficiency; Q-Learning; Sleep Scheduling; Duty Cycling; Network Lifetime.

1. Introduction

Wireless Sensor Networks (WSNs) represent a cornerstone in the architecture of intelligent systems, enabling real-time environmental perception, data acquisition, and decision-making across diverse application domains such as environmental monitoring, industrial automation, smart cities, precision agriculture, and healthcare systems [1],[2]. A typical WSN consists of numerous spatially distributed, low-power sensor nodes that autonomously sense, process, and transmit information to a centralized base station or sink node. These nodes are often deployed in inaccessible or harsh environments and are typically powered by limited-capacity, non-rechargeable batteries, making energy efficiency a critical design constraint [3],[4]. As shown in Figure 1[5], a standard WSN topology includes multiple sensor nodes (SNs) communicate wirelessly with neighbouring nodes and forward data either directly or via multi-hop routing to the base station (BS). These nodes continuously perform sensing, data aggregation, and communication tasks, each of which contributes to energy consumption at different rates. Notably, wireless communication remains the dominant energy consumer, especially during idle listening, redundant data forwarding, and suboptimal routing decisions [6],[7].

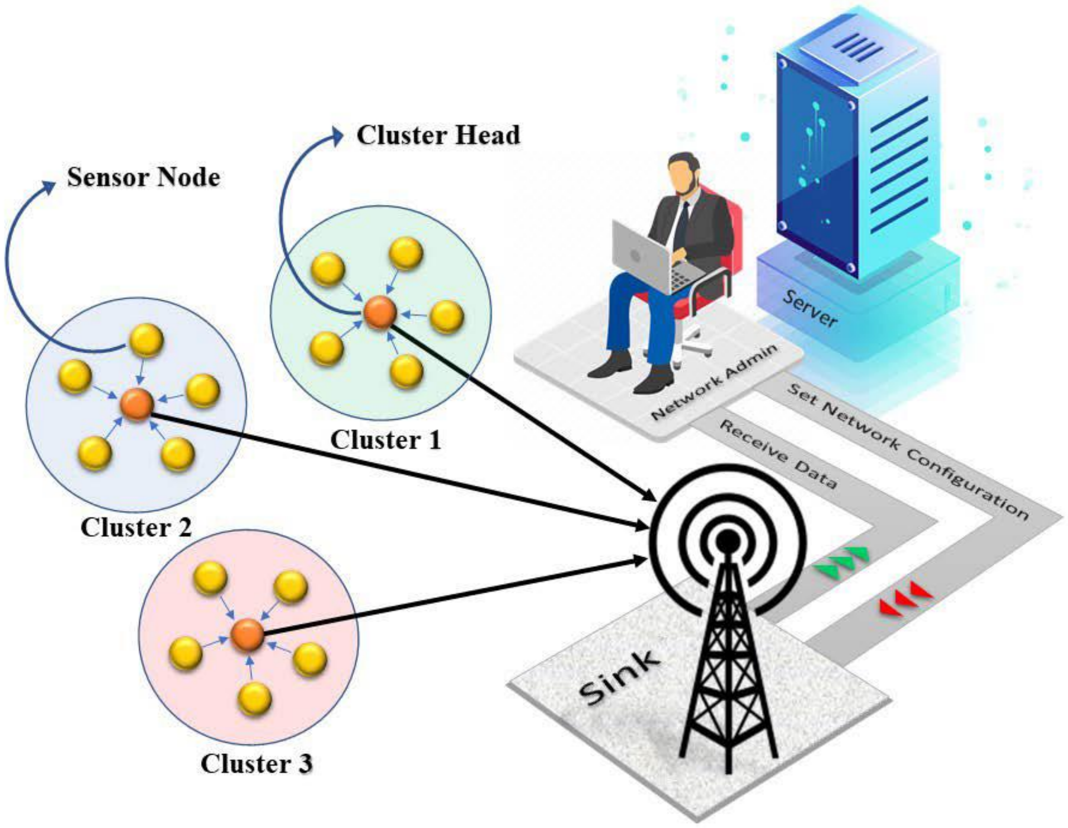

FIGURE 1. Wireless sensor network's general structure [5].

To address the energy shortage problem, recent research has explored multiple complementary strategies at different layers of the network protocol stack. Among the most promising developments are reinforcement learning (RL)-based routing protocols, particularly those using Q-Learning, which enable sensor nodes to dynamically learn optimal routing paths by interacting with the environment and receiving feedback based on remaining energy, distance, and transmission success [8]. Traditional optimization algorithms, such as ant colony optimization (ACO), whale optimization algorithm (WOA), and modified Dijkstra-based methods, provide centralized or semi-distributed optimization for cluster head (CH) selection and energy-dependent path discovery [9],[10]. Clustering-based protocols, including Low-Energy Adaptive Clustering Hierarchy (LEACH) and its variants, reduce long-range transmissions by forming local clusters where specific CH channels handle data aggregation and forwarding. These protocols have been improved by incorporating fuzzy logic, artificial neural networks (ANNs), and quantum-inspired methods [11],[12]. Duty-cycle and sleep-scheduling techniques aim to reduce idle listening and extend network lifetime by selectively turning off nodes' radios during inactivity. When implemented effectively, these techniques can reduce overall power consumption by over 50% without degrading data reliability [13]. Despite the richness of these approaches, most existing protocols have been evaluated only in simulation environments and lack real-world validation. Furthermore, major limitations remain unresolved, including power imbalances near draining nodes, poor scalability under heterogeneous conditions, and the absence of interlayer integration strategies [14],[15]. This review paper aims to present a structured, comprehensive, and comparative synthesis of the latest energy-aware strategies in WSNs, categorized into four critical domains: 1 -Q-Learning-based routing algorithms. 2- Traditional optimization methods (e.g., ACO, WOA). 3- Clustering-based communication protocols. 4- Sleep scheduling and duty cycling frameworks. Through detailed analysis and comparative evaluation tables, the paper highlights key advancements, identifies research gaps, and suggests future directions for building sustainable, real-world-deployable WSNs capable of adapting to dynamic environmental and application conditions.

2. Q-Learning-Based Routing Protocols in Wireless Sensor Networks.

Energy efficiency and adaptive decision-making remain critical challenges in WSNs, especially in dynamic and resource-constrained environments. Reinforcement learning (RL), a branch of machine learning, has emerged as a promising paradigm to address these challenges by enabling autonomous agents (sensor nodes) to learn optimal behaviours through environmental interactions and reward feedback [16]. Among various reinforcement learning techniques, Q-Learning stands out due to its model-free nature, computational simplicity, and ability to operate without global network knowledge, making it particularly suitable for distributed and decentralized WSN architectures [8].In the context of routing, Q-Learning enables sensor nodes to iteratively learn the most energy-efficient routes to a destination typically a base station by evaluating factors such as remaining energy, hop count, link reliability, and proximity to the sink. Nodes dynamically adapt to changes in topology, node failures, and fluctuating power levels by updating their Q values over time in response to feedback from their surroundings. With little validation in actual sensor hardware, its applications are still mostly limited to simulation-only research. Furthermore, Q-Learning has problems with convergence because it takes a lot of iterations to reach stable policies, which lengthens the training period. Another drawback is the state-space complexity, which causes scalability problems and high memory demands as the number of nodes and routing states rises exponentially. These drawbacks show that although Q-Learning shows promise for adaptive routing, more study is required to determine its scalability and practical implementation in large-scale WSNs [17].

This section provides a thorough review of current Q-Learning-based routing protocols in WSNs, each of which addresses distinct performance objectives like scalability, load balancing, lifetime extension, and packet delivery reliability.

Guo et al. (2019) provided Reinforcement Learning-Based Routing (RLBR) , a groundbreaking technique that defined network lifetime in three dimensions: delivery success, connectivity, and the number of live nodes. In order to dynamically choose routing paths according to link distance, hop count, and energy availability, RLBR used Q-values. The protocol was restricted to simulations without physical deployment, but it performed better than traditional methods like BEER and Q-Routing [18].

Similarly, **Wang et al. (2020)** proposed Energy-efficient Distributed Adaptive Cooperative Routing (EDACR) , which integrates lightweight Q-Learning for relay node selection in Wireless Multimedia Sensor Networks (WMSNs) under quality of service (QoS) constraints. This work decreased computation and communication overhead while balancing load by restricting routing table updates to high-energy nodes. In terms of reliability and energy efficiency, evaluation in Network Simulator 2 (NS-2) showed better performance than Distributed Adaptive Cooperative Routing (DACR) and Trust-based Cooperative Routing (TCR) [19].

Mutombo et al. (2021) made another noteworthy contribution by introducing Energy-Efficient Reinforcement Learning (EER-RL), a protocol for IoT-based WSNs that used a three-phase RL approach (clustering, formation, and transmission). Nodes functioned as independent agents that modified Q-values according to hop count and energy. Although there were still issues with practical implementation, the method showed scalability and notable performance gains over LEACH and Power-Efficient Gathering in Sensor Information System (PEGASIS) [20].

Reinforcement Learning-Based Energy-Efficient Routing Protocol (RLBEERP), a reinforcement learning model that combined Q-Learning, sleep scheduling, and event-triggered communication to prevent pointless transmissions, was introduced by **Abadi et al. (2022)** to further this trend. In contrast to Reinforcement Learning-Based Routing (RLBR) and Data-Aware Dynamic Forwarding (DADF), the protocol achieved a longer network lifetime and throughput by rewarding nodes based on transmission changes, residual energy, and proximity to the sink. However, in order to manage real-time learning, strong sink nodes were needed [5].

A cluster-based RL routing strategy that incorporates periodic re-election of cluster heads based on residual energy was proposed by **Jayabalan and Pugazendi (2023)** for Wireless Body Sensor Networks (WBSNs). Healthcare settings with limited energy resources can benefit from the hierarchical architecture's enhanced packet delivery, decreased jitter, and optimized delay [21].

Wang et al. (2023) suggested CRP-Optimizer, a more general and adaptive framework. In contrast to conventional RL routing models, this protocol used Probabilistic Advantage Multi-Dimensional Policies (PAMDPs) and Hybrid Proximal Policy Optimization (H-PPO) to make meta-decisions about which cluster heads to exclude from multi-hop transmission and whether to re-cluster. Although improvements in delivery success and lifetime were confirmed by simulation results across several protocols (e.g., LEACH, Hybrid Energy-Efficient Distributed Clustering (HEED)), deployment in physical WSNs was not pursued [22].

Lastly, **Chaudhari et al. (2025)** developed a Q-Learning model that dynamically updates routing decisions based on real-time residual energy. The protocol preferred nodes with energy > 0.1 J, ensuring reliable transmission. Although simulations in MATLAB showed improved PDR and reduced packet loss, the model suffered from energy concentration around the sink, leading to potential routing failure over time [23].

While these studies demonstrate the potential of Q-Learning in extending network lifetime and improving adaptive routing, most of them are limited to MATLAB or NS-2 simulations. Critical challenges persist in achieving real-time convergence, addressing state-space complexity, and handling real-world uncertainties such as mobility, link variability, and hardware constraints [14][15]. A detailed comparison of these studies is provided in **Table1**, highlighting each protocol's core features, environment, performance, and limitations.

Table1: A Comparative Analysis of Q-Learning-Based Routing Protocols for Energy-Efficient Wireless Sensor Networks.

Study (Author, Year)	Protocol Name	Main Technique	Research Objective	Simulation Environment	Compared Protocols	Key Improvements	Limitations
Wenjing Guo et al., 2019	RLBR	Reinforcement Learning (Q-Learning)	Extend network lifetime by optimizing routes using residual energy, hop count, and connectivity	Simulated (unspecified tool)	EAR, BEER, Q-Routing, MRL-SCSO	Significant improvement in energy efficiency, packet delivery, and network longevity	Evaluated only in simulation; lacks real-world validation
Denghui Wang et al., 2020	EDACR	Lightweight Q-Learning	Optimize routing in WMSNs for QoS and energy efficiency via adaptive relay selection	NS-2	DACR, TCR	Higher energy efficiency and extended lifetime under delay/reliability constraints	Only simulated; no hardware or real deployment testing
Mutombo et al., 2021	EER-RL	Reinforcement Learning (3-phase: CH election, formation, transmission)	Improve energy-aware routing scalability and efficiency for IoT-based WSNs	MATLAB	LEACH, PEGASIS, FlatEER-RL	Improved lifetime, energy use, scalability	Lack of real-world testing; no hardware implementation
Elah Abadi et al., 2022	RLBEEP	Q-Learning + Sleep Scheduling + Event-triggered Transmission	Enhance routing and control via reinforcement learning with reduced communication overhead	Python + wsn-indfeat-dataset	RLBR, DADF	Improved throughput, delayed FND, enhanced lifetime	High processing requirements at sink; no physical testbed
Jayabalan & Pugazendi, 2023	Cluster-based RL routing for WBSNs	Q-Learning with hierarchical WBSN architecture	Energy-efficient routing in healthcare applications using cluster head re-election based on energy	Simulation (tool not mentioned)	Previous WBSN routing models	Better delay, jitter, throughput, node survival rate	Simulation only; lacks real-world WBSN evaluation
Yan Wang et al., 2023	CRP-optimizer	Hybrid PPO + PAMDP-based RL	Optimize reclustering decisions and multi-hop relay exclusion for energy balancing	Simulation across LEACH, HEED, etc.	LEACH, HEED, LEACH-C, WCHSA, OPSKC	Increased lifetime, higher delivery rate, improved survival	No physical deployment; evaluated via simulations only
Chaudhari et al., 2025	Unnamed Q-learning model	Energy-aware Q-Learning routing	Energy-efficient forwarding with dynamic Q-value update based on node energy	MATLAB 2022	Basic Q-Learning	Better PDR, reduced PLR, higher throughput, extended lifetime	Nodes near sink drain faster; lacks real test validation

3. Routing Using Traditional Optimization Algorithms in WSNs

Before the integration of learning-based approaches in WSNs, traditional optimization algorithms particularly metaheuristic and bio-inspired methods played a central role in addressing routing, clustering, and energy-efficiency challenges. These algorithms, known for their ability to explore large solution spaces without requiring exhaustive computation, were especially useful in decentralized, resource-constrained, and dynamically changing sensor environments [24],[25].Among the most commonly applied techniques are Ant Colony Optimization (ACO), inspired by the pheromone trail-following behaviour of ants [24]; Whale Optimization Algorithm (WOA), which simulates the bubble-net hunting strategy of humpback whales [10]; and modifications of Dijkstra’s shortest-path algorithm, adapted to incorporate energy-awareness and multi-hop constraints in WSN topologies [26]. These algorithms typically rely on fitness functions that consider metrics such as residual energy, transmission distance, node density, and link quality, enabling them to find near-optimal routing paths and cluster head (CH) assignments under uncertain or incomplete network knowledge. In the context of WSN routing, these optimization techniques serve as search mechanisms that adaptively balance energy consumption, extend network lifetime, and improve packet delivery rates, often through simulation-driven evaluations. They are useful baselines for protocol development because of their adaptability and simplicity, particularly in deployments that are homogeneous, static, or have limited mobility [27-30].

A thorough analysis of current routing protocols in WSNs that make use of these conventional optimization techniques is given in this section. In order to improve performance in terms of lifetime, throughput, load balancing, and resilience to node failure, each of the following contributions adds special improvements to the base algorithms.

The WOA-Clustering (WOA-C) model created by **Jadhav and Shankar (2017)** is among the pioneering contributions in this field. Using a fitness function that combined residual and neighbouring node energy, this protocol centrally selected the best CHs using the Whale Optimization Algorithm. WOA-C outperformed LEACH, LEACH-C, and PSO-C, according to simulation results, especially terms of lowering total energy consumption and extending network lifetime [31]. However, real-world heterogeneity and mobility were not taken into consideration during the protocol's validation, which was limited to static, homogeneous networks.

Sharada et al. (2024) proposed Adaptive Ant Colony Distributed Intelligent Clustering (AACDIC) , protocol for Cognitive Radio Sensor Networks (CRSNs), to overcome the adaptability constraints in traditional clustering. This algorithm improved convergence time and power efficiency by dynamically adjusting CH election based on signal-to-noise ratio (SNR) by combining distributed decision-making and ant colony optimization. Simulation outcomes indicated a detection probability of 93.7% at 0 dB SNR and energy reductions up to 24.2% for secondary users, but again, real-world deployment was absent [32].

A significant enhancement in routing cost modelling was introduced by **Mohammed et al. (2024)** through a Modified Dijkstra Algorithm. By integrating residual energy and communication cost into the path cost function, the algorithm avoided premature node depletion. When compared to ACO, the proposed model achieved substantial gains: a 605-round network lifetime versus 81 rounds for ACO, with a marginally improved packet delivery ratio (99.9% vs. 98.7%). Nevertheless, the approach remains better suited for static topologies due to its deterministic structure [33].

Further advancements were seen in a Modified Ant Colony Optimization Algorithm (MACOA), introduced by **Tawfeek et al. (2025)**. This model incorporated multi-objective fitness, adaptive pheromone decay, and self-healing routing mechanisms to address node failure and energy imbalance. Evaluated in NS-3, MACOA outperformed protocols such as the Enhanced Genetic Algorithm (EGA), Deep Reinforcement Learning (DRL), and the Energy-aware Reliable Adaptive Routing Protocol (E-RARP) in terms of throughput, lifetime, and load balancing. However, future work is needed to implement the algorithm in real-world sensor networks and incorporate fuzzy logic for improved flexibility [34].

Despite the proven advantages of these algorithms particularly in load distribution, route stability, and low-complexity deployment, they tend to underperform in highly dynamic**,** heterogeneous, or real-time WSN applications compared to adaptive learning-based models. Their reliance on static configurations or global optimization phases limits responsiveness to rapid topology or energy shifts [35]**.** A full comparison of these studies is presented in **Table 2**, highlighting the protocols' methods, simulation platforms, strengths, and key limitations.

Table2: Benchmarking Traditional Optimization Algorithms for Cluster Head Selection and Routing in Wireless Sensor Networks.

Study (Author, Year)	Protocol Name	Main Technique	Research Objective	Simulation Environment	Compared Protocols	Key Improvements	Limitations
Ashwin R. Jadhav & T. Shankar, 2017	WOA-C (Whale Optimization Algorithm - Clustering)	Whale Optimization Algorithm (WOA)	Select energy-efficient cluster heads by evaluating residual and neighborhood energy using centralized WOA	MATLAB (Simulated)	LEACH, LEACH-C, PSO-C, DT	Improved energy efficiency, prolonged network lifetime, higher throughput	Only tested on homogeneous, static networks; no heterogeneous or real-world evaluation
Sharada K. A. et al., 2024	AACDIC (Adaptive Ant Colony Distributed Intelligent Clustering)	Ant Colony Optimization (ACO) + Distributed Intelligence	Dynamic CH selection, minimize power, and improve spectrum access in CRSNs based on SNR	NS-2, MATLAB	DGSC, DCFGC, DCJFGC	Reduced energy (9.6% PUs, 24.2% SUs), improved convergence (by 47s), and high detection rate (PD=0.937)	Simulation only; no validation in real environments
Mohammed, Hasan, & Hamza, 2024	Modified Dijkstra Algorithm	Modified Dijkstra (Energy-Aware Path Cost)	Incorporate residual energy and energy cost in Dijkstra's cost function for routing in WSNs	Python	ACO	Extended lifetime (605 vs 81 rounds), lower death rate, slightly higher delivery rate (99.9%)	Better for static environments; not robust for dynamic or multi-objective cases

Tawfeek et al., 2025	MACOA (Modified Ant Colony Optimization Algorithm)	Multi-objective ACO with Self-healing & Adaptive Exploration	Improve reliability, load-balancing, and energy efficiency through adaptive pheromones and fault-tolerance	NS-3	EGA, IABC, DRL, PSO, E-RARP	Better lifetime, throughput, residual energy and stability	No real-world testing; future work suggests fuzzy-logic integration and deployment

4. Clustering-Based Routing Protocols in Wireless Sensor Networks.

Clustering-based routing has emerged as a cornerstone strategy in WSNs to mitigate energy constraints and enhance network scalability, fault tolerance, and data aggregation efficiency. By grouping sensor nodes into clusters and designating one node per cluster as the Cluster Head (CH), this hierarchical structure reduces redundant data transmissions and long-range communications between individual nodes and the base station (BS), thereby significantly conserving node energy and extending the overall network lifetime [36],[37]. The foundational Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol, introduced by Heinzelman et al. [38], pioneered this approach through probabilistic CH rotation to uniformly distribute energy consumption. Although LEACH provided substantial improvements in simulated environments, it lacked adaptability to heterogeneous energy distributions and mobility, leading to performance degradation in practical deployments. These limitations prompted the development of enhanced clustering frameworks that integrate intelligent decision-making techniques to optimize CH election and routing strategies. Recent advances have introduced hybrid clustering models that incorporate artificial intelligence, fuzzy logic, and metaheuristic optimization to refine CH selection, inter-cluster routing, and load balancing. Techniques such as K-Means, Kohonen Self-Organizing Maps (KSOM), Mamdani Fuzzy Inference Systems, Quantum Annealing, Particle Swarm Optimization, and Multi-Strategy Snake Optimization have been employed to adaptively adjust clustering structures in response to dynamic network conditions [11],[30],[34],[39]. Moreover, some protocols have extended clustering logic to support mobility awareness, sector-based thresholding, and reinforcement learning, enabling CHs to be selected not only based on residual energy, but also considering contextual factors like proximity to sink, communication overhead, and neighbourhood density. This diversification of clustering methodologies demonstrates the potential of hybrid intelligent systems to enhance WSN energy efficiency under real-world constraints [40],[41].

This section provides a comprehensive review of recent clustering-based routing protocols in WSNs, focusing on energy-aware techniques that improve CH election and inter-cluster routing. Each protocol is evaluated based on its methodological framework, simulation platform, performance gains, and limitations.

Heinzelman et al. (2000) first proposed the original LEACH protocol, which used randomized cluster-head rotation to divide the energy load among all nodes. Premature node death occurred close to the base station as a result of LEACH's setup overhead and lack of mechanisms to handle dynamic energy variation, despite its effectiveness in simulation [42].

Razzaq et al. (2018) developed the Optimal Packet Size with K-Means Clustering (OPSKC) protocol to overcome the static nature of LEACH. It combined an analytically determined optimal packet size that was adapted to the channel conditions with centralized K-Means clustering. Additionally, this method made a distinction between intra-cluster and inter-cluster communication energy consumption. Mobility and retransmission factors were not taken into account, but MATLAB simulation results showed reductions in overall energy usage and delayed node death when compared to K-Means Energy-Aware Clustering (KEAC) [43].

Bataineh et al. (2019) created a hybrid solution that combined Kohonen Self-Organizing Maps (KSOM) with K-Means clustering, which was improved by a neural conscience function. Although their model outperformed KSOM alone in real-world WSN scenarios, it increased network lifetime by 11.11% and reduced energy consumption by 3.33% [44].

To further enhance energy efficiency and scalability, **Hu et al. (2024)** introduced the Cluster Head Harris Hawk Fuzzy Optimization (CHHFO) protocol, leveraging a Mamdani fuzzy system and Harris Hawk Optimization (HHO). This dual-phase strategy identified CHs based on energy, proximity, and neighbourhood density, while HHO optimized relay node selection. The protocol reduced energy consumption by up to 39.79% and improved throughput, but lacked evaluation under dynamic topologies [45].

Another hybrid framework, Fuzzy-Quantum Annealing (FQA), was developed by **Wang et al. (2024)**. It integrates Fuzzy Logic for CH election and Quantum Annealing for optimal multi-hop routing. Simulation across four scenarios revealed enhanced lifetime, throughput, and number of alive nodes, yet the protocol was limited to static WSN environments without mobile sink testing [46].

Yang et al. (2024) proposed a novel combination of the Multi-Strategy Snake Optimizer (MSSO) and Minimum Spanning Tree (MST) for both CH and relay selection. Their approach optimized intra- and inter-cluster performance using dynamic mutation strategies and fuzzy C-Means. The results showed consistent improvements of over 25% in energy savings and throughput compared to five benchmark protocols, though it remained simulation-based [47].

In their second contribution, **Hu et al. (2024)** proposed the Quantum Particle Swarm Optimization (QPSOFL) protocol, and merging it with fuzzy-based relay selection. The algorithm incorporated Sobol sequence initialization, Lévy flights, and Gaussian perturbation to avoid local optima. This resulted in superior network longevity and performance metrics, albeit tested only in MATLAB [48].

The KMSC algorithm, proposed by **Zeng et al. (2024)**, introduced a threshold-based K-Means sector clustering approach, which applies clustering only when node density in a sector that exceeds a predefined limit. The CHs were selected based on energy and total communication cost. Hybrid routing (single-hop/multi-hop) enabled the protocol to outperform traditional K-means and Energy-Efficient Clustering Protocol based on K-means (EECPK-means) schemes across several node death benchmarks [40].

Finally, **Wang and Duan (2025)** proposed Fuzzy-Logic and Q-Learning based Unequal Clustering and Routing (FQ-UCR) , combining Fuzzy Logic and Q-Learning for both CH election and inter-cluster routing. The model incorporated node centrality, residual energy, and neighbour count in fuzzy inference and dynamically selected the next-hop CH via reinforcement learning. While it outperformed EEUC and

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CHEF in stability and lifetime, the absence of real-world validation and dataset use limits its applicability [49].

An in-depth comparative summary of these clustering-based protocols is provided in **Table 3**, capturing the diversity of hybrid techniques, energy models, and simulation outcomes.

Table3: A Detailed Comparative Review of Clustering-Based Routing Protocols in Energy-Constrained Wireless Sensor Networks.

Study (Author, Year)	Protocol Name	Main Technique	Research Objective	Simulation Environment	Compared Protocols	Key Improvements	Limitations
Heinzelman et al., 2000	LEACH	Randomized Cluster Head Rotation	Reduce energy via randomized cluster-head assignment and local aggregation	MATLAB (First-order radio model)	Direct Comm., MTE	8x less energy use; 3x longer network lifetime	Simulation only; no real deployment; setup overhead ignored
Razzaq et al., 2018	OPSKC	K-Means + Optimal Packet Size	Reduce transmission energy via packet optimization and energy-aware CH selection	MATLAB	KEAC	Lower energy use, delayed FND, higher throughput	Simulation only; ignored mobility, retransmissions
Bataineh et al., 2019	KSOM + K-Means	Hybrid K-Means + Self-Organizing Maps	Enhance clustering with neural network conscience function and residual energy	MATLAB	KSOM	11.11% better lifetime, 3.33% energy savings	Simulation only; no real validation
Hu et al., 2024	CHHFO	Fuzzy Logic + Harris Hawk Optimization	Optimal CH and relay selection based on fuzzy fitness functions	MATLAB R2022a	EFCR, HHO-UCRA, IHHO-F	Up to 39.79% energy reduction; better scalability & throughput	No dynamic testing or hardware validation
Wang et al., 2024	FQA	Fuzzy Logic + Quantum Annealing	CH selection using fuzzy metrics; optimal multi-hop via Hamiltonian search	MATLAB	FRNSEER, FC-RBAT, BOA-ACO, OAFS-IMFO	Superior lifetime, throughput, and alive nodes count	Static sim only; no mobile sinks or real-world trials

Yang et al., 2024	MSSO + MST	Multi-Strategy Snake Optimizer + MST	CH and relay selection based on energy/distance + optimal inter-cluster routing	MATLAB	LEACH, ESO, EEWC, GWO, EECHS-ISSADE	25–52% better stability, energy, throughput	Only simulation; no testbed or mobility adaptation
Hu et al., 2024	QPSOFL	Quantum Particle Swarm Optimization + Fuzzy Logic	CH selection via QPSO, relay via fuzzy logic on energy and distance	MATLAB	E-FUCA, IHHO-F, F-GWO, FLPSOC	Improved scalability, energy savings, lifetime	No real-world or mobile node validation
Zeng et al., 2024	KMSC	Threshold K-Means Sector Clustering	Balance energy using sector-based clustering with CH thresholds	MATLAB	EECPK-means, K-means, TSC, LSC, SEECP	Improved FND, HND, LND metrics	No mobility scenarios or field deployment
Wang & Duan, 2025	FQ-UCR	Fuzzy Logic + Q-Learning	CH selection via fuzzy metrics; Q-Learning for inter-cluster next-hop	MATLAB	EEUC, CHEF	Better stability, lifetime, throughput	No real datasets or deployment

5. Sleep Scheduling and Duty Cycling Techniques in WSNs.

Energy conservation remains a critical design objective in WSNs, especially for nodes operating in idle listening mode, which can account for a significant portion of total energy consumption even in the absence of active data transmission or reception. While advances in routing and clustering protocols have mitigated energy waste during communication, idle listening continues to drain energy unnecessarily particularly in dense or large-scale networks with intermittent sensing demands [36],[37]. To address this inefficiency, sleep scheduling and duty cycling techniques have emerged as essential strategies that dynamically transition sensor nodes between active and low-power states. These mechanisms aim to reduce idle energy consumption without compromising the quality of service (QoS), especially in long-term deployments, time-critical applications, and energy-constrained environments [50],[51]. Sleep scheduling algorithms can be broadly classified into deterministic, adaptive, and intelligent schemes. Among the most promising are learning-based and optimization-driven frameworks that autonomously determine optimal wake or sleep intervals based on real-time network conditions, traffic patterns, residual energy, and data redundancy. To increase decision-making precision and responsiveness in the face of uncertainty, these frameworks are increasingly integrating neural networks, fuzzy systems, reinforcement learning, and evolutionary algorithms [13],[8].

This section provides a thorough analysis of current sleep scheduling and duty cycling strategies in WSNs, focusing on learning-driven and hybrid models that show reduced performance degradation, increased network lifetime, and enhanced energy efficiency. Each protocol is examined according to its methodology, scalability, real-world applicability, and simulation results.

Huang et al. (2021) suggested a Q-learning-based MAC layer scheduler enhanced with linear regression function approximation as one of the more recent contributions. Their approach used the idle listening ratio as the action, and defined the system state as the normalized queue load. A reward function incorporating both energy consumption and latency was used to learn optimal duty cycles. The approach outperformed Sensor-Medium Access Control (S-MAC) and Fully Active (FA) protocols in NS-3 simulations under varying traffic loads but lacked theoretical modelling and real-world validation [13].

Wang et al. (2023) introduced Reinforcement Learning-based Sleep Scheduling Algorithm for Compressive Data Gathering (RLSSA-CDG), a model-free Q-Learning algorithm designed to enhance compressive data gathering (CDG) through energy-aware sleep scheduling. Each node participated in a distributed learning process using a shared Q-table to decide when to activate or sleep. Simulation results demonstrated substantial energy savings (42.42%) and extended network lifetime by over 57%, with an 84.7% improvement in data recovery accuracy. However, the forwarding phase relied on traditional routing, and the solution was validated only in simulated environments [52].

A more complex and integrated solution was offered by **Nithyanandh et al. (2023)** through their Energy-Aware Protocol with Improved Fitness-Based Algorithm (EAP-IFBA) protocol, which combines Firefly Algorithm, Elliptic Curve Cryptography (ECC), and Recurrent Neural Networks (RNNs). This protocol aims to jointly optimize adaptive sleep scheduling, secure data transmission, and anomaly detection in large-scale IoT networks. Evaluated on OMNET++ with up to 2500 nodes, the method achieved 98% sleep efficiency, a network lifetime of 98%, and strong resilience (96.5%) to security threats. However, its performance degraded under uneven deployments and in heterogeneous environments [53].

Jeyakarthic and Selvakumar (2024) focused on a smart CH selection and sleep scheduling model with real-time duty cycle optimization and data aggregation. Their gradient-based adaptive scheduler minimized redundant transmissions and conserved energy by adjusting node states dynamically. The system achieved a packet delivery ratio (PDR) of 98.24% and an energy consumption rate of only 85 mJ per packet, surpassing threshold-based and dynamic scheduling approaches. Still, validation was limited to MATLAB simulations without real IoT traces [54].

A learning-driven approach was also employed by **Chaya and Shylaja (2024)**, who proposed an Artificial Neural Network (ANN)-based model for predictive sleep-wake scheduling. Their method integrated dynamic programming for routing optimization and used ANN to model energy trends and decide on sleep states in real-time. Despite achieving improved energy efficiency and network longevity, the protocol introduced high computational complexity and potential latency due to ANN training and frequent state transitions [55].

Lastly, **El-Shenhabi et al. (2025)** developed RLDCSSA-CDG, a comprehensive Q-learning-based framework that combines cluster formation, UCB-driven CH selection, and sleep scheduling for compressive data gathering. The system reduces redundant transmissions using compressive sensing (CS) and adjusts node activity adaptively to maximize lifetime and accuracy. Simulations showed 63.3% fewer transmissions and 91.1% data recovery accuracy compared to existing models, yet the approach was still untested on physical hardware [56].A comparative evaluation of these protocols is provided in **Table 4**, summarizing key techniques, objectives, performance outcomes, and limitations.

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Table4: Comparative Evaluation of Sleep Scheduling and Duty Cycling Techniques for Prolonging Wireless Sensor Network Lifetime.

Study (Author, Year)	Protocol Name	Main Technique	Research Objective	Simulation Environment	Compared Protocols	Key Improvements	Limitations
Huang et al., 2021	Q-learning + Linear Regression Duty Scheduler	Q-Learning + Linear Regression (Function Approximation)	Optimize MAC layer scheduling by minimizing idle listening using queue load and delay metrics	NS-3 (linear/tree topologies)	S-MAC, Fully Active (FA)	Improved energy efficiency, lower latency, higher throughput under dynamic traffic	Empirical tuning, no analytical model; not field tested
Wang et al., 2023	RLSSA-CDG	Model-Free Q-Learning for Sleep Scheduling + Compressive Data Gathering	Minimize energy via active node selection based on residual energy and uniform sampling	Simulated (not specified)	DSSA-CDG, Sparse-CDG	4.64–42.42% energy savings, 57.3% longer lifetime, 84.7% better accuracy	Still uses shortest-path forwarding; no real deployment
Nithyanandh et al., 2023	EAP-IFBA	Firefly Bio-Inspired + ECC + RNN + Q-Learning	Secure, energy-aware adaptive sleep scheduling and abnormal data detection for IoT WSNs	OMNET++, 2500-node scale	IWD-ARP, ECC-ILEACH, RLSSA-CDGP	High robustness (96.5%), 98% sleep efficiency, 8% depletion rate	Less effective in uneven deployments; homogeneous settings only
Jeyakarthic & Selvakumar, 2024	Smart CH Selection with Duty Cycling & Aggregation	Gradient-based duty scheduling + data aggregation optimization	Reduce transmission energy via smart scheduling and optimized cluster head operation	MATLAB	Threshold-based, Dynamic Scheduling, EE-Scheduling	Throughput = 2800 pkt/s, PDR = 98.24%, 85 mJ/pkt consumption	Only simulation; lacks IoT test data validation
Chaya & Shylaja, 2024	ANN-based Routing + Sleep Scheduling	Artificial Neural Networks + Dynamic Programming	Predictive energy modeling and real-time adaptive duty cycling	Simulated	Traditional routing + static scheduling	Longer lifetime, efficient energy use, reliable delivery	High complexity, possible latency, needs large-scale hardware

			with routing optimization				
El-Shenhabi et al., 2025	RLDCSSA-CDG	Q-Learning + UCB + Compressive Sensing	Balance intra-cluster correlation and sleep scheduling for efficient CDG	MATLAB	RLSSA, RLDCA	Up to 63.3% transmission reduction, 38.8% energy saving, 91.1% recovery accuracy	No hardware validation; simulated only

6. Discussion and Future Research Directions

The reviewed literature across four key domains Q-Learning-based routing, traditional optimization algorithms, clustering-based protocols, and sleep scheduling, highlights a rich diversity of strategies aimed at reducing energy consumption and improving data delivery in WSNs. Each category contributes distinct strengths and faces inherent limitations, suggesting that no single strategy offers a universal solution for all WSN scenarios.

From the Q-Learning-based routing protocols, it is evident that model-free reinforcement learning enables nodes to dynamically adapt routing decisions to environmental changes and residual energy levels. However, nearly all proposed models including RLBR, EDACR, RLBEEP, and CRP-Optimizer remain limited to simulation environments, with no large-scale real-world deployments. Furthermore, congestion near sink nodes, state-space complexity, and convergence speed remain open challenges for Q-Learning-based systems. Even though Q-Learning has proven to be highly adaptive and capable of making wise decisions in WSN routing, its real-world uses are still mostly limited to simulation-based research. Additionally, the algorithm suffers from state-space complexity that restricts scalability and convergence delays that necessitate multiple iterations to stabilize. These drawbacks imply that more investigation is necessary to resolve Q-Learning's scalability issues and validate it in actual sensor deployments.

Traditional optimization methods like WOA, ACO, and modified Dijkstra continue to serve as baseline references, especially in static or homogeneous environments. These models are often more interpretable and computationally efficient, but their slow adaptation to dynamic events and dependence on global knowledge hinder their scalability. Moreover, most of them such as MACOA and AACDIC focus predominantly on CH selection, with limited attention to inter-cluster or multi-hop optimization, which is increasingly crucial in large-scale deployments.

In clustering-based routing, recent studies have shown strong performance improvements when hybrid techniques are used—especially when combining fuzzy logic, swarm intelligence, or quantum-inspired methods. Protocols such as FQA, CHHFO, and MSSO+MST demonstrate measurable gains in lifetime and load distribution. Nonetheless, many of these models assume static network topologies and homogeneous energy distributions, which are rarely applicable in practical WSNs. There is a growing need for mobile-sink-aware and heterogeneous node clustering mechanisms.

Sleep scheduling and duty cycling approaches remain underutilized in many energy-aware WSN models. Although protocols like RLSSA-CDG and EAP-IFBA achieve impressive results reducing idle listening and prolonging network lifetime many routing models, they do not integrate sleep management, leading to avoidable energy wastage. A key observation is that joint optimization of routing, clustering, and sleep scheduling through reinforcement learning or hybrid models offers the greatest potential for achieving sustainability, yet remains underexplored.

7. Identified Research Gaps and Future Opportunities:

1. Real-World Validation: Most reviewed protocols rely solely on simulation (MATLAB, NS-2/3). Future research should prioritize hardware implementation or deployment on WSN testbeds (e.g., IoT-LAB, FIT IoT).
2. Heterogeneous and Mobile Environments: Many models assume homogeneous node energy and static topologies. Future designs must address node mobility, energy harvesting capabilities, and non-uniform energy distributions.
3. Cross-Layer Design Integration: The decoupling of routing, clustering, and duty cycling in most works limits holistic optimization. Integrated frameworks that jointly optimize these layers, possibly using deep reinforcement learning (DRL), represent a promising avenue.
4. Lightweight and Distributed Learning: Given the constraints of sensor nodes, there's a critical need for low-overhead RL models that do not depend on centralized learning or require large memory.
5. Security-Aware Energy Optimization: Protocols like EAP-IFBA demonstrate the feasibility of combining encryption, anomaly detection, and energy scheduling. Future work could explore multi-objective optimization models that balance energy, delay, and security.
6. Dataset Availability and Benchmarking Standards: A key limitation in current research is the lack of standardized datasets and performance benchmarks. Building open-source simulation environments with realistic WSN traces would improve reproducibility and comparison.

8. Conclusion

This review has systematically analyzed and compared recent advances in energy-efficient routing techniques for WSNs, focusing on four major categories: Q-Learning-based routing, traditional optimization algorithms, clustering-based protocols, and sleep scheduling and duty cycling strategies. Each of these domains offers unique approaches to addressing the energy constraints inherent in WSNs, and their comparative evaluation reveals critical insights into the current state of research and future innovation paths. Reinforcement learning, particularly Q-Learning, enables nodes to learn optimal forwarding decisions dynamically, enhancing adaptability and network lifetime. While conventional algorithms such as WOA and ACO provide basic robustness and simplicity, they are not flexible in real-time or mobile environments. Clustering-based approaches remain effective in reducing transmission overhead, especially when enhanced through fuzzy logic, neural networks, or evolutionary computation. Meanwhile, duty cycling and sleep scheduling continue to play a fundamental role in minimizing idle energy waste, yet remain under-integrated in many current routing protocols. Despite the significant progress, a recurring limitation across most protocols is their exclusive reliance on simulation environments. Furthermore, few models address the complexities of heterogeneous networks, mobile sinks, or integrated cross-layer optimization. The future of WSN design lies in holistic and intelligent systems that combine adaptive routing, cluster management, and power scheduling into unified, lightweight frameworks capable of learning and evolving over time. By identifying key strengths, limitations, and research gaps in the existing literature, this review provides a foundation for the development of next-generation, energy-aware WSN protocols. These protocols should be capable of sustaining long-term operations in real-world environments while adapting to dynamic network conditions, security threats, and evolving data demands.

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