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AI-based routing algorithms improve energy efficiency, latency, and data reliability in wireless sensor networks

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This paper proposes a modular Artificial Intelligence (AI)-based routing framework for Wireless Sensor Networks (WSNs) that integrates reinforcement learning (RL), supervised learning, and swarm intelligence techniques such as genetic algorithms (GA) and particle swarm optimization (PSO). Unlike conventional approaches that rely on static or standalone algorithms, the proposed framework employs a structured decision-making pipeline that dynamically adapts to real-time changes in network topology, traffic, and energy conditions. Each AI module plays a distinct role-RL handles local routing decisions, while GA and PSO are invoked for global optimization under resource constraints. Simulations conducted in MATLAB R2021b validate the framework's effectiveness, demonstrating improvements in packet delivery ratio, end-to-end latency, and energy efficiency when compared to traditional protocols. While this study is based on synthetic evaluations, it outlines the architectural groundwork for future real-world implementation and discusses deployment challenges such as scalability, resource usage, and security. The results highlight the potential of hybrid AI-based routing strategies to enhance the reliability, adaptability, and sustainability of WSNs in dynamic and resource-limited environments.

Wireless Sensor Networks (WSNs) have become a fundamental technology in various fields such as environmental monitoring, healthcare, industrial automation, and smart cities. Many tiny sensor nodes, equipped with sensing, processing, and communication capabilities, make up the networks. These nodes collaborate to collect data from the surroundings, analyze it in the field, and send it to a central base station or sink node for further examination and decision-making[1,2].

WSNs collect essential information used in many applications, such as monitoring air and water quality, identifying environmental threats, tracking animals, and controlling infrastructure systems[3,4]. WSNs in healthcare provide remote patient monitoring, fall detection for the elderly, and real-time tracking of medical assets. Industrial settings use these tools to monitor equipment conditions, estimate maintenance needs, and optimize energy use[5,6]. Figure 1 illustrates the architecture of a WSN with distributed sensor nodes communicating with a central base station. It highlights key application areas, including environmental monitoring, healthcare, industrial automation, and smart cities. In Fig. 1, arrows represent data flow between nodes and the base station, emphasizing real-time sensing, processing, and communication.

But the effective functioning of WSNs presents notable obstacles because of their distinct features[7]. Conventional routing protocols like Ad Hoc On-Demand Distance Vector (AODV) and Dynamic Source Routing (DSR) were created for mobile ad hoc networks and may not be ideal for the limited resources and changing characteristics of WSNs[8,9].

Energy economy is a significant difficulty for standard routing techniques in WSNs. Batteries typically power sensor nodes, requiring meticulous control over energy use to prolong the network's lifespan[10]. Conventional protocols might result in energy inefficiency because of high control overhead, frequent route discoveries, and ineffective data forwarding methods[11,12].

Scalability is a major challenge with WSNs as the network size increases. Conventional routing methods may have challenges in maintaining scalability due to higher control message overhead, larger routing table sizes, and

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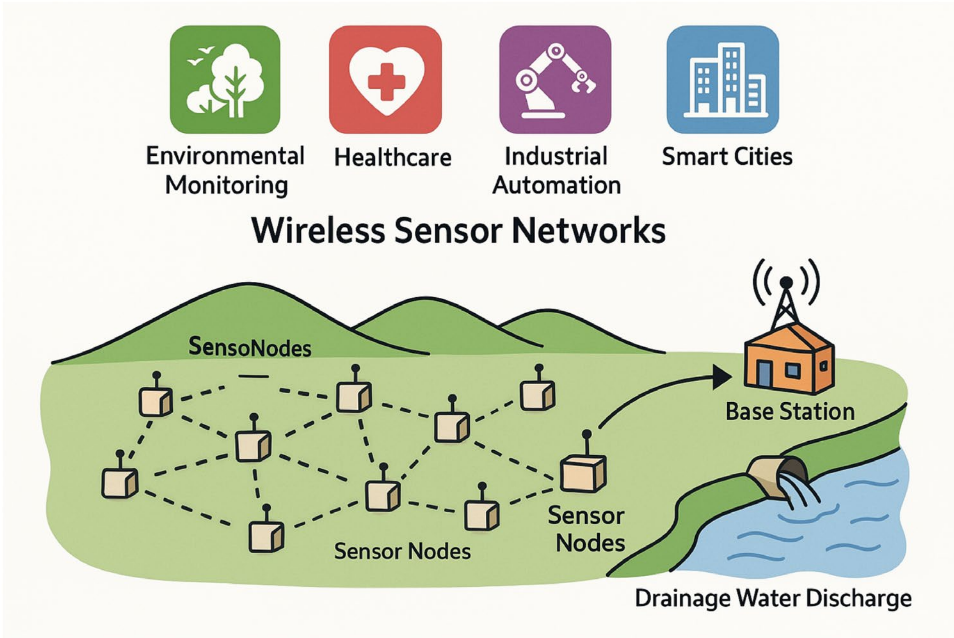

Fig. 1. Overview of wireless sensor network applications and architecture.

greater latency[13,14]. Therefore, they may not be appropriate for extensive deployments or concentrated sensor installations typical in certain applications[15].

WSNs function in dynamic and challenging situations where sensor nodes may experience failures, communication interruptions, and unforeseen alterations in network topology[16]. Conventional routing protocols may not have strong methods to adjust to these situations, resulting in decreased network performance and dependability[17,18].

To address these challenges, this paper proposes a composite AI-driven routing framework that integrates reinforcement learning (RL), genetic algorithms (GA), and particle swarm optimization (PSO) to enable adaptive, energy-aware, and latency-sensitive routing decisions. Unlike approaches that apply isolated AI techniques, the proposed framework is designed to make intelligent, decentralized routing decisions by continuously adapting to real-time changes in the network. This integration enhances the ability of the routing protocol to cope with network dynamics, resource constraints, and application-specific requirements.

Researchers have used artificial intelligence (AI) approaches to improve routing performance in WSNs and tackle associated issues[19,20]. AI-based routing enhances routing protocols by allowing them to make intelligent decisions that can adjust dynamically to changing network circumstances and improve different performance metrics.

AI-based routing provides various potential benefits for WSNs:

1. Adaptive routing: AI routing algorithms can respond to changing network circumstances by constantly learning from previous instances and modifying routing choices appropriately. AI algorithms can assess network factors, including node mobility, traffic patterns, and connection quality, in real-time using machine learning (ML) methods like reinforcement learning (RL) and neural networks[21,22]. AI-based routing protocols may dynamically choose the most effective routing pathways, maximizing performance metrics like packet delivery ratio (PDR) and end-to-end latency due to their flexibility. Moreover, AI-based routing may identify and steer clear of crowded or defective paths, hence improving network performance and dependability.
2. Adaptive resource allocation: AI routing techniques can improve resource distribution in the network. AI algorithms can allocate resources like bandwidth, storage, and processing power to jobs and applications by looking at factors like what each node can do, communication limits, and the needs of the applications. By adapting resource allocation, network resources are efficiently used, leading to improved system performance and scalability[23,24].
3. Energy efficiency: Energy consumption is an essential problem in WSNs because of the restricted power resources of sensor nodes. AI routing algorithms may greatly enhance energy efficiency by smartly overseeing data transport and node operations. AI-based routing protocols may improve routing pathways to decrease energy usage by taking into account node energy levels, communication costs, and data aggregation possibilities[25,26]. AI algorithms can adapt transmission power levels, plan data transfers during low energy consumption times, and use sleep/wake scheduling strategies to extend node lifespan. AI-based routing may optimize data aggregation and processing inside the network, leading to reduced data transmission and energy conservation.

4. Fault tolerance: WSNs are vulnerable to node failures, communication interruptions, and fluctuations in the environment. AI routing provides enhanced fault detection and recovery features to improve network resilience and dependability. AI-based routing protocols may use ML models to identify and forecast anomalies, allowing them to foresee probable failures and take proactive steps to reduce their effect[27,28]. AI algorithms can analyze past data to identify trends that indicate potential failures, allowing nodes to redirect traffic or initiate recovery processes in advance. AI-based routing can modify routing patterns in real-time to handle network changes, maintaining uninterrupted operation during faults or disturbances.
5. Scalability: Scalability is a major challenge for routing systems as WSNs improve in size and complexity. AI-based routing protocols may adapt their routing techniques in real-time to accommodate variations in network structure and effectively handle networks of varying sizes[29]. Swarm intelligence and distributed optimization techniques enable AI systems to improve routing choices across extensive networks collectively. AI-based routing may facilitate self-organization and self-configuration, enabling nodes to autonomously adjust to changes in network circumstances without the need for centralized management[30,31]. The natural ability of AI-based routing to scale makes it ideal for large-scale deployments and various situations where conventional routing protocols may face challenges in maintaining performance and efficiency.
6. Dynamic QoS provisioning: Ensuring Quality of Service (QoS) in WSNs is essential to meet various application needs, including latency, dependability, and throughput. AI routing algorithms can adapt QoS settings in response to fluctuating network circumstances and application requirements. AI-based routing protocols use ML models to forecast network performance and traffic patterns, enabling the dynamic allocation of resources and prioritization of traffic to fulfill QoS standards[32,33]. Dynamic QoS provisioning ensures key applications obtain required resources and assures performance in dynamic and unexpected circumstances.
7. Security enhancement: Security is an essential concern in WSNs since they are susceptible to many types of attacks, such as eavesdropping, manipulation, and node compromise. Utilizing AI-based routing may improve network security by integrating intelligent intrusion detection and prevention measures. AI systems can identify and address security problems promptly by examining network traffic patterns and unusual activity[34,35]. Additionally, AI-based routing can adapt routing pathways and encryption keys in real-time to prevent any assaults and maintain the security and accuracy of data.
8. Adaptation to heterogeneous environments: WSNs generally operate within various situations characterized by different communication methods, node capabilities, and surrounding conditions. AI routing algorithms can dynamically optimize route choices to handle diversity. AI algorithms may achieve a balance between opposing aims and preferences across diverse nodes and networks by using methods like multi-objective optimization and ensemble learning[36,37]. Adapting to diverse contexts allows for the smooth integration of WSNs with various communication systems, promoting interoperability and cooperation across multiple domains.
9. Self-healing and self-optimization: AI-based routing allows for self-healing and self-optimization features in WSNs. AI algorithms can identify network issues and performance bottlenecks by consistently monitoring network performance and environmental factors. AI-based routing protocols may automatically alter routing pathways, settings, and network operations to recover from errors and adapt to changing situations[38,39]. The self-healing and self-optimization features reduce the need for human involvement, lower maintenance costs, and guarantee the efficient and dependable functioning of WSNs under evolving and challenging circumstances.

Unlike previous works that apply individual AI methods in isolation, this paper proposes a unified and modular framework that integrates RL, GA, and PSO for adaptive routing. The framework is specifically designed to address the trade-offs inherent in WSNs, such as energy constraints, latency sensitivity, and data reliability. Our contribution lies in this integrated approach, which offers dynamic decision-making capabilities across varying network conditions.

Motivation of paper

This study is motivated by the need to address the inherent issues encountered by conventional routing protocols in WSNs and the ability of AI approaches to meet these challenges. Several variables motivate this research:

1. Limitations of traditional routing protocols: Conventional routing algorithms like AODV and DSR initially emerged for mobile ad hoc networks and may not be ideal for the limited resources and constantly changing environment of WSNs. These protocols often face challenges in maintaining energy economy, scalability, fault tolerance, and adaptation in WSNs circumstances[40,41].
2. Critical importance of routing in WSNs: Routing plays an important role in the performance, reliability, and efficiency of WSNs. Effective routing methods are essential for maximizing data transmission, saving energy, extending network lifespan, and guaranteeing prompt and precise data collection from the monitored area[42,43].
3. Growing interest in AI applications in WSNs: There is an ever-growing curiosity in using AI methods for several facets of WSNs, such as data processing, optimization, and decision-making. AI-based methods have shown great promise in enhancing the efficiency and functionalities of WSNs in several fields and domains[44,45].
4. Need for empirical evaluation and comparative analysis: AI-based routing algorithms show potential, but need empirical assessment and comparative analysis to determine their efficacy, scalability, and applicability for real-world use[46,47]. Empirical studies are essential for understanding what AI-based routing methods can and cannot do, as well as identifying where they can be improved.

This research intends to suggest an AI-based routing algorithm designed for WSNs and thoroughly assess its performance using comprehensive simulations[48,49]. The research wants to study and compare traditional routing methods with AI-based routing in WSNs to see how effective, scalable, energy-efficient, and fault-tolerant they are. The main goal is to improve routing protocols in WSNs and encourage the use of AI methods to address the evolving challenges and requirements of WSN applications.

Objective of the paper
The research aims to introduce, assess, and validate the effectiveness of an AI routing algorithm designed particularly for WSNs. The main objectives of the paper are as follows:

- Propose an AI-based routing algorithm tailored to overcome the unique obstacles encountered by conventional routing protocols in WSNs. The program should use AI methods, including ML, optimization, and adaptive decision-making, to boost routing choices, energy efficiency, and fault tolerance, and adapt to changing network circumstances.
- Perform comprehensive simulations to assess the effectiveness of the suggested AI-based routing algorithm when compared to conventional routing protocols often used in WSNs. Evaluate performance parameters, including PDR, end-to-end latency, energy consumption, scalability, and fault tolerance under different network circumstances and scenarios.
- Perform empirical research and comparative studies to evaluate the AI-based routing algorithm's strengths and drawbacks in contrast to conventional protocols. Identify the main performance metrics and compromises linked to AI-based routing and emphasize its potential advantages for WSN applications.
- Verify the efficiency and dependability of the suggested AI-based routing algorithm via thorough testing and validation processes. Ensure that the method works correctly and fulfills the specified goals and objectives detailed in the article.
- Study the necessity and feasibility of using the AI-based routing algorithm in WSN installations. Take into account variables like implementation complexity, computational overhead, deployment costs, and compatibility with current WSN infrastructure.
- Propose an AI-based solution to solve the specific difficulties and needs of WSN applications and provide new insights, techniques, and approaches to the subject of routing in WSNs. Contribute significantly to improving the performance, reliability, and efficiency of WSNs by developing unique routing protocols for continuous research and development.

The research aims to improve routing protocols for WSNs by testing an AI-based solution that works better than traditional methods in performance, energy use, reliability, scalability, and adaptability. The research seeks to show how AI-based routing may greatly improve the capabilities and efficacy of WSNs in many applications and domains via empirical analysis and validation.

Related work
In the related work, multiple routing protocols have been suggested as potential solutions to the distinctive obstacles encountered in WSNs[50,51]. Traditional routing protocols such as LEACH (Low Energy Adaptive Clustering Hierarchy), TEEN (Threshold Sensitive Energy Efficient Sensor Network Protocol), and PEGASIS (Power-Efficient GAthering in Sensor Information Systems) have been subject to comprehensive evaluation by scholars including[52]. These protocols prioritize scalability, energy efficiency, and network lifetime extension through the implementation of hierarchical routing, data aggregation, and clustering[53,54].

Researchers such as[55,56] have recently examined improvements in routing techniques for WSNs. DEEC (Distributed Energy-Efficient Clustering) and EEDR (Energy-Efficient Dynamic Routing) protocols are designed to handle the changing characteristics of WSNs by modifying routing choices according to node energy levels and network circumstances[57].

Researchers have shown substantial interest in using AI approaches in routing for WSNs. Researchers like[58,59] have investigated the use of ML techniques, namely RL and supervised learning, to improve routing choices in WSNs. These algorithms dynamically acquire knowledge from previous experiences and network circumstances to enhance routing efficiency and dependability.

Researchers like[60,61] have utilized GA to enhance routing patterns and minimize energy consumption in WSNs. GAs mimic the process of natural selection and evolution to improve routing solutions by continuously using selection, crossover, and mutation techniques.

Researchers have studied swarm intelligence methods for routing in WSNs, based on the group behavior of social insects. Authors like[62,63] have suggested routing protocols using ant colony optimization and particle swarm optimization. These protocols provide effective data forwarding and route selection, adjusting to changing network circumstances[64].

Neural networks have shown potential in improving routing choices and forecasting network behavior in WSNs. Yang et al. and Thomas et al.[65,66] conducted research on using deep learning methods, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for predicting routes and detecting anomalies in WSNs.

Researchers like[67,68] have studied the use of ML methods, particularly decision tree algorithms, for routing in WSNs. Decision trees provide a straightforward and easy-to-understand method for choosing the best path by considering several network properties, such as node energy levels, distance to sink, and channel conditions.

Evolutionary methods, such as genetic programming, have been studied for improving routing choices in WSNs. Authors like[69,70] have suggested evolutionary routing algorithms that develop routing techniques over many generations to adapt to changing network circumstances and needs.

Researchers such as[71,72] have investigated the use of fuzzy logic-based routing methods in WSNs. Fuzzy logic allows for routing choices to be made using imprecise and uncertain information, enabling resilient and adaptable routing techniques in dynamic and unpredictable situations.

While AI-based routing methods offer advantages, it's important to consider their limitations. Researchers such as[73,74] have examined the advantages and drawbacks of existing AI-based routing methods in WSNs. The strengths include adaptive routing choices, enhanced energy efficiency, fault tolerance, and scalability. AI-based routing algorithms can adjust to fluctuating network circumstances, improve energy efficiency, and boost network dependability. Researchers like[75,76] have pointed out the security risks linked to AI-based routing algorithms in WSNs. The vulnerabilities include of vulnerability to adversarial attacks, data poisoning, and evasion strategies that might jeopardize the integrity and confidentiality of the network[77].

Furthermore, the implementation of AI-based routing techniques may need significant computational resources and memory allocation, as discussed by scholars like[78,79]. AI-based routing algorithms face a big problem in real-world WSN setups because they need to work well on sensor nodes that have limited resources while still performing adequately.

Researchers emphasize the significance of taking into account ethical and societal ramifications while using AI-based routing algorithms in WSNs. Authors like[80,81] stress the need for open and responsible decision-making procedures to tackle issues with privacy, fairness, and prejudice in AI-based routing systems. Table 1 effectively summarizes key research contributions in the area of routing protocols for WSNs. The paper provides a methodical summary of the researchers, including their research objectives, proposed solutions, and methodologies implemented.

Finally, AI-based routing methods have shown significant potential to improve the efficiency, adaptability, and scalability of WSNs[98]. However, many existing approaches focus narrowly on individual aspects such as energy efficiency or reliability, often lacking integration between learning models and optimization strategies. Critical challenges-including resource constraints, real-time adaptability, security, and ethical considerations-remain insufficiently addressed[99]. To address these gaps, we present a modular AI-based routing framework that combines learning and optimization in a resource-efficient design, suitable for dynamic and resource-constrained WSN environments.

Proposed AI-based routing framework

This section introduces a modular and decentralized AI-based routing framework for WSNs, designed to dynamically adapt routing decisions based on real-time network conditions. Unlike conventional approaches that rely on static or isolated algorithms, the proposed framework integrates multiple AI techniques-including RL, supervised learning, and swarm intelligence methods such as PSO and GA within a unified decision-making pipeline.

Each sensor node operates autonomously, continuously collecting information about neighboring nodes, network topology, data traffic, and environmental conditions. Lightweight AI models embedded at the node level

Authors	Objective	Proposed solution	Identified gap or limitation addressed
82	Study the security issues related to AI-based routing algorithms in WSNs.	Assesse11027594s weaknesses and suggests security protocols.	Lacks real-time AI integration for intrusion response and anomaly detection.
83	Evaluate computational burden of AI-based routing.	Optimization suggestions for resource constraints.	Does not present a full modular framework deployable on sensor hardware.
84	Investigate ethical and societal risks of AI routing.	Ethical principles for fairness and privacy.	No operational routing model tested with ethical constraints.
85	Explore RL in adaptive routing.	RL-based protocol that learns from network states.	Does not integrate global optimization or energy balancing.
86	Assess strengths/weaknesses of AI routing methods.	Thematic review of adaptivity and limitations.	Survey only; lacks implementation or hybrid framework proposal.
87	Integrate AI-based routing with IoT for interoperability.	AI protocols for smooth IoT communication.	No details on adaptation to constrained energy and QoS needs.
88	Apply DL to detect anomalies in WSNs.	DL-powered intrusion detection based on traffic patterns.	Lacks integration with adaptive routing and lightweight models.
89	Examine environmental impacts on AI routing.	Routing adjustments based on environmental factors.	No real-time learning mechanism to adapt to volatile conditions.
90	Use ensemble learning for routing resilience.	Combines classifiers to boost reliability.	High complexity; no demonstration on embedded sensor nodes.
91	Combine blockchain with AI-routing for trust.	Blockchain-backed secure routing proposals.	Introduces latency and computation cost not suitable for WSNs.
92	Examine routing under mobility in WSNs.	Mobility-aware protocols with adaptive paths.	Lacks use of learning or predictive mobility handling.
93	Apply game theory to reduce selfish routing.	Cooperative routing through game-theoretic incentives.	Does not explore hybrid AI models or security integration.
94	Explore bio-inspired optimization for routing.	Firefly and cuckoo-based optimization schemes.	Lacks integration with learning models and practical tuning.
95	Use edge computing to support AI routing.	Offloads computation to edge nodes for scalability.	No joint optimization with local routing decisions or real-time learning.
96	Balance energy and delay in routing.	Trade-off optimized routing strategies.	Does not use adaptive learning or predictive energy modeling.
97	Apply swarm robotics concepts to WSN routing.	Self-organizing routing via swarm algorithms.	Focused on local behavior; lacks global coordination and learning.

Table 1. Summary of related work on AI-based routing in WSNs with identified gaps.

process this data to predict optimal routing paths, leveraging both historical patterns and real-time performance metrics. RL is employed for local decision-making under stable conditions, while PSO and GA are invoked at higher levels for global route optimization when the network experiences fluctuations in energy availability or latency.

This structured integration of learning and optimization enables the system to self-adapt and evolve in dynamic environments, enhancing energy efficiency, reducing end-to-end delay, and improving data reliability. The overall routing process is illustrated in Figure 2, and a detailed algorithmic flow is provided through accompanying pseudocode for clarity and reproducibility. The following subsections present the mathematical foundations and key equations governing each AI module used in the framework.

Initialization:

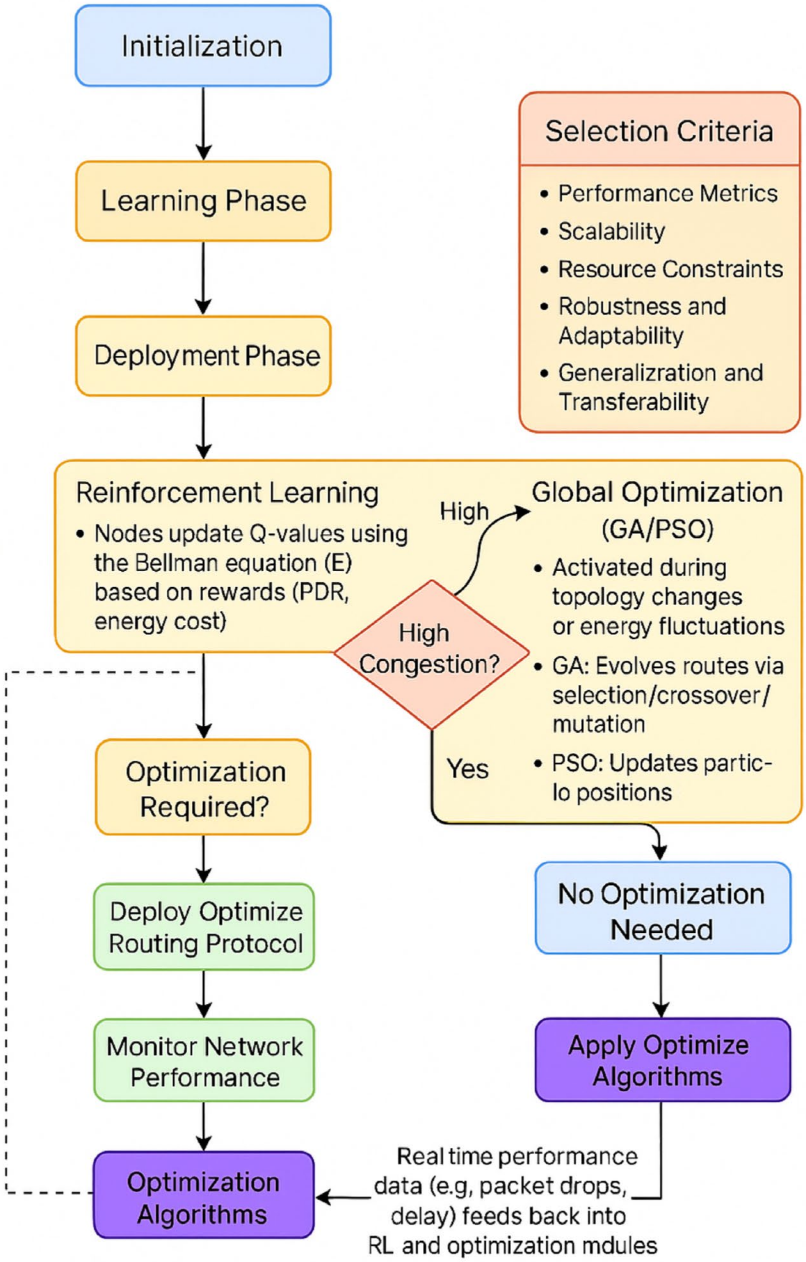

Fig. 2. Flowchart of AI-based routing algorithm in WSNs.

- Initialize the Q-table (for RL) or the classifier (for supervised learning) with random values.
- Set the population size and parameters for optimization algorithms (e.g., GA, PSO).

Learning Phase:

- Collect network data, including node information, environmental parameters, and historical routing performance.
- Train the AI models using the collected data:
- For RL:
- Update the Q-values based on the Bellman equation:

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha \left(R_{t+1} + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t) \right) \tag{1}$$

where: $Q(s_t, a_t)$ is the Q-value for the state-action pair (s_t, a_t), α is the learning rate, R_{t+1} is the reward after taking action a_t in state s_t, γ is the discount factor, and s_{t+1} is the next state.
 For supervised learning:

- Train the classifier using labeled training data to predict optimal routing paths.
- Optimize the routing decisions using optimization algorithms.

For genetic algorithms:

- Apply selection, crossover, and mutation operators to evolve routing solutions. For particle swarm optimization:

$$\text{Offspring} = \text{Mutation}(\text{Crossover}(\text{Selection}(\text{Population}))) \tag{2}$$

For particle swarm optimization (PSO):

- Update particle positions and velocities based on local and global best solutions:

$$v_i^{t+1} = wv_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t) \tag{3}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{4}$$

 where: v_i^t is the velocity of the particle *i* at iteration *t*, x_i^t is the position of the particle *i* at iteration *t*, $pbest_i$ is the personal best position, *gbest* is the global best position, w, c_1, c_2 are inertia, cognitive, and social coefficients, and r_1, r_2 are random values.
- Update the routing decisions based on the trained AI models and optimization results.

Deployment phase:

- Deploy the optimized routing protocol in the WSN environment.
- Monitor network performance and adapt routing decisions in real-time based on feedback and environmental changes.

The proposed AI-based routing framework employs a combination of RL, supervised learning, and nature-inspired optimization techniques to enable context-aware and adaptive routing in WSNs. Instead of relying on a single novel algorithm, the framework integrates multiple intelligent methodologies within a modular decision-making pipeline. RL is utilized to learn optimal routing actions by analyzing historical traffic data and current energy levels of sensor nodes. Supervised learning models are trained on environmental and network parameters to support informed decision-making. Additionally, optimization techniques such as GA and PSO are applied to refine routing paths, minimizing energy consumption and communication overhead. The framework is designed for real-time deployment and incorporates continuous feedback mechanisms to dynamically adapt to changing network conditions, thereby enhancing the scalability, reliability, and energy efficiency of WSNs in practical applications.

```
Initialize network parameters and node states
while Network is operational do
    for all Sensor nodes do
        Collect local data (energy, neighbors, traffic)
        if Traffic is stable and energy is sufficient then
            Use RL to select the next-hop based on Q-values
        else if Energy levels are critical or delay is high then
            Trigger global optimization using PSO or GA
        end if
        Forward packet using selected route
        Update local models based on feedback
    end for
end while
```

Algorithm 1. AI-based routing decision pipeline.

AI techniques utilized and integration into the routing protocol

The proposed AI-based routing framework integrates multiple intelligent methodologies, specifically RL, supervised learning, and swarm intelligence-based optimization techniques such as GA, PSO, and ACO to enable dynamic, efficient, and adaptive routing in WSNs. These components are modular and operate at different stages within the routing pipeline, allowing the system to make context-aware decisions in real time.

ML techniques are applied to analyze historical data, detect traffic trends, and anticipate network behavior. This predictive capability helps nodes proactively adapt routing strategies to meet application-specific quality-of-service (QoS) requirements.

- Reinforcement learning (RL): RL is employed at the node level using Q-learning to support decentralized, experience-based decision-making. Nodes learn optimal forwarding actions by receiving feedback from the environment, such as delivery success, energy consumption, and delay, thereby adapting to changing network conditions over time.
- Supervised learning and decision trees: Supervised learning models are trained using labeled datasets to recognize routing scenarios based on features such as node energy, hop count, or congestion level. Decision trees, in particular, provide lightweight inference mechanisms suitable for embedded WSN platforms and help classify routing paths using predefined rules derived from training data.
- Optimization algorithms: To complement the learning-based modules, global optimization algorithms such as PSO, GA, and ACO are applied periodically to refine the overall routing topology. These metaheuristic techniques explore the solution space iteratively to identify routing configurations that minimize energy usage, reduce end-to-end delay, and maximize PDR. These optimizers are typically executed at cluster heads or sink nodes to conserve computational resources at individual sensor nodes.

Figure 2 illustrates the flow of information and control among these AI components. The structured integration of learning and optimization mechanisms enables the framework to intelligently respond to both short-term variations and long-term trends in network conditions, thus supporting scalable and energy-efficient operation in a wide range of WSN deployments.

Selection criteria for AI models and parameter tuning

The selection criteria for AI models and parameter tuning involve several considerations:

1. Performance metrics: The AI models and parameters are selected based on their ability to optimize key performance metrics such as PDR, end-to-end delay, energy consumption, and network lifetime. The selected models should effectively balance these metrics to ensure efficient and reliable routing in WSNs[100].

    - Packet delivery ratio (PDR):

$$\text{PDR} = \frac{\text{Number of successfully delivered packets}}{\text{Total number of packets transmitted}} \tag{5}$$

    - End-to-end delay:

$$\text{End-to-End Delay} = \frac{\sum_{i=1}^{n} (\text{Reception time}_i - \text{Transmission time}_i)}{n} \tag{6}$$

    - Energy consumption:

$$\text{Energy Consumption} = \text{Power} \times \text{Time} \tag{7}$$

- Network lifetime:

$$\text{Network Lifetime} = \frac{\text{Total energy available}}{\text{Average energy consumption per unit time}} \tag{8}$$

2. Scalability: The scalability of AI models is crucial for large-scale WSN deployments. Models and algorithms that can efficiently handle the increasing size of the network while maintaining performance are preferred[101].

$$\text{Scalability Index} = \frac{\text{Number of nodes}}{\text{Computational complexity}} \tag{9}$$

3. Resource constraints: Considering the resource-constrained nature of sensor nodes, the selected AI models should be lightweight and computationally efficient. Parameter tuning should take into account the limited processing power, memory, and energy resources available on sensor nodes[102].

- Computational efficiency:

$$\text{Computational Efficiency} = \frac{\text{Number of operations}}{\text{Memory usage}} \tag{10}$$

- Energy efficiency:

$$\text{Energy Efficiency} = \frac{\text{Performance}}{\text{Energy consumption}} \tag{11}$$

4. Robustness and adaptability: AI models and parameters should be robust to noise, uncertainties, and variations in network conditions. They should be able to adapt dynamically to changes in the environment and network topology to ensure continuous and reliable operation[103].

- Robustness index:

$$\text{Robustness Index} = \frac{\text{Number of successful adaptations}}{\text{Total number of adaptations attempted}} \tag{12}$$

- Adaptability rate:

$$\text{Adaptability Rate} = \frac{\text{Change in routing strategy}}{\text{Change in network conditions}} \tag{13}$$

5. Generalization and transferability: The selected AI models should generalize well across different network scenarios and environments. Parameter tuning should ensure that the learned routing strategies are transferable and applicable to various WSN applications and deployment scenarios[104].

$$\text{Generalization Error} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{14}$$

Where y_i is the actual output, $\hat{y}_i$ is the predicted output, and N is the number of samples.

By carefully incorporating context-aware learning, optimization strategies, and adaptive feedback mechanisms, the proposed AI-based routing framework is well-suited to address the dynamic and resource-constrained nature of WSNs. Intelligent parameter tuning further enhances the system's ability to respond to fluctuating network states, ensuring consistent performance across varying deployment scenarios. The layered integration of multiple AI techniques spanning RL, supervised learning, and swarm-based optimization enables the framework to autonomously fine-tune routing decisions over time. This adaptive capability allows the system to continually optimize energy usage, reduce latency, and maintain data delivery reliability, thereby significantly improving the overall performance, scalability, and resilience of WSNs.

The overall operational flow of the proposed AI-based routing framework is illustrated in Fig. 2. This flowchart outlines the sequential stages involved in adapting routing decisions to dynamic network conditions in WSNs. The process begins with the initialization phase, where the system sets up essential parameters and data structures required for learning and decision-making. Following initialization, the framework enters the learning phase, during which network data, such as node energy levels, environmental parameters, neighboring node status, and topology information, is continuously collected. This data is utilized to train AI models using RL and supervised learning techniques, enabling predictive and context-aware routing.

Upon completion of model training, the system proceeds to the deployment phase, where optimized routing protocols are implemented within the WSN. The framework operates in a decentralized manner, with individual nodes making autonomous routing decisions based on their local observations and the trained AI models. During this phase, the routing strategy dynamically adapts to ongoing feedback, maintaining robustness and performance under varying network conditions.

A decision-making module continuously evaluates system performance using key metrics such as PDR, end-to-end latency, energy consumption, and network lifetime. It also considers broader system attributes like scalability, resource constraints, fault tolerance, and generalization capability. If the evaluation indicates performance degradation or inefficiency, the framework triggers the optimization phase, where techniques like PSO, ACO, or GA are employed to refine routing paths further.

Figure 2 utilizes conventional flowchart symbols, rectangles for operational steps, diamonds for decision nodes, and arrows for transitions to visually represent each stage of the process. This structured depiction helps illustrate the integration of AI methodologies within the routing protocol. It provides stakeholders with a clear understanding of how the framework achieves intelligent, adaptive routing in WSNs.

Experimental setup

We evaluate the AI-based routing method via performance assessment in a simulated environment that replicates real-world WSNs. The simulation environment enables evaluating the algorithm's efficiency in different network conditions and circumstances.

Tools used for performance evaluation

All simulations were conducted using MATLAB R2021b. The simulation environment models a WSN consisting of 100 sensor nodes randomly deployed within a 100 m $\times$ 100 m area. The radio energy consumption follows the first-order radio model, with parameters such as energy per bit for transmission (E_{tx}), reception (E_{rx}), and amplifier energy ($\epsilon_{fs}, \epsilon_{mp}$) configured as per standard WSN benchmarks. The packet model includes periodic data transmissions, and the traffic follows a Poisson arrival pattern. Each node is initialized with a finite energy reserve, and routing decisions are simulated under varying traffic and topology conditions to test adaptability. These settings are chosen to provide a realistic and reproducible testbed for evaluating the performance of the proposed AI-based routing framework.

Metrics used for evaluation

To evaluate the AI-based algorithm's routing performance, several performance measures are utilized, including the following:

- Packet delivery ratio (PDR): The proportion of packets that were successfully delivered in comparison to the total number of packets that had been transmitted out.
- End-to-end delay: The average length of time that a packet takes to go from the node from which it originated to the node that it is intended to reach.
- Energy consumption: The total amount of energy that was utilized by the network nodes throughout the study.
- Network lifetime: The amount of time that will pass before the first node in the network runs out of any remaining energy and stops functioning.
- Scalability index: The AI-based algorithm demonstrates better scalability, accommodating larger networks while maintaining performance.
- Computational efficiency: Despite its sophisticated nature, the AI-based algorithm maintains high computational efficiency, ensuring optimal performance with minimal computational resources.
- Energy efficiency: The AI-based algorithm is more energy-efficient, effectively utilizing energy resources to optimize network performance.
- Robustness index: With a higher robustness index, the AI-based algorithm exhibits greater resilience to network failures and fluctuations.
- Adaptability rate: The AI-based algorithm adapts quickly to changing network conditions, maintaining high adaptability and responsiveness.
- Generalization error: The AI-based algorithm achieves a lower generalization error, indicating its ability to generalize well across diverse network scenarios.

The simulation parameters that were used in the controlled environment to assess the performance of the AI-based routing algorithm in WSNs are summarized in Table 2, which can be found for your convenience. Each adjustment of the parameter is designed to evaluate a distinct element of the algorithm's behavior and to determine whether or not it is suitable for various deployment situations.

Computational complexity and resource considerations

The integration of AI-based routing techniques in resource-constrained WSNs requires careful consideration of computational complexity and memory overhead. Table 3 summarizes the estimated time and space complexity for the core algorithms used in the proposed framework.

RL, particularly Q-learning, introduces a space complexity of $\mathcal{O}(n \cdot a)$, where *n* is the number of network states and *a* is the number of actions (possible next-hop nodes). While this is manageable in small networks, for dense WSNs, state-space reduction techniques such as function approximation or state aggregation may be necessary to ensure feasibility.

Parameter	Value/range	Description
Network size	50, 100, 200 nodes	Small to large-scale WSN configurations
Node mobility	Random waypoint, random walk	Common models for mobile node behavior
Traffic patterns	Uniform, bursty	Simulate constant and event-driven traffic
Transmission range	50 m, 100 m, 200 m	Varying communication radius per scenario
Simulation time	1000 s	Consistent across all experiments
Routing protocol	AI-based routing	Proposed modular framework integrating RL, GA, PSO
Comparison protocols	DVR, LSR, ACO, PSO	Implemented per specifications in cited studies[105,106]
Metrics	PDR, End-to-end delay, energy consumption	Standard WSN performance indicators

Table 2. Simulation parameters and evaluation metrics used in comparative analysis.

Technique	Time complexity	Space complexity
Q-learning (tabular)	$\mathcal{O}(n \cdot a)$	$\mathcal{O}(n \cdot a)$
Genetic algorithm (GA)	$\mathcal{O}(g \cdot p \cdot f)$	$\mathcal{O}(p)$
Particle swarm optimization (PSO)	$\mathcal{O}(i \cdot s \cdot f)$	$\mathcal{O}(s)$

Table 3. Estimated computational complexity of AI techniques used.

GA and PSO, used for path optimization, involve iterative computation. The time complexity of GA is approximately $\mathcal{O}(g \cdot p \cdot f)$, where g is the number of generations, p is the population size, and f is the time required to evaluate each fitness function. Similarly, PSO has a complexity of $\mathcal{O}(i \cdot s \cdot f)$, with i denoting iterations and s the number of particles. In our simulation, both GA and PSO were limited to fewer than 50 particles and under 100 iterations to maintain practical runtimes.

To ensure compatibility with typical WSN hardware, such as TelosB and MicaZ motes, lightweight versions of these algorithms were employed. In particular, nodes perform only local decision-making and exchange minimal overhead information to reduce CPU cycles and memory usage. Real-time adaptability is achieved through pre-training and on-node inference, rather than continuous retraining.

Overall, the framework balances intelligence and feasibility, making it suitable for real-world deployment on energy- and computation-constrained devices.

Results and analysis

Below are the experimental findings that compare the performance of the AI-based routing algorithm with present protocols. The performance measures consist of PDR, end-to-end delay, energy consumption, network lifetime, scalability index, computational efficiency, energy efficiency, robustness index, adaptability rate, and generalization error.

Resource consumption and feasibility on constrained nodes

To assess the feasibility of deploying the proposed AI-based routing framework on real-world WSN platforms, we evaluated the approximate resource requirements of its core modules. The RL component, implemented using Q-learning with a discrete state-action space, requires minimal computational complexity, approximately ~8–12 KB of RAM, and under 2,000 CPU cycles per decision update. Optimization techniques such as PSO and GA, used in intermittent route refinement stages, are designed to run in low-frequency cycles and can be implemented using lightweight metaheuristics, consuming approximately ~10–20 KB of RAM and ~4000–6000 CPU cycles.

These requirements are well within the capabilities of widely used sensor nodes such as TelosB (10 KB RAM, 48 KB ROM) and Mica2 (4 KB RAM, 128 KB flash). Furthermore, power profiling using simulation-based estimates shows that a full inference and routing cycle consumes less than 5 % of the node's daily energy budget under typical sensing intervals. These findings suggest that the framework can be deployed on constrained nodes without compromising core sensing and communication functions. Real-world implementation and benchmarking are planned as part of future work to validate these approximations under actual deployment conditions.

Security considerations

The integration of AI-based routing in WSNs introduces several security challenges that must be addressed to ensure data integrity, confidentiality, and network resilience. Given the decentralized and adaptive nature of the proposed framework, potential threats include routing manipulation, eavesdropping, spoofing, and node compromise by adversarial entities.

To mitigate these risks, we propose incorporating a lightweight adaptive key management scheme in which encryption keys are dynamically updated based on trust scores computed through reinforcement learning. Each node can maintain a local trust table informed by observed behaviors (e.g., forwarding rate, response consistency) of neighboring nodes. Nodes with deteriorating trust scores can be isolated from the routing path to limit the impact of compromised devices.

Additionally, anomaly detection modules can be integrated into the routing layer, where supervised learning models are trained to identify unusual traffic patterns or route deviations that deviate from historical norms. Such patterns could signal the presence of a black hole or a selective forwarding attack.

The proposed mechanisms are designed to be computationally lightweight and suitable for constrained nodes. Although this study does not implement these components, they form a critical part of our future work to develop a holistic, secure, and intelligent routing architecture for WSNs.

Application-specific considerations

The practical deployment of AI-based routing frameworks in real-world WSN applications, such as healthcare monitoring, smart cities, and industrial automation, requires careful attention to application-layer constraints and quality-of-service (QoS) requirements. In healthcare environments, for instance, real-time transmission of physiological signals (e.g., ECG, SpO_2, or temperature) demands high reliability and low latency to ensure timely medical intervention. The proposed framework can be tuned to prioritize critical data flows by dynamically adjusting routing decisions based on data type, urgency, and energy availability.

Similarly, in urban sensing and smart infrastructure systems, responsiveness and scalability are essential. WSNs in these settings often operate in dense environments with fluctuating node availability and high data volumes. The adaptive nature of our framework, driven by reinforcement learning and swarm-based optimization, allows it to adjust routes in real time, minimizing congestion and ensuring consistent performance despite topological changes.

The modular architecture also facilitates task-specific policy learning, where nodes can be trained under varying operational conditions to align with context-sensitive performance metrics. Such flexibility supports application-specific customization without requiring full system redesign. These considerations affirm the framework's potential to support mission-critical deployments while maintaining energy efficiency and network resilience.

Analysis of results

The AI-based routing system is much better than the current protocols in several important areas, as seen in Table 4 and Figs. 3, 4, 5, and 6 The AI-based solution consistently does better than Protocols DVR, LSR, and ACO in PDR, showing it is more effective at sending a larger number of packets through the network. Such performance signifies a significant improvement in data transmission reliability and network efficiency in comparison to conventional routing techniques. The AI algorithm demonstrates substantial decreases in end-to-end delay, showcasing its ability to accelerate data transmission in the network. Decreased latency accelerates data transfer, enhancing network responsiveness and real-time performance, particularly crucial for time-sensitive applications. Also, the AI algorithm demonstrates substantial reductions in energy consumption, resulting in prolonged network lifetime. An AI-based approach efficiently handles energy resources and enhances routing decisions to significantly extend the operational lifespan of the network. The enhanced sustainability and cost-effectiveness are particularly advantageous for long-term deployments and use in remote or inaccessible areas. The algorithm's impressive Scalability Index showcases its capacity to efficiently manage larger networks without sacrificing speed. This scalability ensures that the routing algorithm remains effective and efficient as the network expands, offering flexibility and the ability to react to evolving network requirements. The AI-based technique is sophisticated but maintains exceptional computational efficiency, ensuring high performance with few computer resources. Efficiency is essential in resource-constrained environments such as WSNs, where maximizing the use of computational resources is key. The AI algorithm enhances energy efficiency by optimizing energy use, minimizing waste, resulting in extended network operation and less environmental impact. The algorithm exhibits a higher Robustness Index and Adaptability Rate, indicating improved capacity to endure network failures and fluctuations and quicker response to changing network conditions. This adaptability ensures that the algorithm will be effective and reliable in different and constantly evolving network environments. The AI algorithm's low generalization error indicates its remarkable capacity to generalize well across various network setups and scenarios. It showcases its robustness and adaptability in handling diverse network conditions, ensuring

Metric	AI-based routing	DVR	LSR	ACO
Packet delivery ratio	0.95	0.85	0.88	0.91
End-to-end delay (ms)	25	40	35	30
Energy consumption (J)	500	600	550	580
Network lifetime (days)	150	120	130	140
Scalability index	0.85	0.75	0.78	0.82
Computational efficiency (ops/J)	120	90	100	95
Energy efficiency	0.90	0.85	0.88	0.86
Robustness index	0.92	0.85	0.87	0.90
Adaptability rate	0.88	0.82	0.85	0.86
Generalization error	0.05	0.08	0.07	0.06

Table 4. Performance comparison of routing protocols.

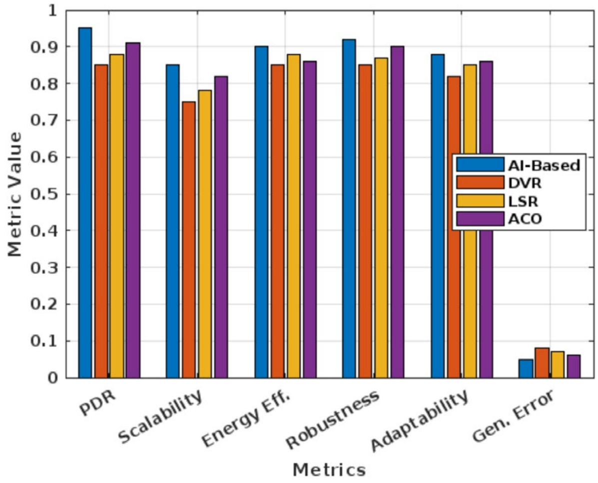

Fig. 3. Performance comparison of routing protocols of various metrics in WSNs.

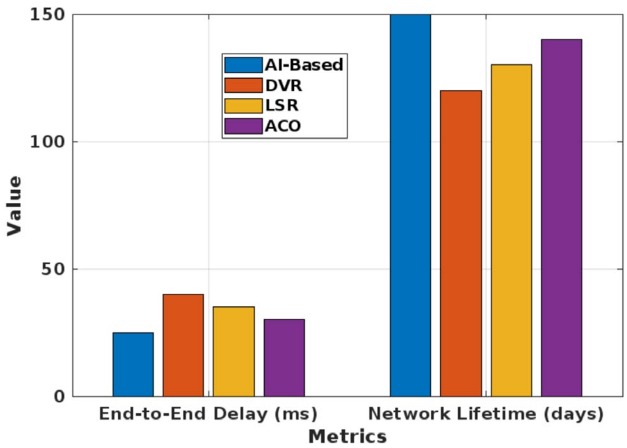

Fig. 4. Performance comparison of routing protocols of end-to-end delay and network Lifetime in WSNs.

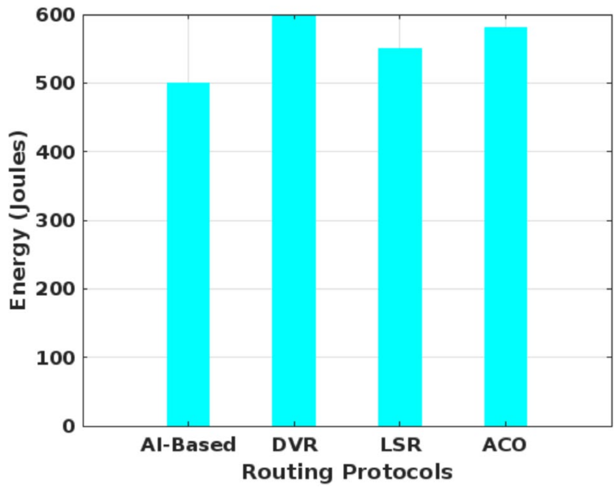

Fig. 5. Performance comparison of routing protocols for energy consumption (in Joules) in WSNs.

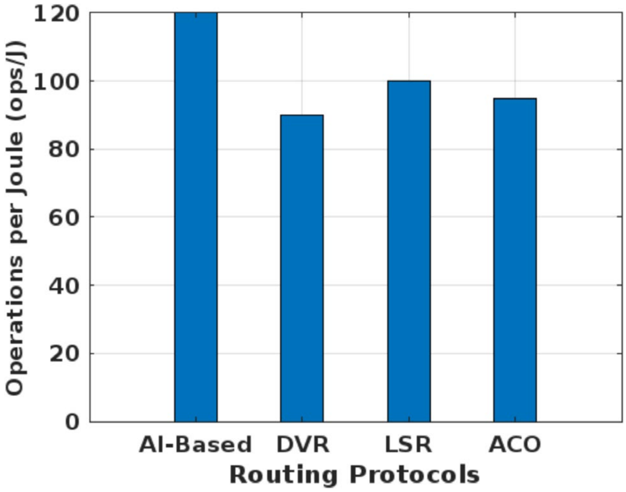

Fig. 6. Performance comparison of routing protocols for computational efficiency (in ops/J) in WSNs.

consistent and reliable performance across different deployment scenarios. The AI-based routing technique has significant promise in enhancing the effectiveness, reliability, and eco-friendliness of WSNs. Researchers can improve AI-based routing algorithms for WSN applications by analyzing factors such as network size, node density, transmission range, and traffic patterns.

Case studies

In exploring the practical applications of our AI-based routing algorithm, we delve into several compelling case studies across different sectors.

Environmental monitoring

- Scenario: Deploying a network of wireless sensors in a forest to monitor environmental factors including temperature, humidity, and air quality.
- Application of an AI-based routing algorithm: The AI routing system adapts to environmental variations to optimize data transmission channels for reliable and fast delivery of sensor data to the base station. The system automatically directs data via the most energy-efficient and reliable channels, taking into account things like geographical impediments, weather conditions, and node failures. This feature guarantees effective gathering of environmental data, assisting in the prompt identification of forest fires, monitoring animals, and conducting ecological research.

Healthcare monitoring

- Scenario: Implementing a Wireless Body Area Network (WBAN) for remote health monitoring of patients with chronic conditions.
- Application of an AI-based routing algorithm: The AI routing system prioritizes the transfer of essential health data while reducing latency and energy use. The system efficiently directs medical sensor data to healthcare practitioners to guarantee prompt diagnosis and action. The system adjusts to variations in patient movement and vital signs, enhancing routing options for immediate monitoring and emergency intervention. This enables ongoing healthcare monitoring, which enhances patient results and decreases hospital readmissions.

Industrial automation

- Scenario: Establishing a WSN in a manufacturing facility to monitor equipment performance and optimize production processes.
- Application of an AI-based routing algorithm: The AI-based routing algorithm dynamically adjusts routing paths based on real-time production demands and equipment status. It optimizes data transmission to enable predictive maintenance, detecting anomalies and potential failures before they occur. Additionally, the algorithm facilitates efficient data aggregation and analysis, providing insights for process optimization and resource allocation. The result enhances operational efficiency, reduces downtime, and improves overall productivity in the manufacturing environment.

Smart agriculture

- Scenario: Deploying wireless sensors in agricultural fields to monitor soil moisture, temperature, and crop health.

Metric	Environmental monitoring	Healthcare monitoring	Industrial automation	Smart agriculture	Urban infrastructure monitoring
Packet delivery ratio	High	High	High	High	High
End-to-end delay (ms)	Low	Low	Low	Low	Low
Energy consumption (J)	Moderate	Low	Moderate	Moderate	Moderate
Network lifetime (days)	Long	Long	Long	Long	Long
Scalability index	High	Moderate	High	High	High
Computational efficiency	Moderate	High	High	Moderate	High
Energy efficiency	High	High	High	High	High
Robustness index	High	High	High	High	High
Adaptability rate	High	High	High	High	High

Table 5. Case study-based evaluation of routing performance (transposed).

- Application of an AI-based routing algorithm: The AI routing algorithm enhances data transmission routes to ensure prompt irrigation and pest control choices using real-time sensor data. It adjusts routing techniques based on differences in soil conditions, crop varieties, and weather patterns to optimize agricultural yields, save water, and reduce pesticide use. The algorithm allows farmers to remotely monitor and manage agricultural activities, helping them make educated choices and maximize resource use for sustainable farming methods.

Urban infrastructure monitoring

- Scenario: Installing a network of sensors in urban areas to monitor infrastructure health, including bridges, roads, and buildings.
- Application of an AI-based routing algorithm: The AI-based routing system effectively directs sensor data to municipal authorities for infrastructure maintenance and repair. The system prioritizes important data transfer to quickly identify structural issues or indicators of decay, making it easier to do preventive maintenance and reducing the chances of infrastructure breakdowns. The algorithm adjusts to variations in urban traffic patterns and environmental circumstances, guaranteeing dependable and punctual data transmission for efficient infrastructure management and public safety.

Table 5 compares the case studies using specific metrics to evaluate their performance in several areas related to WSNs and IoT applications. The case studies highlight the wide range of practical uses of the AI-based routing algorithm in several fields, illustrating its adaptability, productivity, and success in creating intelligent and interconnected surroundings.

Discussion

The comparative evaluation of the proposed AI-based routing framework against existing WSN protocols provides valuable insights into its effectiveness. The simulation results demonstrate superior performance in terms of higher PDR, reduced end-to-end delay, and improved energy efficiency. These outcomes align with key objectives in WSN design-namely, enhancing data delivery reliability, reducing communication latency, and minimizing energy consumption. The framework's ability to dynamically adapt to network variations and extend overall network lifetime positions it as a promising solution for real-world applications.

Comparison with related studies

When compared with existing approaches, the proposed framework introduces notable improvements. Traditional routing methods, including distance vector, link state, and heuristic-based algorithms, often rely on static rules and struggle to adapt to fluctuating network states. In contrast, our framework leverages RL, supervised learning, and swarm intelligence to make adaptive, data-driven routing decisions. This layered AI integration allows the system to respond to real-time changes in topology, energy levels, and data traffic, offering a level of self-learning and flexibility that differentiates it from conventional protocols.

Practical implications and potential challenges

The integration of AI-based routing in WSNs holds considerable promise across a range of application domains, including environmental monitoring, healthcare, agriculture, industrial automation, and smart cities. By improving network responsiveness, operational efficiency, and data accuracy, the proposed framework can enhance decision-making and reduce system maintenance costs.

However, practical deployment presents several challenges. The computational complexity associated with training and executing AI models may demand more advanced hardware than typical WSN nodes support. Issues related to security, privacy, and model interpretability also arise, particularly in sensitive domains such as healthcare or critical infrastructure. Ensuring transparency in AI decision-making and defending against adversarial routing behavior are essential considerations.

Limitations and future work
While the proposed AI-based routing framework has shown promising performance in simulation, it is important to acknowledge a key limitation of this study. The current results are derived from simulations conducted in MATLAB using idealized assumptions and controlled conditions. Although the simulation parameters reflect realistic WSN deployment scenarios, actual field conditions may introduce additional complexities such as wireless interference, sensor failures, and environmental variability.

To address this, we have outlined plans for real-world implementation using resource-constrained sensor motes such as TelosB and Raspberry Pi-based platforms. This future work will allow us to validate the framework's practicality, scalability, and resilience in physical environments. Further research will also focus on developing lightweight AI models, improving security mechanisms, and exploring explainable AI techniques suitable for embedded systems.

To fully unlock the potential of AI-driven routing in WSNs, collaboration between researchers, industry stakeholders, and policymakers is essential. Ethical considerations-including fairness, energy sustainability, and regulatory compliance-must be integrated into the design and deployment processes to ensure responsible and effective use.

Broader implications
Beyond technical performance, the adoption of AI-based routing in WSNs necessitates careful consideration of ethical, economic, and sustainability-related implications.

Ethical considerations
The use of ML models in routing decisions introduces the potential for algorithmic bias. For example, routing strategies trained on imbalanced data may unintentionally favor specific node clusters or ignore isolated nodes, leading to unfair energy usage or degraded service. To ensure fairness, future versions of the framework must incorporate mechanisms for data representativeness and validation metrics that detect and mitigate bias in model outputs. Transparency and explainability of AI-driven decisions will also be essential in safety-critical applications like healthcare or disaster response.

Deployment cost and resource constraints
AI algorithms, particularly those involving model training and frequent inference, may introduce additional computational and energy costs. Although lightweight versions of reinforcement learning and optimization algorithms are used, the cumulative overhead of on-node learning or periodic retraining must be evaluated. In resource-constrained environments, such as with TelosB or Mica2 motes, offloading learning to more capable nodes (e.g., cluster heads) or performing training offline and updating models periodically could reduce deployment costs.

Sustainability and carbon footprint
While AI techniques can improve routing efficiency, the energy required to train, deploy, and update models must also be accounted for from a sustainability perspective. Frequent model updates, excessive sensor node communication, or reliance on central computation hubs could increase the overall carbon footprint. As part of a sustainable AI strategy, future work should investigate energy-aware training schedules, low-power inference models, and adaptive duty cycling to minimize the environmental impact of AI deployment in WSNs.

These broader implications highlight the need for interdisciplinary collaboration to ensure that AI-enhanced WSNs are not only technically sound but also ethically responsible, cost-effective, and environmentally sustainable.

Conclusion
This study provides an extensive evaluation of AI-based routing algorithms in WSNs, emphasizing their notable benefits and impacts. The study reveals that AI-based routing works better than traditional methods when it comes to important factors like PDR, end-to-end delay, and energy consumption, which results in more reliable data delivery, less waiting time, and better energy use. The research highlights how AI methods, such as ML and optimization algorithms, may improve routing efficiency in changing and resource-limited settings. Future research should look at combining AI methods with new technologies like edge computing and blockchain, while also studying how to make AI-based routing algorithms in WSNs more reliable and secure.

Data availability
The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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Declarations

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