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Research Article

Leveraging AI in Mixed Hierarchical Topologies to Improve WSN: A Survey

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ABSTRACT

The Internet of Things (IoT) as Wireless Sensor Networks (WSNs) holds a significant role in various areas: Military surveillance, Industrial automation, Smart housing, Security Systems, Intelligent Vehicular Traffic control, as well as Healthcare monitoring. So, the sensor nodes performance and life-time with limited power, memory and processing capabilities are significant issues to face in the network. To overcome these limitations, a wide range of energy-aware packet forwarding mechanisms and routing protocols have been proposed to optimize network throughput and lifetime. A WSN's performance is strongly dictated by its node deployment approaches, energy consumption profiles, communication latency, and data aggregation techniques. Furthermore, as the aspects of the network topology (chain-based or cluster-based hierarchical) and the criteria for choosing aggregator nodes to further transmit the sensed data to the sink node strongly affect delivery time and energy balance. Existing hierarchical routing protocols are well studied by several surveys, for example LEACH, PEGASIS, PDCH, CHIRON, CCBRP, CCM, TSCP, DLRP and DCBRP. To do so, it underlines why the addition of Artificial Intelligence (AI) to mixed hierarchical topologies is improving decision-making processes, and adaptive clustering while making WSNs more efficient, scalable and resilient in their performance. We further provide a comparative analysis, primarily emphasizing the advantages and limitations of different chain-based and cluster-based AI-assisted routing solutions.

1. INTRODUCTION

The As it has found ease of deployment and versatile applicability to real world scenario, Wireless Sensor Networks (WSNs) have become a widely popular and continuously evolving area of research. They find applications in a wide range of domains such as environmental monitoring, industrial automation, smart cities, security systems, and health care [1,2]. Sensors used for monitoring and actuating; WSNs have been gaining interest from the international research community up to this date as they have the potential of simplifying daily life and maximizing different industrial processes. Wireless Sensor Networks (WSNs) are formed by a large number of spatially distributed sensor nodes capable of monitoring physical or environmental parameters and communicating wirelessly to send the data into a sink. Usually, these nodes are resource-constrained with limited battery life, low transmission range, storage, and processing capacity [3]. Despite these drawbacks, they are small, inexpensive, and can be easily assimilated into a variety of environments: highly desirable features for extensive deployment, for example as part of smart lighting, HVAC systems, intrusion detection and emergency alert systems [4].

Modern WSNs have two main communication modes: pull (data is retrieved upon request) and push (sensor nodes autonomously transmit data to the sink) [5]. Routing is a key challenge as the number of deployed nodes scales. Due to the multi-hop flat or hierarchical topology of most WSNs, energy-efficient and scalable routing protocols are required [6]. These protocols should address many challenges regarding the asymmetries of communication links, frequent topology changes, node failures, and environmental interferences, which make the reliable delivery of data difficult [7]. Recently, some hierarchical topologies—especially chain-based and cluster-based models—are becoming popular because of their ability to decrease transmission overhead and to balance energy consumption of nodes [8]. In addition, the use of Artificial

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Intelligence (AI) in routing strategies has created new potential opportunities for network performance optimization. AI methods can be applied to assist decisions regarding cluster formation, node choice, and data aggregation, thus promoting adaptability, energy efficiency, and fault tolerance [9,10].

Given these challenges and opportunities, in this survey we consider mixed hierarchical topologies which leverage AI for optimizing routing, extending the lifespan of WSNs, and improving the reliability of communication. It offers comparison among multiple popular hierarchical routing protocols and discusses how intelligent algorithms help to overcome the limitations of traditional routing and enable novel solutions for next-generation WSN. Figure 1 shows a conceptual diagram of the architecture to include Artificial Intelligence (AI) with mixed hierarchical topologies of WSN. The hierarchical model of the AIWSN is a representation of hierarchical arrangements of sensor nodes into clusters and chains with associated optimized cluster heads. AI is integrated at the cluster head level because it facilitates efficient decisions regarding energy-aware routing, adaptive node election, and dynamical control of the network [11,12]. Data from individual sensor nodes is transmitted to their respective collection points (cluster heads): this is illustrated in the figure below. Cluster heads aggregate the information from their network and relay it to a centralized sink or base station. Real world deployments: smart cities, environmental monitoring, healthcare, industrial automation. Also, constantly adjusting the internal structure to fit a dynamic state, thoroughly designing the structure of the network can also render the whole process scalable and energy efficient [13].

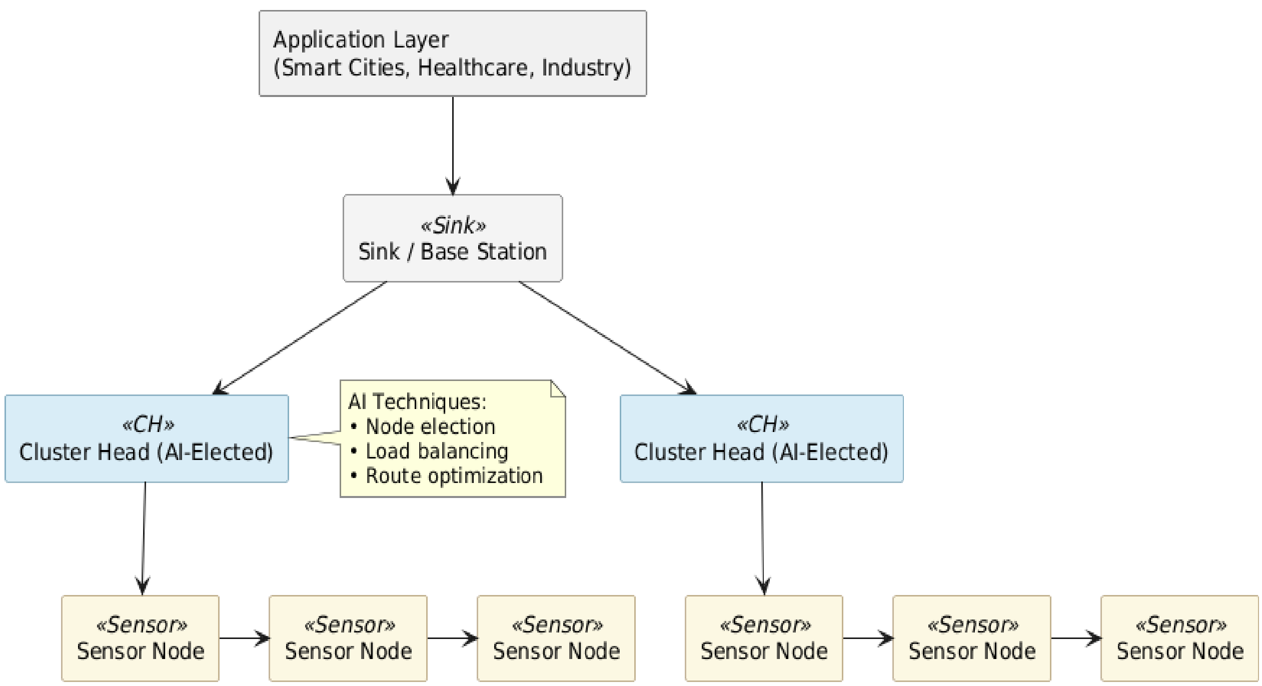

Fig. 1. Conceptual Overview of AI-Enhanced Mixed Hierarchical Wireless Sensor Networks

2. CHALLENGES IN WSN AND THE ROLE OF AI-BASED SOLUTIONS

Wide-ranging technical and operational challenges in Wireless Sensor Networks (WSNs) greatly impact the performance, efficiency, and scalability of WSNs. However, this can be achieved only when these challenges are handled by innovative and intelligent solutions. This segment describes the main problems faced by current WSNs, and explains how AI and mixed hierarchical topologies can synergistically address them. For a better understanding of the main challenges in the WSNs field, as well as, the possible impact of Artificial Intelligence (AI) in heterogeneous hierarchical topologies, Table 1 presents a summary of main limitations and the intelligent solutions proposed in the literature. It emphasizes the position of AI methods such as machine learning, optimization algorithms, and so on, as well as the component where its use can help improve performance, scalability, and versatility across the layers of the WSN architecture.

TABLE I. KEY CHALLENGES IN WSNS AND AI-DRIVEN SOLUTIONS IN MIXED HIERARCHICAL TOPOLOGIES

Challenge	Description	AI-Enabled Solution
Security and Data Integrity	WSNs are prone to data interception, spoofing, and unauthorized access due to their open and unattended nature.	AI techniques (e.g., anomaly detection, intrusion detection systems, adaptive encryption) enhance threat detection and security response.
Data Aggregation and Redundancy	Dense deployments lead to duplicate data collection, increasing energy usage and network congestion.	Machine learning and fuzzy logic algorithms optimize data fusion, reduce transmission overhead, and enable efficient aggregation strategies.
Network Coverage and Topology Design	Irregular sensor distribution may cause coverage holes or inefficient energy use in CH selection and routing.	AI supports optimal cluster head placement and dynamic topology adjustment to maintain balanced coverage and energy-aware communication.
Latency and Delay	Real-time applications require low-latency data delivery; delays impact system performance.	Predictive AI routing models help identify the shortest energy-efficient paths, reducing end-to-end delays.
Scalability and Network Growth	Large-scale WSNs risk performance degradation and state management challenges as the network grows.	AI-based routing adapts dynamically to larger node counts using learning algorithms that efficiently manage routing updates and topology changes.
Throughput and Data Rates	Inefficient routing and network congestion lower data transmission success between nodes and base station.	AI enables intelligent load balancing and congestion prediction, improving throughput by optimizing packet scheduling and traffic flow.

3. AI-ENHANCED ROUTING PROTOCOLS IN MIXED HIERARCHICAL TOPOLOGIES

Routing protocols in Wireless Sensor Networks (WSNs) are fundamental in establishing energy efficiency, data transmission reliability, and the network lifetime. Routing mechanisms have a significant effect on the survival of sensor nodes and successful data delivery paths from source nodes to BS. Routing Protocols in IOTS (Internet of Things) Because of resource constraints like battery life, processing ability, and communication range, the routing protocols, thus, should be optimized not only for efficiency but also for adaptability and scalability. Hence, hierarchical routing models, especially tree-based, cluster-based, and chain-based topologies, have proven to be an excellent architectural paradigm for energy conservation and load balancing [14-18].

In tree-based topologies for example those found in the DRINA protocol (Data Routing for In-Network Aggregation), sensor nodes send data using a hierarchical tree topology. This design is particularly appropriate for frequent data reports to the BS [19]. Parent-child paths are organized and aggregated, but could fail at pivotal nodes with AI managing data and re-composing the topologies. On the contrary, using cluster-based approaches have been found to substantially lessen WSNs operational time limitations. Protocols such as LEACH (Low-Energy Adaptive Clustering Hierarchy) allow sensor nodes to autonomously form clusters in which cluster heads (CHs) supervise intra-cluster communication and aggregate data to be forwarded to the BS [20-22]. The BS uses global knowledge such as node energy levels and locations to optimize selection of CHs in a centralized form of this protocol, LEACH-C, to obtain better energy efficiency [23-25]. International Journal future wireless networks are equipped with advanced computer technology with dynamic learning ability, thereby promoting cooperative smart communications among nodes and environmental information, Intelligent CH election and energy balance consumption through AI Algorithms.

Power-Efficient Gathering in Sensor Information Systems (PEGASIS) is an enhancement to the LEACH protocol that organizes nodes into chains, rather than into clusters. It is only allowed to exchange information with neighboring nodes under bi-directional channels, while the aggregated data to the BS is transmitted by a chosen chain leader [26]. This approach unifies the transmission distances and minimizes energy dissipation greatly. Intelligent chain formation, leadership roles rotation and optimal routing path prediction can be managed through AI techniques to balance the network and so as to prolong the network lifetime [27-31]. However, it has limitations in sending data from a distant chain leader to the BS in an efficient way. The phenomena are: To avoid this, many protocols like Distance based energy efficient routing protocol (DERP) consist of many pre-chain leaders and relay nodes for multi visited data delivery. AI-based DERP can be improved with machine learning to select the relay node and predict the path using dynamic data like throughput and latency of the network in real time [32].

In these advanced chain-based protocols, DLRP (Direct Line Routing Protocol) reduces redundancies in data transmission by choosing chain heads according to energy metrics. These protocols combine advantages of both cluster- and chain-based architectures. For example, CCM (Chain-Cluster Mixed) uses two-stage communication that aggregates in the chains and sends the first one from each CH through the cluster-based layer to a communicated super-head [33]. TSCP and DCBRP follow similar principles, working on homogenizing load balancing and energy consumption by establishing a structure for communication through multiple stages of chain and cluster respectively [34-36].

Recent trends led by AI advancements in Cognitive Radio Networks (CRNs) Porter et al. (2021), wherein intelligent Channel (CH) selection, mobility prediction, and energy-aware routing complement these protocols, which on their own may produce limited performance. For instance, Multi-hop Deterministic Energy Efficient Routing (MDR) protocol uses deterministic and energy-based metrics for CH selection and inter-cluster routing. Abstract AI approaches could extend such techniques through the automatic processing of decisions and adaptive solutions to protocols in a highly changeable setting [37]. Lastly, the deployment of nodes also has a significant impact on routing efficiency. Although random placements work well in large-scale or emergency situations, deterministic deployments can provide coverage with fewer nodes. By leveraging AI algorithms, operators can implement optimal node placement strategies, simulate various deployment scenarios, and adapt to changes in the environment in real-time to ensure network stability and performance [38–40]. A detailed comparison of the different hierarchical routing protocols and their relative suitability for AI integration is shown in Table 2. The following table summarizes the topology type, energy efficiency, scalability, and how Artificial Intelligence can improve the different protocols. Utilizing AI in key aspects of WSNs, including cluster head selection, energy-aware routing, and adaptive topology control, nearly allows protocols to enhance their performance and sustainability. This comparison is intended to emphasize the strengths of traditional protocols as well as how intelligent features can mitigate increasing problems within contemporary WSN deployments.

TABLE II. COMPARISON OF ROUTING PROTOCOLS WITH AI FEATURES

Routing Protocol	Topology Type	AI Enhancement Potential	Energy Efficiency	Scalability
LEACH	Cluster-based	Smart CH selection, adaptive clustering	Moderate	Medium
LEACH-C	Cluster-based (Centralized)	AI-driven energy-aware clustering	High	High
PEGASIS	Chain-based	AI-optimized chain formation and leader rotation	High	Medium
DERP	Chain-based (Distance-aware)	AI-based relay and P-CL optimization	Very High	High
DLRP	Chain-based (Direct Line)	AI-enhanced chain head selection	High	Medium
CCM	Mixed (Chain + Cluster)	Adaptive role assignment via machine learning	Very High	High
TSCP	Two-Stage Chain	AI for load balancing and routing prediction	Very High	High
DCBRP	Chain-based (Deterministic)	Deterministic CH placement via AI models	High	High
MDR	Chain-based (Multi-hop)	Predictive CH election, dynamic path management	Very High	Very High

4. AI TECHNIQUES IN WSN ROUTING OPTIMIZATION

Information about Artificial Intelligence in Wireless Sensor NetworksAI-based approaches are newly developing that can improve routing in WSNs in addition to energy management and adaptability in dynamic environments. Traditional routing algorithms often depend on static decision-making rules and may not work well in unpredictable network conditions or under large-scale deployments. In contrast, AI techniques have the potential to be data-driven and self-learning, which can support adaptive and intelligent routing decisions in real-time for WSNs. Various AI approaches have been effectively employed in WSN routing optimization. These include:

a) Machine Learning (ML): Predominantly, supervised and reinforcement learning based ML models have been used to predict optimal routing paths, energy levels, and traffic patterns. For example, Q-learning has been a candidate solution with respect to energy-efficient routing by reducing both packet loss and delay [41].
b) Fuzzy logic: There is a rich set of fuzzy-based systems used in cluster head (CH) selection and decision-making processes in the domains where crisp thresholds do not work. They consider factors including residual energy, degree of node, and distance to sink to select the best CH [42].
c) Neural Networks: Load balancing and fault detection have been studied by using Artificial Neural Networks (ANNs). In this regard, deep learning models are applied to analyze the data of sensor nodes to discover anomalies or predict failures that will enable proactive rerouting strategies [43].
d) Reinforcement Learning (RL): RL approaches allow nodes to learn from their interactions with the environment and make routing decisions that optimize long-term performance of the network. In dynamic topologies where centralized control is not appropriate, algorithms such as Deep Q-Networks (DQN) become especially beneficial [44].

Figure 2 shows the typical AI techniques implemented in hierarchical topologies to achieve the perception of the role of AI in the optimization of wireless sensor network (WSN) routing. These techniques include, but are not limited to, the following: Machine Learning (ML), Fuzzy Logic, Neural Networks and Reinforcement Learning (RL), focusing independent components of routing such as energy utilization, fault detection, dynamic adaptation and cluster head selection. It also enhances the routing mechanism with an overview of its adaptive and robust routing mechanism in IoT-intensified WSNs.

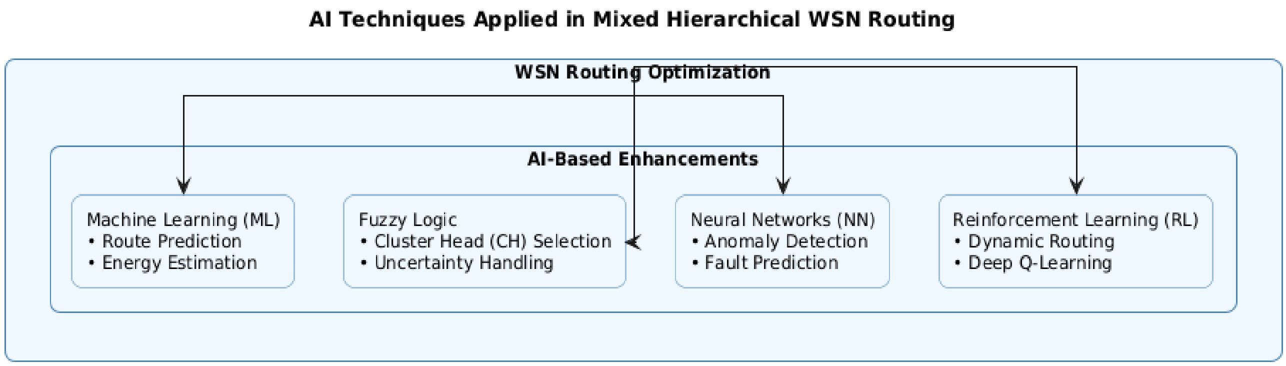

Fig. 2. Overview of AI techniques used in WSN routing optimization within mixed hierarchical topologies.

4.1 Application Areas and Effectiveness of AI in WSN Routing

Usage of AI techniques in WSNs improves various critical aspects that have a direct impact on the performance and lifetime of the network. These tasks consist of CH election, energy balancing, fault tolerance, and intelligent routing.

a) Cluster Head Election: AI-based algorithms ensure dynamic CH selection by multi-criteria analysis, which utilizes node characteristics like residual energy, node density, and distance to sink node. This leads to equal energy consumption over the nodes and extends the network lifetime [45].
b) Energy balancing — AI techniques allow for energy optimization through predictive learning, allowing to identify routes through the most efficient paths and understand the allocation of the network load. This allows sustained network operation in dense deployments, preventing early node failure.
c) Fault Tolerance: Intelligent models have the ability to detect faulty nodes and unreliable links at an early stage. This proactive monitoring allows the system to reroute data ahead of time, avoiding any interruptions for communication and enhancing the system resilience.
d) Routing Decision Making: The AI algorithms will continuously have learning from each path and update the next hop to minimize all variables They dynamically adjust routing paths for low latency, reduced packet loss, and lower energy usage, thereby improving Quality of Service (QoS).

Empirical studies on AI in WSN routing demonstrate its applicability in WSN routing. A fuzzy logic-based CH selection method, for example, showed a remarkable enhancement in the network's lifespan [46], as opposed to classical LEACH protocols. One more study [47] proposed the use of reinforcement learning in large-scale WSNs to improve the routing efficiency to achieve less energy consumption and better throughput. These findings further confirm the disruptive potential of AI in the development of adaptive, energy-efficient, and resilient WSN infrastructures. Figure 3 shows an overview of various AI technique and WSN functionalities improvements. This shows how strategies such as fuzzy logic, machine learning, neural networks, and reinforcement learning assist the cluster head election, communication energy balancing, fault tolerance, and wise routine, which are essential components to augment the performance and longevity of the system.

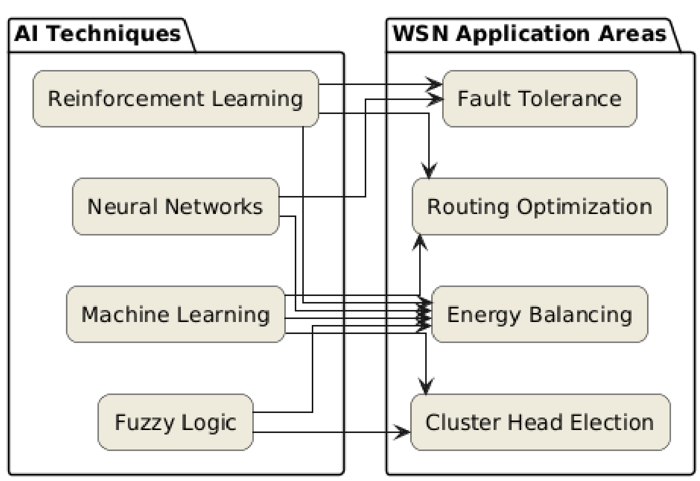

Fig. 3. AI-based optimization techniques mapped to core functional areas in Wireless Sensor Networks (WSNs), showing the role of each approach in enhancing network performance and resilience.

5. PERFORMANCE METRICS AND EVALUATION CRITERIA

Performance metrics are essential for assessing the efficiency and reliability of Routing Protocols in the context of Wireless Sensor Networks (WSNs), especially those augmented by Artificial Intelligence (AI). These metrics allow for a quantitative comparison of conventional routing schemes with AI-based approaches. The following sections summaries the most relevant used evaluation criteria in WSN studies, as well as how AI integration enhances the performance results.

5.1 Key Performance Metrics

A classic set of performance metrics are widely used to evaluate and compare the performance of Wireless Sensor Networks routing protocols, especially when enriched with Artificial Intelligence. These measures encompass key performance indicators like energy efficiency, reliability, responsiveness, and network scalability. This section describes the key performance indicators and how AI is used for its improvement. Table 3 outlines each metric, its definition, and the contribution of AI to improving it.

TABLE III. KEY PERFORMANCE METRICS IN WSNS AND AI CONTRIBUTION

Metric	Definition	AI Contribution
Energy Consumption	The amount of energy used by sensor nodes during sensing, processing, and communication.	AI reduces redundant transmissions and selects energy-efficient routes [48].
Network Lifetime	Time until the first node or a significant portion of nodes depletes energy.	AI balances workload among nodes to extend operational life [49].
Packet Delivery Ratio (PDR)	Ratio of successfully delivered packets to the total packets sent.	AI dynamically adjusts paths to avoid congested or failing nodes [50].
Latency	Time delay between packet transmission and reception.	AI predicts low-delay routes and avoids bottlenecks in real time [51].
Throughput	Amount of data successfully transmitted over the network in a given time.	AI improves traffic management and packet scheduling for higher efficiency [52].

5.2 Impact of AI on Performance

As the AI has been incorporating in different applications, more directly it has tremendously improved the optimizing routing protocol in WSN and thereby affecting the performance metrics (Energy Balanced Routing Protocol energy efficiency, reliability and scalability). Though traditional protocols are partially effective, they are limited by the static or reactive way they operate. In contrast, AI-enabled models utilize learning and prediction to respond to network conditions adaptively and in real time. Energy Efficiency is a key challenge in WSNs, where nodes are mostly powered by non-renewable batteries. AI techniques like fuzzy systems and Q-learning dynamically optimize routing decisions and cluster head (CH) elections. By weighing current network status to find the optimal communication paths for each source [41], [46], these approaches greatly reduce unnecessary data transmissions and energy overhead.

This is achieved by distributing the load intelligently around the network which results in a longer Network lifetime. They also do not allow for the premature depletion of energy in critical nodes (e.g., CHs or gateways) that would otherwise cause fast fragmentation of the network. By means of intelligent workload balancing and adaptive scheduling, the network longevity is preserved even in conditions of high data load [43].

Similarly, Reliability and Packet Delivery are improved by AI-based predictive models. These techniques proactively reroute anticipating node failures, congestion, or degraded links. The design causes an improvement in the PDR, for propelling a more stable and efficient network performance even in unfavorable environments [47]. Reinforcement algorithms can be used to minimize latency as nodes will learn low-delay communication paths over time. These algorithms respond to topology changes, due to node mobility or energy consumption, by choosing alternative paths that minimize transmission delay [44].

Then, intelligent congestion control and traffic forecasting increases Throughput. AI Models predict the network load and adapt the routing strategies or the data rates. This addresses the higher communication rates and increases the WSN's capability to tolerate high-density deployments without degrading performance [45]. This will help us gain insights into how the application of AI techniques improve WSN performance; therefore, a summary of the main performance metrics and how the AI-based methods contribute to them is given in Table 4. This summary highlights how smart algorithms have established themselves as decisive tools to cope with classical routing requirements while improving the overall efficacy, robustness, and sustainability of sensor networks.

TABLE IV. AI TECHNIQUES AND THEIR IMPACT ON WSN PERFORMANCE METRICS

Performance Metric	AI Contribution	References
Energy Efficiency	Optimized CH selection and path planning using Q-learning, fuzzy logic	[41], [46]
Network Lifetime	Intelligent workload distribution and adaptive scheduling	[43]
Packet Delivery Ratio (PDR)	Predictive rerouting and failure anticipation	[47]
Latency	Low-delay routing through reinforcement learning	[44]
Throughput	Traffic prediction and congestion-aware routing	[45]

5.3 Evaluation from Existing Studies

Many researches have been conducted to experimentally prove the effect of AI on routing performance on WSNs. The researchers have proven through comparative analyses and simulations how AI-based techniques outperform significantly on the metrics of energy efficiency, packet delivery and fault tolerance. For example, a fuzzy logic-based advanced version of LEACH protocol showed 32% increase in network lifetime and 15% in Packet Delivery Ratio (PDR) compared to its default implementation [46]. This improvement was mainly attributed to AI's ability to continuously assess the energy status of individual nodes and the ambient conditions while selecting the cluster head.

In a different study, routing protocols based on reinforcement learning were able to do so with a 30–40% increase in performance in terms of energy efficiency and latency. These models were applied to large-scale WSNs that have up to 100 nodes or more, and they adapt to environmental and traffic changes in real-time [47]. The neural network-based routing algorithm also showed good fault tolerance, with PDR and throughput remaining close to high levels in the face of high node failure. These techniques could predict link failures and reroute data dynamically to maintain communication nodes throughout the network [43]. Table 5 summarizes the findings of these studies and provides an overview of the effectiveness of AI-based enhancements across various protocols and evaluation metrics.

TABLE V. SUMMARY OF AI-BASED WSN PROTOCOL EVALUATIONS FROM EXISTING STUDIES

AI Technique Used	Enhanced Protocol	Evaluation Scenario	Key Improvements	Reference
Fuzzy Logic	LEACH with Fuzzy CH	100 nodes, random deployment	+32% network lifetime, +15% PDR	[46]
Reinforcement Learning	Q-Learning Based Routing	100+ nodes, dynamic topology	30–40% more energy efficient, lower latency	[47]
Neural Networks	ANN-Based Fault Tolerant	Varying failure rates, large scale	Maintained high PDR and throughput under failure	[43]

5.4 Comparative Summary

In the Table 6, a comparative summary is provided to further consolidate the influence of Artificial Intelligence (AI) integration upon Wireless Sensor Network (WSN) performance. The summary gives a snapshot evaluation of the performance of multiple AI-based routing protocols via key metrics: energy usage, network lifespan, packet delivery ratio (PDR), latency, and throughput. Fuzzy-LEACH, Q-LEACH, RL-Routing, and ANN-WSN are the protocols used for comparison, representing different paradigms of AI, including Fuzzy Logic, Q-Learning, Reinforcement Learning, and Neural Networks. These techniques have shown differing levels of improvement over classical baseline protocols.

The proposed Reinforcement Learning based routing (RL-Routing), for instance, performs considerably better in all performance indicators. It maintains the highest packet delivery and low latency for stable network traffic under highly dynamic conditions. In the same way, Q-LEACH (led by Q-Learning) shows improved performance (energy saving and lifetime extension) as a result of its adaptive learning mechanics.

The other two classes of protocols, Fuzzy-LEACH and ANN-WSN, while somewhat more balanced in terms of performance, also utilize advantageous methods. Features such as fuzzy-LEACH for enhanced decision-making in CH selection, and ANN-WSN which ensures high throughput and systematic solutions for networks prone to faults. A comparison of these different protocols is shown in Table 6 using a qualitative scale. notes that ✓ is moderate improvement and ✓✓ is significant improvement over standard routing protocols.

TABLE VI. COMPARATIVE SUMMARY OF AI-BASED WSN ROUTING PROTOCOLS

Protocol	AI Technique	Energy Consumption ↓	Network Lifetime ↑	PDR ↑	Latency ↓	Throughput ↑
Fuzzy-LEACH [46]	Fuzzy Logic	✓	✓✓	✓	✓	✓
Q-LEACH [41]	Q-Learning	✓✓	✓✓	✓	✓✓	✓
RL-Routing [47]	Reinforcement Learning	✓✓	✓✓	✓✓	✓✓	✓✓
ANN-WSN [43]	Neural Network	✓	✓	✓✓	✓	✓✓

6. OPEN ISSUES AND RESEARCH DIRECTIONS

No matter how remarkable is the enhanced intelligence provided by AI to WSN routing, this technology still has some barriers to overcome in the practice. Although there is substantial theoretical evidence for enhancing energy efficiency, adaptability, and fault tolerance, computational overhead, deployment feasibility, security, and scalability problems remain.

a) Computational Constraints and Complexity: A number of AI models, particularly deep neural networks and reinforcement learning algorithms, demand a large amount of computation and memory resources. WSN nodes are, however, severely constrained in their processing capability, storage and energy resources. This makes it impossible to run such models directly on sensor nodes in the absence of lightweight AI architectures or edge computing support [53,54].

b) Real-World Deployment Problems: The majority of the considerations that conduct AI-enhanced routing protocols are on simulated conditions of NS-2 or MATLAB. These simulations cannot capture real-world unpredictability, such as dynamic environmental factors, hardware constraints, and physical deployment issues [55]. Closing this gap between simulation and reality requires strong, adaptive protocols that work under live constraints in heterogeneous WSN systems.

c) Security & Trustworthiness of AI Models: The usage of AI in WSNs brings forth new vulnerabilities including adversarial attacks, whaling, and hardware manipulation. Secure learning models are often neglected in current protocols. There is an emerging need for developing resilient, security-aware AI algorithms that can autonomously detect anomalies, isolate compromised nodes, and protect model integrity [56,57].

d) Scalability & Federated Learning (FL): As the sensor network scales, centralized learning becomes impractical due to increased communication latency and energy consumption. Federated Learning has proven to be a promising model that provides the advantages of decentralized model training at the same time keeping data privacy intact. Nevertheless, challenges around model convergence, communication overhead, and synchronization must be solved for FL to work in resource-limited WSNs [58,59].

e) Edge Computing and Hybrid AI Architectures: Edge computing can help in mitigating issues with latencies and processing loads on individual sensor nodes by distributing complex computations to intermediate edge devices. This architecture together with AI provides real-time analytics and makes WSN more responsive. Future work will involve more intelligent task distribution, load balancing and edge-based learning for efficient decision-making [60].

f) Interdisciplinary Opportunities: AI + Blockchain Integration: Recent studies indicate the integration of blockchain technology with AI in WSNs for increased transparency, trust, and decentralized coordination. It can verify routing paths, hold tamper-proof logs and enable consensus-based routing decisions in these AI-driven systems. This synergy ensures a secure and autonomous WSN infrastructure.

Table 7 highlights relevant open issues, implications, and future directions for research to gain a clearer insight into the range of current challenges and novel solutions in AI-enabled Wireless Sensor Networks (WSNs). The above sidewise comparison helps identify in which aspects current protocols do not provide ultimate security and then highlights how some emerging technologies like edge computing, federated learning and transportation level security protocols and blockchain features can fill these gaps in practical implementations.

TABLE VII. SUMMARY OF OPEN ISSUES AND FUTURE DIRECTIONS IN AI-BASED WSNS

Challenge	Description	Future Direction
Computational Overhead	AI models require more resources than typical WSN nodes can provide	Lightweight AI, model pruning, edge-assisted learning [53], [54]
Simulation vs. Real Deployment	Simulated environments do not reflect real-world challenges	Field-tested adaptive models [55]
AI Security Vulnerabilities	Risk of adversarial attacks and compromised learning models	Secure, anomaly-aware AI protocols [56], [57]
Scalability & Federated Learning	Centralized training is inefficient for large-scale networks	FL for decentralized learning and reduced bandwidth [58], [59]
Edge Computing Integration	Sensors need help processing large AI models in real-time	Hybrid AI + Edge architectures [60]
AI + Blockchain Collaboration	Ensuring trust, integrity, and decentralized coordination	Blockchain-enabled secure routing [60]

7. CONCLUSION

A comprehensive survey investigating the implementation of AI mechanisms into mixed hierarchical topologies to improve the performance, scalability and adaptivity of WSNs. WSNs are extensively deployed in applications like environmental monitoring, healthcare, smart cities, and industrial automation, owing to the advancements in technology. But they are restrained by a limited energy availability, scalability limitations and fluctuating environmental scenarios. Such mechanisms are crucial, yet traditional routing protocols may not suffice in terms how to conserve the use of competencies and the network's functional life. The current study presented in handled the other application field of AI, including the hybrid architecture based on clusters, a chain-based hierarchical architecture, and performance operational attributes of the wireless sensor network (WSN). These include methods like Machine Learning, Fuzzy Logic, Neural Networks and Reinforcement Learning and all of these have shown the advantages regarding cluster head selection, load balancing, fault tolerance and routing decisions etc. On empirical evaluation and case studies, we show that significant improvement can be achieved through the application of AI-based enhancement protocols like LEACH, PEGASIS and their derivatives, in energy consumption, packet delivery ratio (PDR), network lifetime and latency and throughput. Moreover, the efficiency gain achieved by deploying AI enhances not only the operational performance but also builds resilience against individual node failure and communication breaks, as evidenced by various performance metrics presented in the paper. However, several challenges still exist around the complexity of deployment, real-time processing, storage awareness, model federated learning, and AI model security and scalability. Next steps, on AI, are to expand beyond Edge computing and federated learning to provide appropriate decentralized intelligence and Hybrid frameworks interconnecting AI and blockchain configured and trust aware routing. Users are in control of the AI algorithms and architecture, which can unlock more functionalities than conventional sensor networks.

Conflict of Interest

The authors declare that there is no conflict of interest.

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