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RESEARCH ARTICLE

Energy-Efficient Cognitive Wireless Sensor Networks: Performance Evaluation and Optimization Techniques

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Abstract – The growing scale of interconnected systems has intensified the demand for energy-efficient communication in wireless sensor networks. Sustained operation under strict energy limits represents a major design challenge that directly affects network lifetime and data reliability. Dynamic power management reduces energy use through selective activation and deactivation of node components, yet the switching overhead often limits its efficiency. The present study introduces a cognitive power management framework that enhances dynamic power management within cognitive wireless sensor networks. The framework applies reinforcement-based logic for the selection of relay nodes and communication channels according to residual energy and channel congestion. Each node acts as a distribution center once its coverage coefficient reaches the highest value, which improves network throughput and lowers power loss. Simulation results show a throughput of 4,000,000 bits, an energy efficiency of 99.98%, a packet delivery ratio of 95%, and a spectrum utilization of 78%. The findings indicate a balanced improvement among energy conservation, data reliability, and spectral efficiency and define a sustainable framework for resilient wireless sensor network architectures in intelligent monitoring and future IoT infrastructures.

Index Terms – Reinforcement Learning, Routing Protocol, Cluster-Head Selection, Dynamic Spectrum Access, Duty-Cycle Optimization, Network Lifetime.

1. INTRODUCTION

Global wireless connectivity expanded at an unmatched pace and caused a sharp rise in data traffic and device deployment. Mobile data volume reached nearly 118 exabytes per month in 2022 and is projected to rise to about 325 exabytes per month by 2028 [1]. The number of connected IoT devices exceeded 16 billion in 2023 [2], which demonstrates a growing dependence on wireless communication systems that require continuous energy supply. Data transmission networks consumed between 260 and 360 TWh of electricity in 2022, equal to about 1 to 1.5 % of global electricity use, while mobile infrastructure accounted for most of this demand [3]. Expansion of 5G networks may raise total energy consumption by as much as 140% compared with 4G systems [4]. Such growth intensified the need for energy-aware architectures and cognitive power-management systems that sustain operational stability and extend the lifetime of large-scale wireless sensor networks.

Wireless sensor networks (WSNs) provide foundational support for sensing, monitoring, and automation across environmental observation, smart-city platforms, industrial systems, and precision agriculture. A typical WSN relies on large numbers of low-power sensor nodes that forward sensed data through multi-hop links toward a sink. Battery-powered operation, limited storage, and restricted processing capability impose severe constraints on protocol design, particularly under dense deployment conditions where interference and medium contention intensify. Conventional WSN operation also relies mainly on unlicensed spectrum, and unlicensed bands often experience congestion due to the co-existence of heterogeneous technologies and overlapping deployments [5]. Node battery replacement remains impractical in many target scenarios, so network lifetime depends on routing stability, careful duty-cycle scheduling, and reduction of redundant transmissions. A large body of WSN research has therefore pursued energy-aware routing, clustering, and data aggregation strategies to reduce communication cost and delay premature node depletion [6], [7]. Spectrum scarcity and interference growth now compound the classical energy problem, because retransmissions and channel contention raise energy expenditure while degrading packet delivery performance. Cognitive radio wireless sensor networks (CWSNs) address that limitation by introducing spectrum awareness and adaptive transmission behavior that can exploit underutilized licensed spectrum opportunities while protecting primary users [8].

A CWSN equips sensor nodes with cognitive radio capabilities that support spectrum sensing, channel selection, and reconfiguration of transmission parameters. Cognitive access differs from static allocation because a node can vacate a channel when primary-user activity appears and can migrate toward channels that offer lower interference or better propagation conditions [9]. Dynamic spectrum access can reduce collisions, lower retransmission rates, and improve end-to-end delivery reliability under crowded unlicensed conditions. Cognitive radio technology therefore offers a plausible mechanism for sustaining large-scale IoT and WSN connectivity without exclusively relying on congested bands, particularly when licensed spectrum occupancy exhibits spatial and temporal gaps that secondary access can exploit under regulatory constraints [10]. CWSN operation can improve spectrum utilization and can enhance reliability when channel selection and power control respond effectively to interference patterns and primary-user dynamics [11]. Cognitive operation also introduces direct costs. Spectrum sensing, channel switching, coordination overhead, and learning computation consume energy, and energy waste can rise when cognitive decisions trigger frequent reconfigurations or unstable access patterns [12]. Therefore, CWSN design requires careful integration of spectrum awareness with energy control so that spectrum agility produces net benefits under strict node-level energy budgets.

CWSN research challenges span network layers and revolve around coupled trade-offs among energy consumption, delivery reliability, and spectrum utilization. Multi-hop routing remains a core determinant of network lifetime because forwarding load concentrates near sinks and along high-utility relays, which accelerates node depletion and increases path break probability [13]. Primary-user activity complicates routing stability because channel availability changes can invalidate links even when node energy remains adequate. Clustering adds another coupled mechanism. Cluster-head nodes perform data aggregation and coordination, and cluster-head selection strongly influences energy balance and reliability because cluster-head failure can fragment clusters, increase control overhead, and trigger packet loss. Cognitive spectrum dynamics further complicate clustering because channel assignment influences intra-cluster communication quality and inter-cluster forwarding feasibility. Spectrum-aware clustering and coordination protocols therefore play a central role in maintaining connectivity and fairness when available channels vary across time and space [14]. Distributed operation adds further difficulty because each node makes local decisions under partial observations, yet the network performance depends on collective behavior that limits collisions, preserves primary-user protection, and maintains acceptable QoS [15]. Opportunistic spectrum access policies must therefore cope with non-stationary environments, multi-user competition, heterogeneous traffic demands, and the coupling between channel access decisions and end-to-end delivery constraints [16]. The problem space couples classical WSN limitations with cognitive-radio constraints, producing an optimization landscape that requires adaptive control under uncertainty.

Machine learning, and reinforcement learning, has gained attention as a mechanism for enabling adaptive decision-making in CWSNs under dynamic spectrum conditions. Reinforcement learning agents can learn channel selection and access policies from interaction outcomes rather than relying on fixed rules that may fail under changing interference or primary-user activity [17]. Multi-agent reinforcement learning approaches have been proposed for distributed channel selection and power control, and the multi-agent setting aligns with the decentralized structure of sensor deployments in which each node experiences local channel conditions and local energy state [18]. Learned policies can balance exploration of alternative channels with exploitation of stable opportunities, which can raise reliability and improve energy efficiency when the reward function penalizes collisions, retransmissions, and excessive switching overhead. Reinforcement learning has also been adopted for routing in WSNs and cognitive sensor networks, where learned forwarding decisions can distribute load, reduce repeated path failures, and extend network lifetime beyond what static shortest-path strategies can sustain under energy depletion and link variability [19]. Deep learning integration can also support spectrum-state inference or traffic prediction, and improved inference quality can reduce unnecessary sensing and switching decisions that waste energy.

Energy-aware mechanisms beyond learning-based control have also advanced in recent CWSN research, particularly through energy harvesting and joint information-energy transfer. Energy harvesting hardware can replenish node energy from ambient sources, and energy harvesting can relax lifetime constraints when harvesting rates remain sufficient and predictable. Simultaneous wireless information and power transfer can provide another pathway for sustaining low-power devices by enabling energy extraction from radio-frequency signals while maintaining communication functionality, which suits dense IoT settings where radio energy density can be significant [20]. Research on energy-harvesting cognitive radio sensor networks has therefore explored clustering, routing, and spectrum-access strategies that account for harvesting opportunities, energy storage dynamics, and sensing costs under imperfect spectrum sensing [21]. Harvesting-enabled designs highlight a scheduling problem that links sensing, transmission, and harvesting decisions under time-varying energy arrival. A node must allocate time and power between data delivery and energy replenishment while maintaining primary-user

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protection and acceptable delivery performance. Data reduction strategies such as compression and data fusion offer another energy-saving pathway by lowering packet count and transmission duration, yet spectrum dynamics can alter latency and delivery constraints, so compression policies require coordination with routing and channel access decisions. Thus, CWSN energy efficiency requires cross-layer coherence that links physical-layer power control, MAC-layer access policy, network-layer routing, and application-layer data generation behavior.

1.1. Problem Statement

A persistent limitation in the CWSN literature arises from fragmented optimization that isolates routing, clustering, duty cycling, or spectrum access. Recent work in spectrum-sharing IoT and cognitive networks has emphasized the value of cross-layer approaches that jointly consider routing, clustering, and power control under spectrum-access constraints, particularly under heterogeneous traffic and dense deployment conditions [22]. An integrated framework that jointly manages energy-aware clustering and learning-driven spectrum selection while remaining lightweight for resource-constrained nodes remains needed.

1.2. Study Aims

The study aims to design and evaluate an energy-efficient CWSN framework that maintains reliable communication under strict energy budgets and dynamic spectrum conditions. The objectives are: (i) develop an energy-aware cluster-head selection mechanism that stabilizes clustering, (ii) integrate Q-learning based channel selection for opportunistic spectrum access, and (iii) quantify impacts on packet delivery ratio, energy efficiency, total energy consumption, throughput, and spectrum utilization through comparative simulation. The comparative evaluation follows a controlled simulation design in which the proposed CWSN is assessed against conventional WSN operation and foundational clustering baselines, including LEACH and SEP. All methods are tested under identical deployment and radio-energy settings (100 nodes, 100 × 100 area, 2 J initial energy per node, and three channels) to ensure fairness.

1.3. Study Contributions

The study contributes: (1) a cross-layer CWSN architecture that integrates energy-aware clustering, adaptive duty cycling, dynamic power control, and Q-learning based channel selection; (2) a residual-energy constrained cluster-head election strategy that reduces cluster instability and premature node depletion; (3) a learning-based channel selection policy that improves reliability under primary-user activity; and (4) a comprehensive evaluation against baseline and recent schemes using standard metrics, demonstrating improvements in energy preservation, delivery performance, and spectrum use.

Section 2 reviews the related work. Section 3 presents the proposed method. Section 4 reports and interprets the experimental results. Section 5 concludes the paper and outlines future directions.

2. RELATED WORK

Cognitive Radio Wireless Sensor Networks (CWSNs) extend traditional WSNs by adding cognitive radio modules that sense spectrum and adapt communication parameters autonomously. Early studies introduced the basic architecture of CR-enabled sensor nodes and highlighted numerous challenges due to this added complexity. For instance, Cavalcanti *et al.* (2008) presented a conceptual design for cognitive radio sensor nodes, identifying potential benefits (improved spectrum usage, better QoS) as well as key challenges such as hardware complexity, energy constraints, and security vulnerabilities, and even suggested possible remedies [23]. Likewise, Akan et al. (2009) outlined the design principles and open research issues for CRSNs, emphasizing that CWSNs were an emerging field requiring more investigation [24]. In general, CWSNs face all the limitations of conventional WSNs (i.e., limited battery power, bandwidth, etc.) plus new issues introduced by cognitive functions, like the overhead of spectrum sensing and learning algorithms. Recent works show growing interest in applying CWSNs to real-world scenarios; for example, Yatsenko et al. (2024) demonstrated an energy-efficient CWSN for loud-noise monitoring to illustrate the practical advantages of CWSNs in dynamic environments (improving detection reliability while conserving energy) [25]. Overall, these studies agree that while CWSNs offer significant potential of higher spectrum efficiency and adaptability, they also demand innovative solutions to address their complexity and ensure sustainable operation.

Energy conservation is paramount in WSNs due to battery limitations, and many routing protocols have been designed to minimize energy consumption. Researchers have long developed energy-aware routing techniques that send data along energy-efficient paths and balance the energy usage across nodes. For example, Heinzelman et al. (2000) introduced LEACH, a pioneering low-energy routing protocol using cluster-head rotation to distribute energy load [26], and numerous successors have aimed to further reduce energy drain by optimizing path selection and duty cycling [27], [28], [29], [30]. A specific early approach by Mahdi et al. (2015) [31] incorporated nodes' residual energy and harvesting capability into the routing decision to prolong network lifetime. Their protocol, named Multi-cluster Power Efficient GAthering in Sensor Information System (MPEGASIS), achieved about 19% longer lifetime than the classic PEGASIS chain-based protocol and about 34% longer than LEACH by intelligently balancing power usage; simulations in NS2 confirmed its superior energy performance.

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Beyond pure routing decisions, reducing communication overhead is another way to save energy. For instance, Abdulminuim (2018) [32] proposed an in-network data reduction scheme (using a hybrid ZaK transform and Eigenface technique) for WSN-based face recognition, which cut transmitted data by 89.5% without degrading the application's accuracy. Such kind of local processing ensures network capacity is not wasted on redundant data, thereby conserving energy. More recently, Ozger et al. (2022) [33] formulated an optimization of the sensor transmission range and duration in a cognitive radio sensor network to minimize the energy expended per unit data delivered. By greedily adjusting each node's transmission power and time based on distance and channel conditions, their method improved overall energy efficiency for reliable communication in a flexible spectrum environment. In summary, the literature shows a progression from fundamental energy-aware routing solutions to more sophisticated techniques (cross-layer optimizations, local data processing, and parameter tuning) that collectively aim to maximize network lifetime in both traditional WSNs and cognitive WSNs.

Clustering is an essential technique for scalability and energy efficiency in sensor networks, including CWSNs. Organizing nodes into clusters with designated cluster-heads (CHs) can greatly reduce communication cost by aggregating data locally and enabling multi-hop delivery through CHs. However, the strategy for electing cluster-heads critically impacts performance. The well-known LEACH protocol selects CHs randomly in each round, without considering nodes' remaining energy. Consequently, even low-energy nodes have equal chance to become CH, often leading to premature battery depletion of those CHs and shortening the network lifespan. Later improvements introduced smarter CH selection criteria to avoid such problems. For example, Threshold LEACH (T-LEACH) only switches CHs when the current CH's residual energy falls below a threshold, and LEACH-C (Centralized LEACH) has the base station choose CHs based on nodes' energy and location, which prevents very weak nodes from being CH [34]. Many recent protocols build on these ideas: Sarkar et al. (2022) [35] proposed an Energy-Aware Threshold Sensitive Election Protocol (EATSEP) that uses a hybrid threshold mechanism to elect CHs to yield more balanced energy consumption and a longer stable network period. Similarly, Al-Mejibli (2024) [36] improved the classic Stable Election Protocol (SEP) for heterogeneous WSNs by refining the probability-based CH selection according to node energy levels to achieve better energy balance and extended lifetime.

In cognitive sensor networks, clustering techniques have evolved to also account for spectrum awareness. Wang and Liu (2023) developed an imperfect spectrum sensing-based multi-hop clustering protocol (ISSMCRP) for CRSNs, where CH and relay nodes are chosen based on a detection-level function (measuring each node's spectrum sensing capability) in addition to residual energy [37]. By prioritizing nodes with strong sensing accuracy as CHs, their protocol mitigates collisions with primary users and strictly controls clustering overhead, which lead to a significantly longer network lifespan and improved network "surveillance" capacity (i.e. consistent sensing coverage) compared to earlier clustering methods. Overall, modern clustering algorithms for CWSNs incorporate multiple factors, residual energy, node density, distance to sink, and even spectrum quality, to elect high-quality CHs and organize clusters optimally. These enhancements ensure that clustering, which is vital for energy saving, does not inadvertently compromise the network by overburdening weak nodes or underutilizing available spectrum resources.

Reinforcement learning (RL) techniques have recently been applied to wireless sensor networks to enable nodes to learn and adapt their behavior for better performance. In cognitive WSNs, RL is particularly attractive for dynamic problems like routing and channel selection, where fixed strategies may not be optimal in changing conditions. Joon and Tomar (2022) [38] introduced the EAQ-AODV protocol, which integrates Q-learning into the AODV routing algorithm for cognitive radio sensor networks. In their approach, each node uses a Q-learning-based reward mechanism to decide whether to act as a cluster-head and or forward packets. Their study aimed to minimize end-to-end delay and energy usage. Their simulation results showed that EAQ-AODV achieves lower average delay and energy consumption and a longer network lifetime compared to the standard AODV protocol (without learning).

Similarly, Kim et al. (2023) [39] applied Q-learning to tree-based routing in WSNs. They defined a state-space of network conditions and reward functions using multiple cognitive metrics (e.g. delay, link quality, and energy) to enable each node to learn the best parent selection over time. Through extensive simulations, they reported that their Q-learning enhanced routing scheme markedly improved end-to-end delay, packet delivery ratio, and energy efficiency relative to traditional static tree routing. Beyond routing, RL has also been used for spectrum management. Li *et al.* (2021) [40] developed a Q-learning based dynamic spectrum access method for a cognitive industrial IoT network, which allowed distributed sensor nodes to autonomously choose channels. The RL-enabled nodes achieved higher channel utilization and lower collision probability than baseline random access methods. Building on such single-agent learning, multi-agent deep reinforcement learning algorithms are now being explored for CWSNs. Recent RL-driven protocols in WSNs and CWSNs have shown significant performance gains (i.e., longer lifetime, higher delivery rates, etc.), though challenges remain in terms of convergence speed and complexity for resource-constrained sensor nodes.

Dynamic spectrum access is a core aspect of CWSNs, as sensor nodes must opportunistically utilize idle channels without interfering with licensed primary users. Accordingly, many studies have addressed how to sense and access spectrum efficiently. Early works proposed cooperative spectrum sensing to improve detection reliability while minimizing each node's sensing energy cost. For example, Maleki et al. (2011) [41] developed an energy-efficient distributed spectrum sensing algorithm for cognitive sensor networks, and Zhang et al. (2011) [42] designed a cooperative sensing scheme to boost detection accuracy in a wireless cognitive sensor network. These techniques allow multiple sensors to share sensing information and achieve high detection probabilities (and low false alarms) with less per-node energy expenditure than single-node sensing. Beyond sensing, researchers have explored how CWSNs can intelligently choose and share channels.

Carie et al. (2019) [43] introduced a hybrid architecture that combines ordinary sensor nodes with dedicated cognitive radio (CR) nodes to forward data via licensed spectrum. In their CR-assisted WSN, sensor data is relayed to a CR node "gateway" which transmits over a licensed channel to a base station. The approach improved network throughput and reduced end-to-end delays (by offloading traffic to less congested licensed bands), and it also lowered energy consumption compared to purely unlicensed spectrum use. However, the method lacked channel state information and did not adapt if primary users' activity changed, which could lead to suboptimal path choices.

Newer studies increasingly apply optimization and learning to spectrum access. Ozger et al. (2022) [33] formulated a cross-layer strategy to optimize the transmission range and duration of CRSN nodes, with an aim to maximize energy efficiency under dynamic spectrum conditions. Their solution effectively adjusts node power and time allocation on each channel, which not only saves energy but also improves spectrum utilization by avoiding excessively conservative transmissions. In addition, multi-agent RL-based approaches (discussed above) have been used to coordinate channel selection among multiple cognitive sensor nodes and showed promising results in reducing collisions and enhancing spectrum usage fairness. Overall, spectrum access strategies in CWSNs have evolved from basic cooperative sensing to sophisticated schemes that exploit collective sensing, predictive modeling, and even AI-driven decision-making. These advancements help CWSNs achieve high spectral efficiency (making the most of available channels) without compromising the energy budget or interfering with licensed users.

Given the energy scarcity in WSNs, hybrid energy harvesting techniques have gained attention to power sensor nodes. Traditional energy sources (batteries) can be supplemented by harvested energy (solar, RF, etc.) to extend network lifetime. An early example is the work of Mahdi et al. (2015) [31], where each node's energy harvesting status was used in routing decisions to balance energy consumption across the network. More recent research has integrated harvesting directly into protocol design.

Wang et al. (2024) [44] proposed a multi-hop clustering protocol for Energy-Harvesting Cognitive Radio Sensor Networks (EH-CRSNs) that leverages Simultaneous Wireless Information and Power Transfer (SWIPT). In their ES-ISSMCRP scheme, nodes use downlink RF signals from the base station to recharge, and cluster members can even transfer energy to their CH during data transmission (by splitting a portion of the radio power for energy harvesting). Such design equalizes the residual energy among nodes and mitigates the "hot-spot" problem where CHs near the sink deplete faster. Simulation results showed that the SWIPT-enhanced protocol significantly prolonged the network lifetime and maintained high sensing performance, outperforming other clustering protocols without energy transfer. Such hybrid energy solutions ensure that CWSNs can sustain operations longer by dynamically replenishing node energy, though they introduce new considerations (e.g. the need to schedule energy transfer without disrupting data flow).

Security is another critical aspect that researchers are improving in WSNs and CWSNs. Because sensors may be deployed in untrusted environments and cognitive nodes must decide on spectrum access autonomously, robust security mechanisms are needed to protect against attacks (e.g. eavesdropping, node compromise, jamming). Recent works have focused on intrusion detection, secure routing, and resilient distributed processing for sensor networks. Khoshkalam et al. (2024) [45] developed a secure multiple adaptive kernel diffusion LMS algorithm for distributed estimation in sensor networks. In this approach, sensors collaboratively run a diffusion least-mean-square algorithm to estimate environmental parameters; the authors introduce adaptive kernel functions and security measures to resist malicious data injections and eavesdropping on the exchange of estimates.

Their secure diffusion method achieved accurate estimation even in the presence of compromised nodes and enhanced the trustworthiness of the network's collective computations. In the realm of routing, Vankdothu et al. (2025) [46] proposed a multicast routing framework for heterogeneous WSNs that emphasizes both security and time efficiency. They evaluated metrics like encryption overhead, transmission delay, and congestion, and introduced optimizations to scale multicast communication while preventing common attacks. The result was a more resilient network that could deliver data securely within stringent time requirements, suitable for mission-critical applications. Other studies (e.g. Ayuba et al. 2024 [47]) have surveyed security issues in cluster-based WSNs and highlighted open research directions such as lightweight authentication and trust management in cognitive sensor networks. Table 1 summarizes the related work and reports the progress being made on CWSNs.

Table 1 Summarization of Related Work

Authors/Refs.	Algorithms	Method/Approach	Results	Advantages	Limitations
Cavalcanti et al. (2008) [23]	Cognitive Radio-based WSNs	Combined cognitive radio techniques (spectrum sensing, channel negotiation) with WSN data gathering; introduced a MAC and routing framework enabling sensors to find and use idle licensed channels.	Demonstrated that cognitive radio can reduce interference and improve network throughput under spectrum scarcity.	Enhanced spectrum utilization and interference avoidance compared with static-channel WSNs.	Increased complexity and energy consumption due to spectrum sensing and negotiation; feasibility on resource-constr ained sensor nodes questioned.
Yatsenko et al. (2024) [25]	Energy-efficien t cognitive WSN	Integrated spectrum-sensing with application-specific noise detection and energy-saving mechanisms; designed an adaptive channel allocation strategy.	Reported reduced energy consumption and accurate noise detection in simulation.	Application-orient ed design shows how CR can support specific sensing tasks while saving energy.	Focuses on a narrow use-case; scalability and generalization to other sensing types or networks not addressed.
Heinzelman et al. (2000) [26]	LEACH (Low-Energy Adaptive Clustering Hierarchy)	Cluster-based routing protocol that randomly rotates cluster heads, performs local data fusion and compresses data before sending to the base station.	Simulations showed LEACH can reduce energy dissipation by a factor of 4–8 compared with direct routing and static clustering.	Distributes energy dissipation across nodes and doubles system lifetime.	Randomized cluster-head selection can result in uneven cluster sizes; not designed for heterogeneous node capabilities.
Guo & Jafarkhani (2016) [27]	Deployment algorithms for sensor placement under limited communication range	Formulated sensor deployment as an optimization problem (coverage and connectivity) in homogeneous and heterogeneous WSNs.	Provided optimal deployment strategies improving coverage while satisfying connectivity constraints.	Offers guidelines for efficient deployment planning.	Focuses on deployment stage; does not address runtime routing or spectrum issues.
Attea (2015) [29]	Multi-objective set-cover problem for WSN reliability and	Proposed algorithms to select a subset of sensors that cover targets while minimizing energy and	Showed improved coverage and lifetime compared with	Balances coverage quality with energy efficiency.	Computational complexity may be high for large-scale networks;

	efficiency	maximizing reliability.	greedy selection.		assumes deterministic coverage models.
Mahdi et al. (2015) [31]	Low-energy consumption scheme based on PEGASIS	Modified Power-Efficient Gathering in Sensor Information Systems (PEGASIS) to reduce energy consumption through improved chain formation.	Achieved longer network lifetime than original PEGASIS by reducing long links in the chain.	Simpler than cluster-based schemes and reduces overhead of cluster formation.	Long chain formation may increase latency; assumes uniform node distribution.
Abdulminuim(2017) [32]	Zak transform–based face recognition model in WSN	Utilized Zak transform for feature extraction and matching, optimized for low-power processing in WSN.	Reported improved recognition accuracy under limited processing capabilities.	Demonstrated that complex signal processing can be adapted to WSN constraints.	Not related to general WSN routing or CR, only to a specific application.
Ozger et al. (2022) [33]	Energy-efficient transmission range and duration control for CRSN	Adaptive scheme that adjusts transmission range/duration based on residual energy and channel conditions.	Simulation results showed extended network lifetime compared with fixed-range schemes.	Matches transmission power to actual communication need, saving energy.	Requires accurate channel knowledge; may increase control overhead.
Handy et al. (2002) [34]	LEACH-like deterministic clustering.	Introduced deterministic cluster-head selection to reduce randomness and improve energy balance compared with LEACH.	Demonstrated more stable cluster formation and reduced re-clustering overhead.	Improves cluster-head distribution relative to pure random selection.	May require global knowledge or synchronization; benefits depend on network density.
Sarkar et al. (2022) [35]	Energy-Aware Threshold-Sensitive Stable Election Protocol (EATSEP)	Modified SEP to account for residual energy thresholds and stability periods; includes adaptive cluster-head election.	Simulation results show longer stability period and higher throughput over LEACH/SEP/TSEP (e.g., stability improved by ~80% in some scenarios).	Enhances network lifetime and stability by considering residual energy in cluster-head selection.	Assumes accurate energy information and does not incorporate dynamic spectrum issues.
Al-Mejibli (2024) [36]	Improving SEP for	Introduced enhanced weight factors for	Achieved longer lifetime	Adapts SEP to heterogeneous	Focuses solely on WSNs; does

	heterogeneous WSNs	cluster-head election and refined energy heterogeneity models.	and more alive nodes compared with SEP and DEEC.	energy levels.	not handle dynamic spectrum or cognitive functions.
Wang & Liu (2023) [37]	Imperfect spectrum-sensing-based multi-hop clustering for CRSN	Designed a multi-hop clustering and routing protocol that accounts for sensing errors and PU interference.	Improved packet delivery and energy efficiency compared with idealized sensing protocols.	Addresses real-world sensing imperfections and balances clustering overhead with spectrum access reliability.	Requires sensing error modelling; performance sensitive to parameter tuning.
Joon & Tomar (2022) [38]	Energy-Aware Q-learning AODV (EAQ-AODV)	Integrated Q-learning with AODV routing to select energy-aware routes in CRSNs.	Simulation results showed longer lifetime and higher packet delivery than standard AODV and fuzzy-based protocols.	Learns optimal routes under dynamic spectrum and energy conditions.	Q-learning convergence may be slow; requires periodic learning updates.
Kim et al. (2022) [39]	Enhanced tree routing protocol based on reinforcement learning	Combined tree-based routing with reinforcement learning to minimize energy and balance load.	Demonstrated better latency and lifetime compared with static tree routing and fuzzy-based approaches.	Learns optimal parent selection and route maintenance.	Training overhead and memory requirements may challenge low-end sensor nodes.
Li et al. (2018) [40]	Q-learning-based dynamic spectrum access for cognitive industrial IoT	Each device uses Q-learning to select frequency channels to maximize successful transmissions, considering interference and energy.	Achieved improved throughput and fairness in industrial CR IoT networks.	Distributed learning avoids central coordination; adapts to interference.	RL overhead and convergence time; requires reward tuning and channel availability monitoring.
Maleki et al. (2011) [41]	Energy-efficient distributed spectrum sensing scheme for CRSNs	Proposed a sensing scheduling algorithm that reduces sensing time and cooperative overhead.	Reduced energy consumption while maintaining detection probability compared with periodic full sensing.	Saves sensing energy and prolongs lifetime.	May miss sporadic PU signals; requires coordination among sensing nodes.
Xue Zhang et al. (2015) [42]	Cooperative spectrum	Nodes cooperate to sense PU activity and	Demonstrated higher	Improves sensing accuracy through	Increases communication

	sensing for cognitive WSNs	share sensing outcomes to improve detection.	detection probability and lower false alarms compared with individual sensing.	cooperation.	overhead and energy consumption; requires synchronized sensing.
Carie et al. (2019) [43]	Interference-aware AODV routing for cognitive WSN	Modified AODV to incorporate interference information into route selection; nodes choose paths with lower PU interference.	Improved network throughput and reduced collision probability compared with standard AODV.	Accounts for interference and PU activity in routing decisions.	Additional overhead to collect interference metrics; reactive routing still suffers from route discovery delays.
Wang & Li (2022) [44]	Weighted energy consumption minimization-based multi-hop uneven clustering protocol	Optimizes cluster size and cluster-head distribution based on node energy and distance to the sink; uses uneven clustering to reduce load on nearer nodes.	Demonstrated lower total energy consumption and longer lifetime versus equal-size clustering.	Balances energy and load across the network, reducing hot-spot problem.	Uneven clustering may create large clusters that increase intra-cluster latency.
Khoshkalam et al. (2024) [45]	Secure multiple adaptive kernel diffusion LMS algorithm for distributed estimation	Uses adaptive kernel diffusion and diffusion least-mean-square (LMS) algorithms to provide secure, robust distributed estimation across WSN nodes.	Improved estimation accuracy and resilience to attacks; maintained convergence.	Enhances security and estimation accuracy in distributed sensing.	Computationally intensive; focuses on estimation rather than routing/spectrum access.
Vankdothu et al. (2025) [46]	Multicast scaling in heterogeneous WSNs for security and time efficiency	Developed scaling techniques to accommodate multicast communication with heterogeneous node capabilities and security constraints.	Achieved reduced latency for secure multicast and improved time efficiency.	Supports scalable secure multicast; adapts to node diversity.	Limited to multicast scenarios; does not address cognitive spectrum.

3. METHODOLOGY

The study develops an integrated framework for CWSNs that unifies system modelling, algorithm and protocol design, performance evaluation, and simulation validation. Figure 1 presents the complete workflow: parameter initialization, network generation, Q-learning-based channel selection, spectrum sensing, cluster formation, data transmission with energy accounting, and final performance evaluation.

3.1. System Modelling and Energy Analysis

The mathematical model captures the parameters that dominate energy behaviour: node density, communication range, sensing frequency, and environmental dynamics. Energy accounting covers cognitive functions such as spectrum sensing, decision logic, and network reconfiguration (Figure 1). The analysis identifies the main trade-offs among energy efficiency, spectrum utilization, and communication reliability.

The following equations define the foundation of the network's energy model. Each node updates its residual energy after every transmission, reception, or aggregation operation. Energy awareness based on these parameters later drives the routing, clustering, and channel-selection decisions embedded in the proposed framework. Energy model equations (Equations 1, 2, and 3) [46], [48].

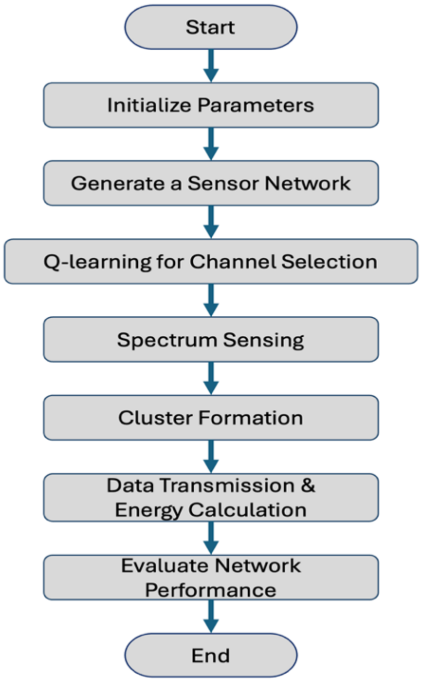

Figure 1 Flowchart of CWSNs Performance Evaluation

Transmission energy:

$$E_{TX}(k,d) = k \cdot E_{tx} + \epsilon_{amp} \cdot d^2 \quad (1)$$

Reception energy:

$$E_{RX}(k) = k \cdot E_{rx} \quad (2)$$

Data aggregation:

$$E_{Agg}(k) = k \cdot E_{DA} \quad (3)$$

Where k is the packet size, d is the distance, and ϵ_{amp} is the amplifier factor.

The energy model separates the electronic and amplifier components of radio energy expenditure. kEtx represents the electronic energy consumed during signal processing and modulation, while $\epsilon_{amp}d^2$ represents the power needed to overcome free-space path loss, which grows quadratically with distance. Reception energy (E_{RX}) accounts solely for electronic processing at the receiver, independent of distance, since no amplification occurs in this stage. Aggregation energy (E_{Agg}) represents the computational cost associated with fusing, compressing, or filtering multiple packets at a node before forwarding them to a cluster head or sink.

3.2. Algorithm and Protocol Development

- Network Generation

Nodes are placed at random within the deployment area. Each node starts with an initial energy budget.

- Q-Learning State Definition

Node state depends on residual energy:

High (>1.5 J) → state = 1

Medium (>0.5 J) → state = 2

Low (≤0.5 J) → state = 3

Q-learning update rule (Equation 4) [48], [49]:

$$Q(s,a) \leftarrow Q(s,a) + a\left[r + \gamma \cdot \acute{\alpha}^{\max Q(\acute{s}\cdot\acute{\alpha})} - Q(\acute{s}\cdot\acute{\alpha})\right] \quad (4)$$

Reward function (Equations 5 and 6) [46], [50]:

$$R = 1 - \text{CollisionPenalty} - \text{Energy Factor} \quad (5)$$

CollisionPenalty ∈ {0, 0.5, 1} according to congestion.

$$\text{Energy Factor} = (E_{\text{init}} - E_{\text{current}}) / E_{\text{init}} \quad (6)$$

The policy steers nodes toward channels with low congestion and balanced energy use.

- Energy-Efficient Spectrum Sensing

Algorithms regulate sensing intervals and decision rules so that accuracy aligns with residual energy and channel conditions.

- Energy-Aware Routing

Routing strategies account for residual energy, communication distance, and network topology to extend lifetime and maintain stable paths.

- Cluster Formation

CHs are chosen with probability pCH when residual energy exceeds 30 % of the initial value. Remaining nodes join the nearest CH.

- Cluster-Based Data Transmission

Member → CH transmission incurs transmit energy with path-loss cost. CH reception incurs receive energy. CH aggregation incurs aggregation energy. CH → sink transmission again applies transmit energy with path-loss cost. The energy equations above governs every sub-step.

- Additional Optimizations

Duty-cycle control keeps nodes active for half of each sensing period. Dynamic power control sets transmit power according to distance to the sink or CH. Data compression lowers payload size by about 80 %.

3.3. Performance Evaluation Framework Design

The evaluation framework treats energy efficiency as a primary metric alongside throughput, latency, and packet delivery ratio. Benchmarks and scenarios cover multiple operating conditions. Analytical and simulation-based

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assessments provide a complete view of behaviour (Equations 7, 8, and 9).

- Performance Metrics [49], [50]

Packet Delivery Ratio (PDR):

$$PDR(r) = \frac{Packets_{Received}}{Packets_{Sent}} \times 100 \quad (7)$$

Energy Efficiency (EE):

$$EE(r) = \frac{E_{total\ I\ net} - E_{Consumed}}{E_{total\ Inet}} \times 100 \quad (8)$$

Spectrum Utilization (SU):

$$SU(r) = \frac{\text{Available Channels}}{\text{Total Channels}} \times 100 \quad (9)$$

3.4. Simulation Model and Parameter Settings

Simulation tools implement and test the proposed algorithms and the evaluation framework. Test scenarios vary node density, traffic patterns, and spectrum availability to measure robustness across conditions. Comparisons with state-of-the-art methods validate effectiveness in minimizing energy consumption and improving overall network performance. Simulation experiments were implemented in MATLAB R2023a (MathWorks, USA) with custom scripts for network generation, energy accounting, and Q-learning updates. The parameter set in Table 2, which includes 100 nodes, 2 J initial energy, three channels, 4000-bit packets, and 10 s sensing intervals, therefore supports a design that stays computationally light while still achieving stable cluster formation and sustained delivery performance.

Table 2 The Parameters for the Code

Number of nodes	100
Area size	100x100
Initial energy	2 joules
Number of channels	3
Transmission/Reception energy cost	50 nJ/bit.
Aggregation energy cost	50 nJ/bit.
Data size	4000 bits
Sensing Interval	10 seconds
p_{CH}	0.1

3.5. Functions and Codes

The proposed framework relies on a sequence of lightweight yet adaptive algorithms that jointly control spectrum access, topology organization, transmission behaviour, and energy expenditure. Each algorithm operates under strict local information constraints and contributes to global performance through coordinated execution at each simulation round. Rather than optimizing isolated layers, the framework integrates learning-based channel selection, energy-aware clustering, adaptive retransmission, duty-cycle optimization, and distance-based power control within a unified execution loop. The design ensures that improvements in one layer do not destabilize others, which is essential for CWSN operating under limited energy budgets and dynamic spectrum conditions.

- Q-Learning for Channel Selection

Algorithm 1 enables each node to autonomously adapt its channel selection strategy based on long-term transmission outcomes rather than instantaneous channel observations. The state abstraction relies exclusively on residual energy levels, which keeps the learning space compact and computationally feasible for resource-constrained sensor nodes. By embedding congestion penalties and energy depletion into the reward function, the learning process discourages both excessive channel contention and aggressive transmission behaviour that accelerates battery exhaustion. Over successive episodes, nodes converge toward channel selections that balance transmission reliability with energy preservation, thereby stabilizing spectrum access without requiring central coordination or global state information.

Input:

N nodes, numChannels, episodes

Alpha (learning rate), gamma (discount factor), epsilon (exploration rate)

Initialize:

Q-table with zeros: Q[States][Channels]

for each episode from 1 to episodes do

Shuffle node order

for each node i do

Determine the energy states of node i

if random () < epsilon then

Select a random action a (explore)

else

Select action a = argmax Q[s][a] (exploit)

end if

Simulate channel congestion (low, medium, high)

Compute reward:

Reward = 1 - congestion penalty - energy penalty

Update Q-table:

Q[s][a] ← Q[s][a] + alpha × (reward + gamma × max Q[s'] - Q[s][a])

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end for

end for

Output:

Assign the best channel to each node based on the learned Q-table.

Algorithm 1 Q-Learning-Based Channel Selection with Primary-User-Aware Reward and Residual-Energy State

- Cluster Head Selection and Clustering

Algorithm 2 performs energy-efficient clustering, where nodes with enough energy are randomly chosen as cluster heads (CHs). Other nodes then join the closest CHs based on distance to reduce overall energy use and communication costs. The algorithm executes once per round and produces a complete clustering map for that round.

The parameter p_{CH} controls the expected cluster-head count, while the energy threshold prevents low-energy nodes from becoming cluster heads and absorbing disproportionate load. The fallback cluster-head rule guarantees at least one cluster head, which prevents network partition under rounds with widespread energy depletion.

The minimum-distance association step reduces intra-cluster transmission distance, which reduces the amplifier-related term in the transmission-energy model.

Input:

N nodes, energy levels, initial Energy, CH probability pCH

Initialize:

Empty list of CHs and clusters

for each node i do

if rand () < pCH and energy[i] > threshold × initialEnergy then

Add node i to CHs

end if

end for

If CH's list is empty, then

Randomly select one node as CH

end if

For each non-CH node i do

Find the closest CH based on distance

Assign node i to that CH’s cluster

end for

Output:

List of CHs and clusters

Algorithm 2 Residual-Energy-Constrained Cluster-Head Election with Minimum-Distance Cluster Association (LEACH-inspired)

- Data Transmission with ACK-Based Retransmission

To ensure reliable communication, Algorithm 3 lets member nodes retransmit data on their communication channel if the previous transmission fails. Each transmission attempt has an acknowledgment (ACK) probability, and retransmissions are limited to a set maximum. Algorithm 3 models link reliability through a round-level acknowledgement probability. Each member-to-cluster-head delivery consumes transmission energy at the sender and reception energy at the cluster head for every attempt, and each unsuccessful attempt increases energy depletion without increasing delivered throughput. The parameter maxRetries limits the energy cost of poor links, and the simulation counts a packet as delivered only after an acknowledgement occurs. The same acknowledgement logic also applies to the cluster-head uplink delivery, which allows packet delivery ratio and retransmission-related energy cost to remain coupled in the evaluation.

Input:

Clusters, CHs, sink, maxRetries, ACK probability

for each CH do

for each member node in cluster do

attempt = 0

success = false

while not success and attempt ≤ maxRetries do

Node sends data to CH

CH receives data

Update energy for Tx and Rx

if random () < ackProbability then

success = true

else

attempt += 1

end if

end while

end for

CH aggregates data

CH sends data to Sink

if random () < ackProbability then

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count as a successful delivery

end if

end for

Output:

Total packets sent and received

Algorithm 3 ACK-Based Data Transmission with Bounded Retransmission for Member-to-CH and CH-to-Sink Links

- Duty Cycle Optimization Using Genetic Algorithm

To conserve energy, Algorithm 4 optimizes the work cycle schedule by deciding which nodes stay active during each sensing period. The genetic algorithm (GA) decreases the number of active nodes while maintaining coverage and data availability, leading to lower energy consumption. Algorithm 4 represents the duty-cycle schedule as a binary vector over the node set, where each bit indicates an active or sleep state within a sensing interval.

The fitness cost function decreases when the number of active nodes decreases, which directly reduces sensing, transmission, and reception opportunities and therefore reduces energy use. The GA operators (selection, crossover, mutation) search for a low-cost schedule while preserving network operability through the clustering and delivery steps executed in the same round. The stopping criterion terminates the search at a predefined generation limit or after negligible improvement in the best fitness value.

Input:

N nodes, sensing Interval

Objective:

Minimize the number of active nodes during sensing

Initialize:

Binary population vectors (active/sleep state)

While stopping criteria not met, do

Evaluate fitness:

Cost = activeNodes / (N × sensingInterval)

Apply genetic operators:

Selection, crossover, mutation

end while

Output:

Best schedule of active/sleep states for all nodes

Algorithm 4 Genetic-Algorithm Duty-Cycle Schedule for Active-Node Selection Under Sensing-Coverage Constraints

- Dynamic Power Control

Algorithm 5 dynamically adjusts the transmission power of each node based on its distance to the sink or channel, using a quadratic distance path loss model, to reduce unnecessary energy consumption. Algorithm 5 applies distance-adaptive scaling to the transmit-energy budget. The simulator computes the relevant distance from each member node to its cluster head for intra-cluster delivery and from each cluster head to the sink for uplink delivery. The quadratic distance factor reflects free-space path loss and aligns the transmit-energy scaling with the amplifier-driven component of the adopted radio-energy model. The power-control module therefore reduces unnecessary energy expenditure for short links and penalizes long links in a controlled manner.

Input:

Distances from nodes to Sink or CHs, base Tx energy

for each node i do

powerLevel[i] = baseTxEnergy × $(\text{distance}[i])^2$

end for

Output:

Power levels for all nodes

Algorithm 5 Distance-Adaptive Transmission-Power Control Under a Quadratic Path-Loss Model

- Compressed Sensing for Data Aggregation

To reduce data transfer size, Algorithm 6 performs basic compressed sensing by retaining only a portion of the collected data based on a pre-defined compression ratio. Algorithm 6 reduces the payload size through sample retention based on the compression Ratio parameter. The simulator retains $\lfloor L \times \text{compression Ratio} \rfloor$ samples from the aggregated data vector, where L denotes the original payload length. The retained length scales the number of transmitted bits in the subsequent cluster-head uplink step, and the energy model therefore reduces transmit and receive costs in proportion to the reduced payload size. The parameter definition treats compression Ratio as the retained fraction, which links directly to the implemented payload-length calculation.

Input:

Raw data vector, compressionRatio

numSamples = floor(length(rawData) × compressionRatio)

aggregatedData = rawData[1 to numSamples]

Output:

Compressed data vector

Algorithm 6 Compression-Ratio-Based Compressed Sensing for Payload Reduction During Cluster-Head Aggregation

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The framework integrates Q-learning for channel selection alongside LEACH-inspired clustering, adaptive duty-cycle optimization, dynamic power control, and data compression prior to collection. Cognitive wireless sensor networks improve upon conventional WSNs by enabling nodes to sense environmental conditions, learn from experience, and adapt operational parameters. Q-learning supports that capability by allowing each secondary user to learn channel choices that maximize successful transmission opportunities while avoiding primary users.

Each simulation round follows a fixed execution order. The duty-cycle module selects the active node set for the current sensing interval. Active nodes evaluate channel conditions and select a transmission channel via the Q-table policy. The clustering module elects eligible cluster heads and assigns members by minimum distance. Member nodes deliver packets to the cluster head under acknowledgement-based retransmission, and the cluster head performs aggregation plus payload-length reduction before uplink delivery. The transmit-power module scales transmit energy based on link distance for both intra-cluster and uplink delivery. The simulator then updates residual energy and performance counters, and the reinforcement-learning module updates the Q-table entries based on the observed reward.

4. RESULTS AND DISCUSSION

4.1. Simulation Design and Comparative Protocol

Various simulation experiments were used to assess the proposed framework under a deliberately constrained setting that reflects realistic sensor deployments, where limited battery capacity and unstable spectrum access jointly determine whether a network survives long enough to remain useful. The EATSEP model received initial validation under simulation, and the same environment and parameter set then supported evaluation of the proposed cognitive wireless sensor network. A single, consistent set of performance metrics and network parameters enabled comparison against a conventional WSN baseline under identical conditions, which preserves fairness across both systems. The study adopted 100 randomly distributed nodes, an initial energy reserve of 2 J per node, three communication channels, a 4000-bit packet size, and a 10 s sensing interval, with energy costs set to 50 nJ/bit for transmission, reception, and aggregation. The settings frame the results as a stress test under resource scarcity rather than a demonstration under generous energy budgets, to result in an outcome that carry practical relevance for field deployments of the proposed framework.

4.2. Energy Consumption Behaviour Under Constrained Resources

Figure 2 illustrates the importance of energy optimization in both conventional WSNs and cognitive WSNs, particularly under the resource limitations that characterize wireless sensor environments. The conventional network architecture wastes a substantial share of available power through inefficient relay selection and redundant data collection, even when every node starts with the same 2 J reserve. Relay selection that ignores stability tends to trigger repeated retransmissions, which forces additional transmission and reception energy expenditure on multiple hops. Redundant sensing traffic adds another structural penalty, because each repeated packet consumes energy at the source node, at the receiving relay, and at any aggregating node [51]. The proposed approach addresses these losses through a coordinated strategy that selects optimal relay nodes and stable cluster heads, which distributes communication load more effectively and reduces energy drain. The coverage-coefficient mechanism plays a direct role in that reduction, because a node becomes a distribution center once its coverage coefficient reaches the highest value, which increases coverage while reducing redundant transmissions. The coverage-based distribution concept therefore supports energy preservation because fewer packets are required to represent the sensed environment, and reduced traffic volume immediately reduces radio energy expenditure across the full delivery chain.

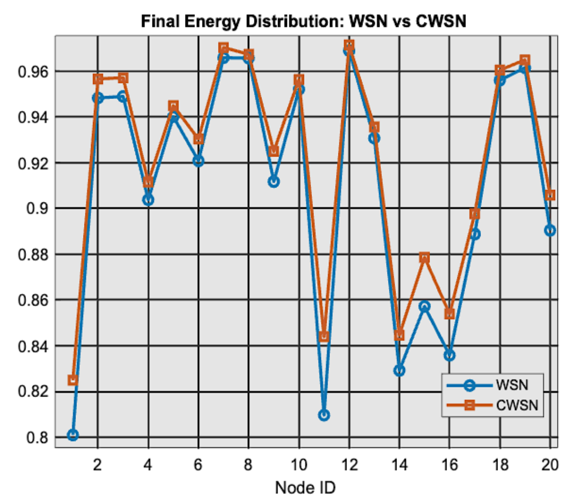

Figure 2 Remaining Energy Consumption of WSN and CWSN

Energy losses accelerate when channel coverage declines, because member nodes must expend higher transmission energy to reach the cluster head under weaker channel availability. The results show that the proposed approach reduced that penalty through adaptive relay selection that preserved reliable communication links and lowered the total energy demand. The framework compensated for reduced coverage by favoring stable relays, which reduced retransmission frequency and avoided route disruptions that would otherwise inflate energy cost. The practical consequence of this mechanism becomes clearer under the

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fixed constraints of the simulation, since every node began with only 2 J, and the network could not rely on excess energy to mask inefficiency. A method that preserves residual energy under such a low budget represents a method that reduces structural waste rather than merely shifting energy expenditure across nodes. The remaining energy separation seen supports the argument that the framework extends operational lifetime by suppressing avoidable energy loss paths.

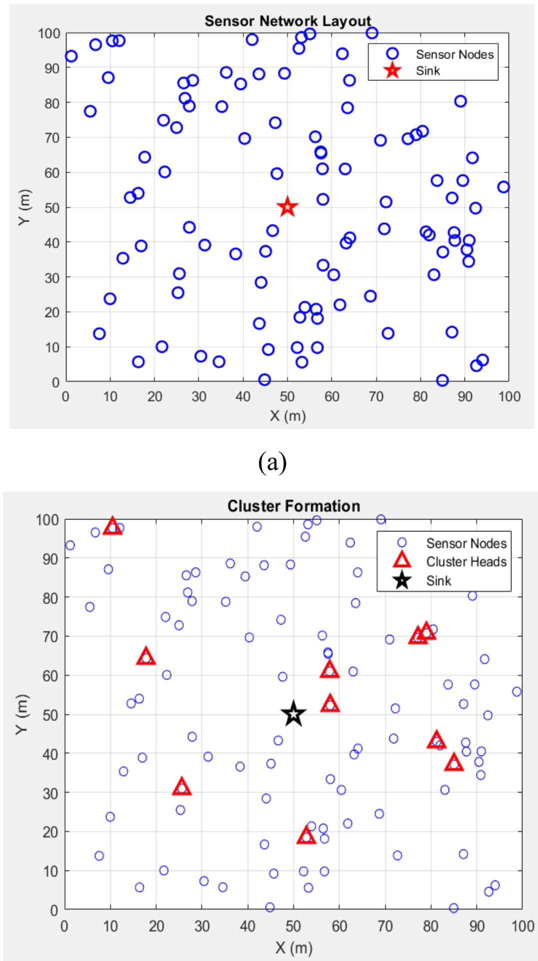
4.3. Relay and Forwarding Decisions Under Traffic Pressure

Routing decisions amplified the same energy-saving effect through traffic-aware forwarding. The forwarding rule selected nodes with lower traffic based on the traffic index parameter, which reduced routing interruptions, lowered retransmission frequency, and mitigated path loss penalties. Under 100 nodes deployed randomly and an initial energy reserve of 2 J per node, the routing choice produced lower average energy consumption than comparable techniques, because it reduced congestion-driven drops and prevented the formation of overloaded forwarding bottlenecks. The network-level impact matters because congestion causes queue overflow and forces retransmission cycles that multiply energy consumption far beyond the nominal 50 nJ/bit energy model. Balanced relay assignment therefore contributed to energy preservation through stability rather than through aggressive reduction of data rate. Controlled transmission power and reduced data redundancy added a complementary contribution, since the framework limited unnecessary transmit energy and reduced the number of repeated packets that would otherwise traverse the network. The combined effect aligns with the energy efficiency of 99.98% reported later, which indicates that most energy expenditure contributed directly to successful network operation rather than to recovery from avoidable failures.

4.4. Cluster Formation and Residual-Energy Constrained Cluster-Head Election

To link the energy outcomes to the spatial and organizational structure of the network, nodes were distributed randomly within a 100 × 100 area, and the sink remained at the center (Figure 3). The cluster formation followed a LEACH-inspired approach [34] with a cluster-head probability p_{CH} of 0.1, which implies that approximately 10 cluster heads emerge per round in a 100-node implementation. The proposed method altered the cluster-head election rule by restricting cluster-head eligibility to nodes with residual energy above 30% of the initial reserve, which translates to a threshold above 0.6 J for a node that started at 2 J.

A random node became cluster head only when the probability rule held and residual energy remained above that threshold, otherwise the system forced a cluster head selection to preserve continuity. Member nodes then joined the nearest cluster head, which reduced transmission distance and reduced energy expenditure for member-to-cluster communication. The design preserved the simplicity of probabilistic clustering while eliminating a key weakness of conventional LEACH, since classical LEACH may select low-energy nodes as cluster heads and accelerate their failure.



(a)

(b)

Figure 3 CWSN with Cluster-Based Performance Metrics, (a) Cluster Formation, (b) Senser Network Layout

Cluster-head collapse disrupts data flow for an entire cluster and forces repeated cluster reformation, and the damage becomes especially severe near the sink because relay duties concentrate there over time [52]. The 30% residual-energy requirement prevents fragile nodes from absorbing cluster-head duties that they cannot sustain, which improves stability and reduces control overhead across rounds.

The proposed method achieves a comparable objective through a simpler eligibility filter. The simplicity matters because additional cluster optimization layers can introduce coordination overhead that also consumes energy.

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4.5. Cognitive Adaptation and Learning-Based Channel Selection

The CWSN improve upon conventional WSNs by enabling nodes to sense environmental conditions, learn from experience, and adapt operational parameters. Q-learning used supports that capability by allowing each secondary user to learn channel choices that maximize successful transmission opportunities while avoiding primary users. Reinforcement-learning strategies improve spectrum management because reward history captures interference behaviour and steers access toward stable opportunities [53]. The proposed system uses that property to reduce channel collision probability and to limit PU-driven communication disruption. Cognitive adaptation used stabilizes the spectrum layer, while residual-energy CH eligibility stabilizes the topology layer. Cross-layer stability is crucial because instability at either layer can contradict gains at the other. A stable cluster structure cannot guarantee reliability when channel access collapses under interference, and an available channel cannot guarantee reliability when cluster leadership collapses under energy depletion.

4.6. Metric-Wise Performance Interpretation

4.6.1. Packet Delivery Ratio (PDR)

The PDR measures end-to-end delivery reliability under simultaneous energy scarcity and spectrum uncertainty. Figure 4 reports an overall PDR of 95.05%, which indicates that most generated packets reached the sink despite cognitive operation that requires channel vacating and interference avoidance. Residual-energy constrained cluster-head election supports that reliability because cluster-head failure disrupts intra-cluster collection and breaks inter-cluster forwarding paths, with the most severe effects near the sink where relay burden concentrates [52]. Panbude *et al.* (2024) reported that energy-aware cluster-head strategies improve stability and delivery performance through reduced premature cluster-head depletion [54].

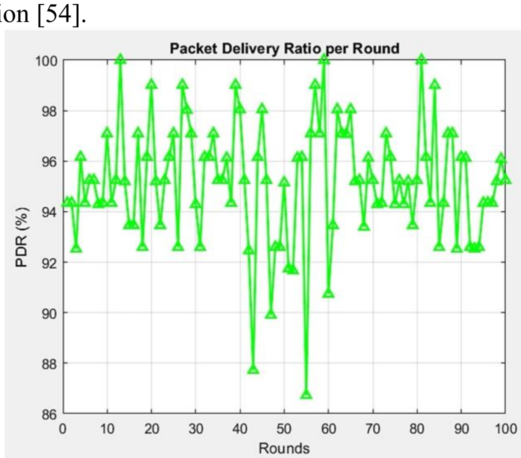

Figure 4 Packet Delivery Ratio Per Round for the Modified Cluster-Head Selection Scheme

The proposed residual-energy threshold achieves a similar stability objective through a lightweight eligibility rule, which limits frequent re-clustering and reduces packet loss events that follow topology repair cycles. Q-learning channel selection adds a spectrum-layer reliability mechanism by biasing access toward channels with higher expected reward under observed interference history, which reduces collisions and protects packets from PU-driven disruptions [55]. Packet delivery ratio reached 95.15%, which stays within the reliability range reported by recent schemes that typically report 95-98.5% under related settings [56]. The combined topology stability and spectrum stability explain the consistently high PDR reported under strict energy limits.

4.6.2. Spectrum Utilization

Spectrum utilization quantifies the proportion of available channel opportunities that the network converts into productive access. Figure 5 reports an overall spectrum utilization of 78%, which indicates that the network exploited spectrum holes rather than leaving channels idle. Conservative cognitive access frameworks historically produced low utilization near 20% because secondary users adopted overly cautious vacating and access policies [57]. Q-learning reduces that conservatism by mapping past outcomes into channel rewards and favoring channels that repeatedly support successful delivery under PU constraints [55]. Spectrum sensing overhead can reduce practical utilization when sensing frequency becomes excessive or when sensing spans too many channels [58].

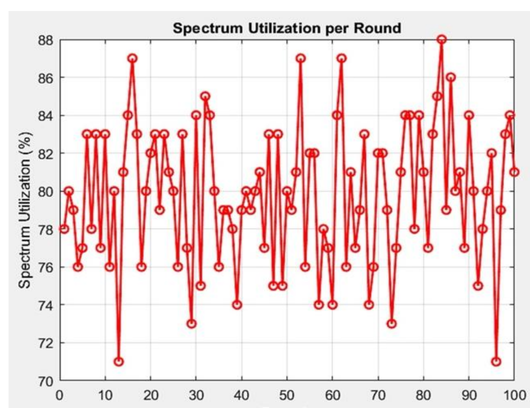

Figure 5 Spectrum Utilization Per Round Under Q-Learning Channel Selection Across Three Channels

4.6.3. Total Energy Consumed Per Round

Total energy consumed per round captures the stability of network expenditure across time and indicates whether the protocol triggers periodic energy spikes from repair operations, congestion, or repeated retransmission cycles. Figure 6 shows a consistent per-round energy-consumption profile, which indicates balanced energy expenditure rather

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than episodic bursts. Residual-energy constrained cluster-head election reduces control overhead because the protocol avoids selecting fragile cluster heads that collapse quickly and force repeated cluster formation. Adaptive duty-cycle control reduces idle listening energy, which represents a major source of avoidable energy loss in sensor radios. Dynamic power control reduces transmit energy for short member-to-cluster-head links, which becomes particularly important when node placement supports near-neighbor association. The consistency in Figure 6 therefore supports a stability interpretation, since the energy profile shows no evidence of repeated instability cycles that would otherwise appear as periodic increases in per-round energy demand.

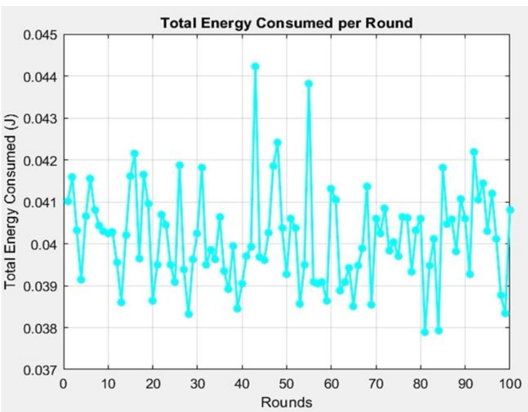

Figure 6 Total Network Energy Consumed Per Round Under the Cross-Layer CWSN Framework

4.6.4. Throughput

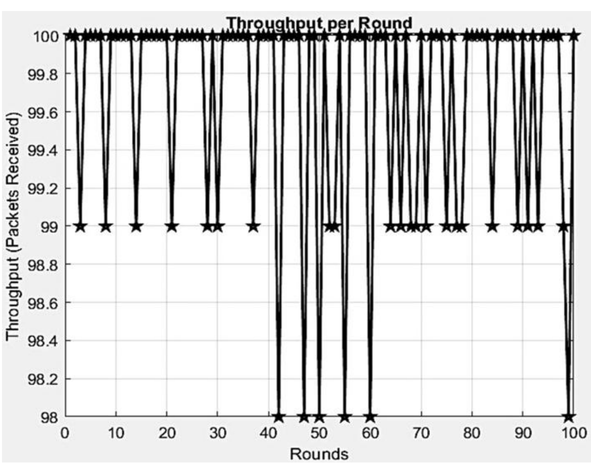

Figure 7 Normalized Throughput Per Round Under Adaptive Clustering and Channel Selection

Throughput represents the sustained delivery rate that the sink receives under the offered sensing load. Figure 7 reports throughput percentage between 97% and 100%, which indicates that delivery remained steady across rounds and that the network avoided prolonged delivery stalls. Cluster-head instability can reduce throughput through intermittent disconnections and repeated re-clustering overhead, particularly when traffic aggregation depends on a small number of cluster heads [52]. Q-learning channel selection supports throughput stability by avoiding interference-prone channels that increase collisions and force retransmissions that reduce effective delivered rate [53]. The throughput data rate reached 4×10^6 bits/s, while higher values such as 8.2×10^7 bits/s appear in the literature under different operating assumptions and traffic models, which limits direct numerical equivalence across studies [59]. High throughput alongside high spectrum utilization indicates that the protocol used channel opportunities productively rather than merely satisfying PU-protection constraints.

4.6.5. Energy Efficiency

Energy efficiency measures the share of energy expenditure that contributes directly to successful network operation rather than to wasted activity such as collisions, retransmissions, and repeated control operations. Figure 8 reports an overall energy efficiency of 99.98%, which indicates minimal waste under the adopted radio-energy settings. Residual-energy constrained cluster-head election reduces waste by limiting topology repair cycles, since fewer cluster-head collapses reduce repeated cluster-formation messaging and associated receptions and transmissions. Q-learning reduces waste by selecting channels with higher expected success probability, which reduces collision-driven retransmissions and lowers energy loss that would otherwise accumulate at both transmitters and receivers [53].

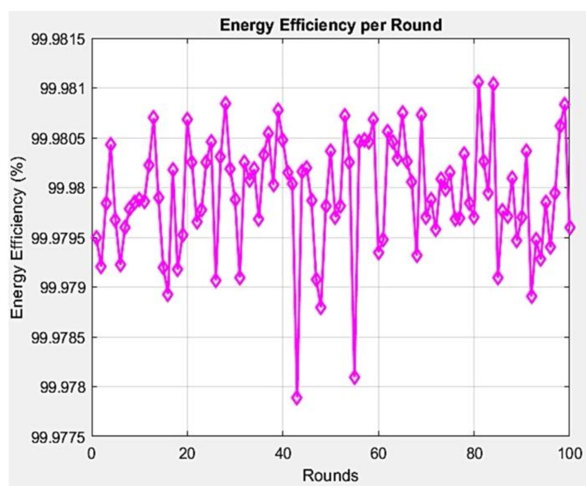

Figure 8 Overall Energy Efficiency Under the Integrated Energy and Spectrum Control Strategy

Energy efficiency exceeds the 68-81% range reported by Mia and Osei (2025) [59] and supports an interpretation that the proposed framework preserved energy through structural stability rather than through traffic suppression. Energy harvesting and SWIPT designs can extend lifetime further in

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cognitive sensing deployments [60], and RF scavenging from primary transmissions can provide supplemental energy under frequent PU activity [61]. Spectrum sensing overhead still requires careful control because sensing cost can erode energy efficiency under aggressive sensing schedules [58]. The near-ideal energy efficiency in Figure 8 indicates a favorable balance between cognitive operation and energy sustainability.

The study outcomes establish that the proposed system maintained operational stability under variable traffic and energy constraints. Packet delivery ratio reached approximately 95.15%, energy efficiency approached 99.98%, and spectrum utilization averaged 78%. The results confirm that the framework achieved an equilibrium among reliability, throughput, spectrum productivity, and energy conservation. Energy-aware clustering stabilized the topology layer by preventing low-energy CH collapse and reducing repair overhead.

Q-learning stabilized the spectrum layer by adapting to interference and PU behaviour through reward-driven channel selection. Comparative benchmarks support the practical significance of the results, since the framework achieved superior energy efficiency compared with recent cognitive efficiency comparisons, competitive reliability relative to recent optimization methods, and higher spectrum utilization than conservative cognitive baselines. The proposed design offers a meaningful advance for energy-limited cognitive sensor deployments where mission value depends on both sustained lifetime and dependable packet delivery, and where spectrum awareness must increase productivity rather than introducing new overhead that undermines the network.

5. CONCLUSIONS

Energy defines the stability and endurance of wireless sensor networks. The transition from conventional static configurations to cognitively adaptive systems mark a fundamental evolution in communication intelligence. The proposed framework achieves efficiency not by expanding energy resources but by rationally managing the existing ones through reinforcement-based channel selection, energy-aware clustering, and adaptive control. The system attains an energy efficiency of 99.98%, a packet delivery ratio of 95%, and a spectrum utilization rate of 78% while maintaining a throughput of 4,000,000 bits. Our results confirm that the model sustains near-optimal operation under variable network conditions and validates the effectiveness of its cognitive coordination. The innovation of this work lies in its ability to simultaneously optimize multiple performance dimensions, energy efficiency, spectrum utilization, and throughput, through coordinated learning and control mechanisms. Such contrasts with most recent solutions that target isolated optimizations. The model's adaptability under constrained resources makes it especially promising for remote or infrastructure-limited deployments. Further progress in this domain will depend on the integration of energy harvesting, embedded machine learning, and self-optimizing routing within sensor nodes. Cognitive decision layers capable of reasoning about both local and network-wide states will define the next generation of autonomous, energy-resilient communication systems. The future of wireless sensor networks will therefore rest on architectures that not only transmit information but also preserve the continuity of their own operational existence.

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