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Exploring Energy-Efficient Communication Strategies in Wireless Sensor Networks: A Survey

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***Abstract*—Wireless Sensor Networks (WSNs) are essential for real-time monitoring applications like industrial automation, healthcare, environmental surveillance, and defense; however, their widespread deployment is limited by energy resources, scalability problems, and security flaws. With an emphasis on MAC protocols, clustering mechanisms, hybrid network architectures, and AI/ML-based optimization techniques, this survey methodically examines current energy-efficient and secure communication strategies used in WSNs. Hybrid designs and learning-driven models greatly improve network lifetime, throughput, reliability, and latency performance, according to a comparative study of current methods. Despite these advancements, many solutions still exhibit high computational overhead, limited flexibility in dynamic environments, and insufficient real-world validation. Future WSN frameworks must prioritize lightweight, adaptive, and cross-layer intelligent designs to achieve sustainable, scalable, and secure next-generation sensor networks.**

***Keywords*—Energy Efficiency, Hybrid Network, Secure Communication, Wireless Sensor Networks, AI/ML Optimization.**

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are widely used in fields like industrial automation, military surveillance, agriculture, and healthcare monitoring. They are made up of a large number of resource-constrained sensor nodes that are able to sense, process, and transmit data to sink nodes or base stations. Clustering, duty cycling, and multi-hop routing schemes are just a few of the many protocols and architectural designs that have been put forth over the years to improve network lifetime, reliability, and data delivery efficiency. Nevertheless, new demands for scalability, security, and adaptability have revealed flaws in conventional methods.

By enabling intelligent decision-making and dynamic adaptation to network conditions, recent developments like energy harvesting, cross-layer optimization, and AI/ML-driven communication frameworks are redefining secure and energy-efficient WSN design. This survey's main contributions include: (1) thorough examination of secure and energy-efficient WSN communication techniques; (2) classification of previous research into protocol-oriented and intelligent hybrid models; (3) critical comparison of performance metrics; and (4) identification of unresolved issues with scalability, computational overhead, and practical implementation. Energy-efficient protocols and AI/ML-based models are reviewed in Section II, research gaps are discussed in Section III, software requirements in Section IV, and conclusions in Section V.

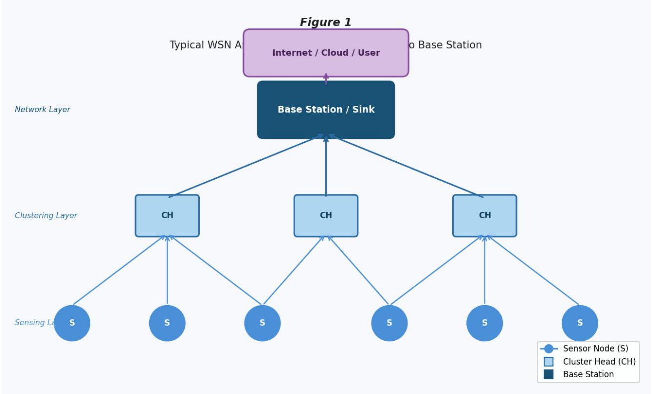

Fig. 1 Typical WSN architecture showing sensor nodes, cluster heads, and the base station arranged in a hierarchical layered structure.

II. LITERATURE REVIEW

A. *Secure and Energy-Saving WSN Protocols*

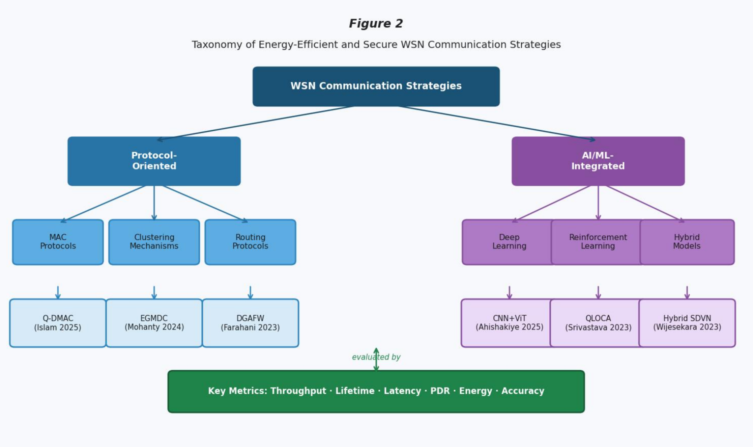

Fig. 2 Taxonomy of energy-efficient and secure WSN communication strategies, classifying approaches into protocol-oriented and AI/ML-integrated categories.

Through optimized MAC and clustering protocols, recent developments in WSNs have concentrated on enhancing security, dependability, and energy efficiency. With the help of directional antennas and regret matching for channel selection, Islam et al. [1] created the Q-DMAC protocol, which achieved 20% higher throughput, 25% longer lifetime, and lower latency but lacked adaptive energy management. Wireless Body Area Networks (WBANs) were improved by Mohanty et al. [2] using a fuzzy logic-based clustering scheme combined with Nash equilibrium and reinforcement learning, resulting in 93% packet delivery, 0.31s delay, and 0.43J energy use, but with limited energy harvesting adaptability.

A Genetic Algorithm (GA)-based data collection method was proposed by Alasadi et al. [3], which improved data throughput by 6.6% and network lifetime but had a high computational overhead. CSPTP, a cooperative image transmission protocol that achieves 99% reliability with balanced energy consumption but has high compression costs and scalability issues, was first presented by Chiwariro et al. [4].

Almarr et al. [5] hybrid circular/star topology with AI-based fire prediction had 99.97% accuracy, cut the number of nodes by 55%, and the latency by 81%. However, it could not adapt quickly to changes in the environment. For healthcare, Saravanan et al. [6] enhanced WBAN routing efficiency through power-aware metrics, decreasing latency to 250 ms and power consumption to 0.915 mW, although this solution is not scalable for dense biosensor networks.

Farahani et al. [7] DGAFW combined Genetic Algorithm and Floyd-Warshall routing, improving lifetime by 48% and residual energy by 19% but remained static in dynamic topologies. Pavithra et al. [8] improved TSCH scheduling with the Cuckoo Search Algorithm (CSA), which increased throughput by 12.4% and delay by 17.8%, but only in simulations. Zheng et al. [9] also created a cross-layer optimized MAC protocol with cooperative transmission that made the network last 3.7 times longer than IEEE 802.15.6, but it was limited by real-world testing conditions. Lastly, Srivastava et al. [10] put forward QLOCA, a Q-learning and clustering algorithm for Cognitive Radio Ad Hoc Networks, which reduced the average delay by 7.2% and the number of collisions by 4.2%, but it could not adapt to changing spectrum conditions.

In all of these studies, hybrid and learning-driven models consistently improve throughput, reliability, and lifetime. However, they are still held back by high computational costs, limited real-time scalability, and static assumptions. Future research should prioritize adaptive, cross-layer, and self-learning designs to maintain energy efficiency and resilience in dynamic WSN environments. Table I below shows a side-by-side comparison of the most recent energy-efficient and secure protocols for WSNs and WBANs.

TABLE I Comparative Summary of Recent Energy-Efficient and Secure Protocols for WSNs and WBANs

Author /Year	**Method/Technique**	**Dataset**	**Limitations**	**Findings**
Islam et al. (2025)	Q-DMAC (Directional MAC, regret matching)	Simulation	Lacks adaptive energy management	↑ Throughput 20%, ↑ Lifetime 25%
Mohanty et al. (2024)	Fuzzy clustering + Nash equilibrium + RL routing	Simulation	Limited energy harvesting	↑ PDR 93%, ↓ Delay 0.31s
Alasadi et al. (2024)	GA-based tree data collection	Simulation	High computation cost	↑ Lifetime, ↑ Alive nodes
Chiwariro et al. (2024)	CSPTP image transmission	Experimental	High compression overhead	↑ Reliability 99%, Energy balanced
Almarr et al. (2025)	Hybrid circular/star topology + AI fire prediction	Hybrid simulation	Limited scalability	↓ Latency 41–81%, ↑ Accuracy 99.97%

Note. PDR = Packet Delivery Ratio; GA = Genetic Algorithm; RL = Reinforcement Learning.

These studies stress hybrid designs and adaptive mechanisms that improve throughput and energy balance. Even though performance has improved, there are still problems with scalability and real-time adaptability.

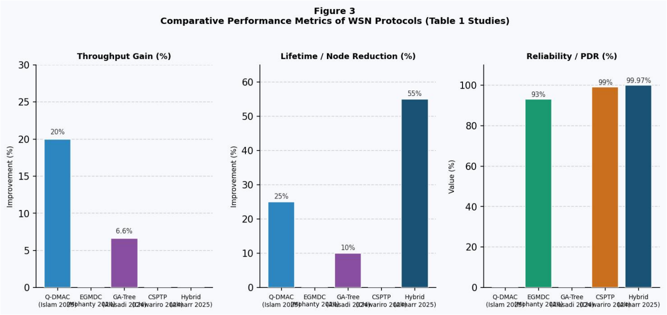

Fig. 3 Comparative performance metrics of WSN protocols surveyed in Table I, showing throughput gain, lifetime improvement, and reliability scores.

B. *Advanced AI/ML-Based Models and Applications*

Recent research has been centered on combining AI, deep learning, and multi-regional modeling to make communication and data management safer and more efficient. Kaushal et al. [11] proposed a hybrid U-Net–Pyramid model for landslide detection, achieving 91% precision and 87% F1-score, though constrained by significant computational demands and dataset dependency.

Ahishakiye et al. [12] developed a CNN–Vision Transformer (ViT) ensemble for malaria diagnosis, achieving 99.6% accuracy, though it is not suitable for low-resource settings. Rahman et al. [13] utilized YOLOv8 for UAV-based WSN data collection, achieving an F1 score of 96%, indicating robust obstacle detection but constrained real-world evaluation. Alhmiedat et al. [14] created a fingerprinting-based localization model with an accuracy of 1.4 m but limited to static setups.

Lan et al. [15] MrCAR model improved facial expression recognition through multi-region attention achieving up to 99% accuracy, although it faced challenges related to preprocessing complexity. Zhang et al. [16] utilized a multi-regional input-output model to evaluate China's electricitywater nexus, providing insights into resource sustainability while neglecting temporal and policy dynamics. Wen et al. [17] CTSPM modeled changes in land use and linked a 1% increase in TFP to a 1.48% increase in GDP, but oversimplified human-environment interaction.

Wang et al. [18] utilized a multi-regional multiplier to model R&D capital spillovers, demonstrating regional disparities with spillover intensity reaching 1.69 in Guangdong but exhibiting constrained dynamic adaptability. Wijesekara et al. [19] developed a hybrid SDVN data collection model that cuts latency by 32.7% and costs by 75.5%, but only under ideal network conditions. Finally, Kasongo [20] used XGBoost feature selection and RNN (LSTM, GRU) together for intrusion detection, achieving 88% accuracy on NSL-KDD and 87% on UNSW-NB15, but with long training times and limited scalability.

These studies show that AI-driven and multi-regional frameworks together improve prediction accuracy, detection precision, and communication reliability. However, problems such as high computational costs, reliance on static datasets, and limited scalability persist. Table II gives an overview of AI/ML-driven models used in WSNs and related fields.

TABLE II OVERVIEW OF AI/ML-DRIVEN MODELS APPLIED IN WSNS AND RELATED FIELDS

Author /Year	**Dataset/ Domain**	**Method/Technique**	**Limitations**	**Findings**
Kaushal et al. (2024)	Landslide 4Sense	Hybrid U-Net + Pyramid Pooling	High computational cost	Precision 91%, Recall 84%, F1 87%
Ahishakiye et al. (2025)	Malaria datasets	CNN + Vision Transformer Ensemble	Dataset dependency	Accuracy 99.6%, F1 99.5%
Rahman et al. (2023)	UAV WSN data	YOLOv8-based detection	Limited real-world testing	F1 score 96%, robust obstacle detection
Alhmiedat et al. (2023)	Indoor localization	Fingerprinting + ML	Indoor-only, low scalability	Accuracy 1.4 m, validated results
Kasongo (2023)	NSL-KDD / UNSW-NB15	XGBoost + RNN (LSTM, GRU)	Dataset bias, high training cost	↑ Accuracy 88%, ↓ Features 17–22

Note. CNN = Convolutional Neural Network; ML = Machine Learning; RNN = Recurrent Neural Network; LSTM = Long Short-Term Memory; GRU = Gated Recurrent Unit.

AI/ML-based models strengthen detection, prediction, and routing capabilities but often face limitations in scalability, generalization, and computational complexity.

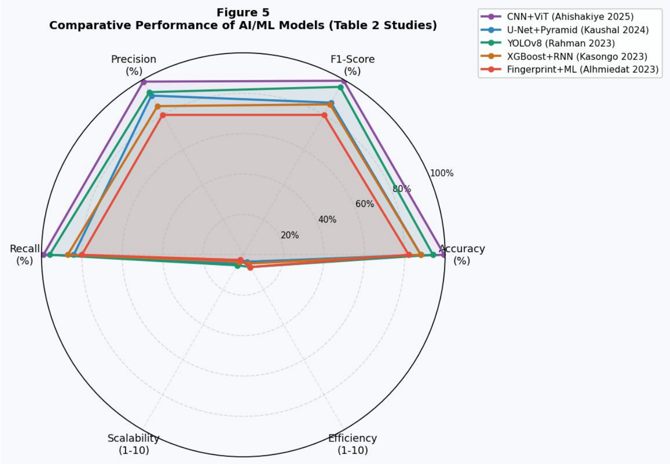

Fig. 4 Radar chart comparing AI/ML model performance across accuracy, F1-score, precision, recall, scalability, and efficiency for the Table II studies.

III. RESEARCH GAPS AND LIMITATIONS

The studies reviewed show some important progress, but there are still gaps in the generalization and real-world use of the proposed frameworks. Many works use benchmark datasets or static network assumptions, which do not work in dynamic IoT and WSN environments. Also, systems that are energy-constrained cannot use approaches requiring high processing power. The necessity for lightweight, self-learning, and multi-modal data-integrated frameworks persists unfulfilled. Scalability, latency, and cross-domain adaptability are problems that keep recurring.

IV. SOFTWARE AND SYSTEM REQUIREMENTS

Instead of using real-world deployments, the majority of the research included in this survey relied on simulation-based evaluation. Low-power microcontrollers, IEEE 802.15.4-compliant radio transceivers, and sensor nodes with a limited battery capacity (≤2 AA batteries) are typical system requirements. Network Simulator NS-2 and NS-3 for protocol analysis, MATLAB for algorithm validation, and Python-based machine learning frameworks like TensorFlow and PyTorch for AI-driven optimization models are among the software environments frequently used for performance evaluation. Furthermore, resource-constrained sensor node behavior is often simulated using lightweight operating systems like Contiki and TinyOS.

V. CONCLUSIONS

This survey thoroughly examined energy-efficient and secure communication strategies in Wireless Sensor Networks, emphasizing the transition from conventional protocol-based designs to advanced, AI/ML-integrated hybrid frameworks. Recent approaches show significant improvements in network lifetime, reliability, and latency, but they still have problems with high computational overhead, limited scalability, and insufficient real-world testing. Most current research relies on static assumptions and simulation-based evaluation, which makes it hard to apply in real life. Future research should look into lightweight, adaptable, and self-learning models that work with edge computing, blockchain-based trust management, and real-time energy harvesting systems to make next-generation WSNs that can grow and remain resilient.

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