

INTELLIGENT ENERGY-AWARE ROUTING PROTOCOL USING ARTIFICIAL INTELLIGENCE FOR MOBILE WIRELESS SENSOR NETWORKS (IEARP-AI)

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Abstract

In Recent years, Mobile Wireless Sensor Networks (MWSNs) have become fairly widespread because they can offer flexible and timely monitoring in changing situations like disaster management, environmental observations, healthcare, and military surveillance. Yet, a big challenge is the limited energy of mobile sensor nodes, which affects how well the network performs, its stability, and its life span. Common routing methods often struggle to keep up with the constant changes in network structure and the unpredictable movement of nodes found in MWSNs. To address these issues, this paper introduces an Intelligent Energy-Aware Routing Protocol using Artificial Intelligence (IEARP- AI). This model focuses on using energy wisely while improving routing in mobile sensor networks. The proposed protocol integrates with machine learning method Fuzzy-PSO which is used to select CHs by estimating the residual energy, distance to sink, node density, and mobility factor. Then the routing using an Reinforcement Learning algorithm called Deep Q-Learning (DQL) method which is continuously learns and updates optimal routing paths based on reward functions like energy usage, delay, and link stability. By combining AI-driven optimization and clustering techniques, IEARP-AI minimizes redundant data transmission, balances energy utilization among nodes, and extends the overall network lifetime. The Simulation results shows that IEARP-AI outperforms conventional routing protocols in terms of Network Lifetime, Average Energy Consumption, Packet Delivery Ratio, End-to-End Delay, Throughput, Scalability Index, Computational Efficiency, Energy Efficiency, Robustness Index, Adaptability Rate and Generalization Error. This intelligent approach provides a promising solution for the development of sustainable and high-performance mobile wireless sensor networks.

Keywords:

Mobile Wireless Sensor Networks (MWSNs), Intelligent Routing Protocol, Energy Efficiency, Fuzzy-PSO Clustering, Deep Q-Learning, Reinforcement Learning, Node Mobility

1. INTRODUCTION

Mobile wireless networks (MWNs), such as mobile ad hoc network (MANET) and wireless sensor network WSNS, are important components in modern communication systems due to their infrastructure-less deployment, scalability and flexibility. These applications include environmental monitoring, disaster management, military surveillance, health care services and smart cities. But MWN is naturally dynamic due to topology, mobility of nodes, distributed control and energy constraint that should be taken into account when designing the efficient routing protocol. Since most of the nodes run on batteries, high power consumption can cause nodes to fail prematurely and partitioning of the network along with decrease in QoS.

Most of the traditional routing protocols such as AODV, DSR and DSDV primarily use metrics based on shortest path, hop count or sequence numbers for route selections. Though effective in static or low-mobility conditions, these protocols often disregard residual energy and the mobility of nodes, leading to

uneven energy consumption and high rate of route failures in dynamic networks [1]. As a consequence, numerous discoveries of routes increase control overhead, packet loss, delay and finally deplete the overall energy that in turn results in reduced network lifetime.

To address these limitations, routing protocols have increasingly been scrutinized to include techniques derived from artificial intelligence (AI) and machine learning (ML). The AI-guided routing techniques support the ability to make smart decisions based on lessons we have learned from our wireless network, predicting the behavior of each node and adjusting the routing strategy at run time. Machine learning based algorithms, such as reinforcement learning, fuzzy logic and deep Learning, have all shown a good potential vehicle in controlling energy consumption and enhancing the route stability of MWNs and improving the performance of packet delivery [2], [3]. These methods are enabling the nodes to make distributed energy-aware routing decisions based on many factors with dynamic routing practices.

In this situation, the proposed IEARP-AI protocol is designed to handle MWN energy efficiency and adaptability issues using artificial intelligence. IEARP-AI uses AI-based learning and optimization techniques to intelligently distribute energy consumption on network nodes such that the nodes maintain reliable communication. The protocol chooses optimal routing paths dynamically based on critical factors, which include residual energy, link quality, node mobility and traffic load to reduce the transmission of data along erroneous routes and energy wastage. Reinforcement learning and fuzzy logic approach allows the protocol to learn from network feedback in an active environment [4].

IEARP-AI provides a self-optimizing and context-aware routing solution designed for highly dynamic mobile wireless environments when its compare to conventional routing schemes. The intelligent energy-aware design significantly reduces packet loss, end-to-end delay, and frequent route breakages, increasing the network lifetime. Recent research on intelligent routing for IoT and MANET contexts further supports the effectiveness of AI-driven techniques in attaining dependable and sustainable network performance [5]. Therefore, IEARP-AI advances next-generation routing protocols by combining energy awareness with intelligent decision-making for mobile wireless networks.

The main research goals can be enumerated as follows:

- The proposed schema Intelligent Energy-Aware Routing Protocol using Artificial Intelligence (IEARP-AI) aims to design a robust and adaptive routing system that can efficiently handle energy issues and dynamic topological changes in mobile wireless sensor networks.
- The proposed work aims to design a sector-based clustering strategy that can efficiently reduce communication distance

and traffic load, thus improving energy efficiency in the routing, data transmission, and data aggregation phases.

- Fuzzy-Particle Swarm Optimization (Fuzzy-PSO) approach for optimal cluster head selection, taking into account the most important parameters such as residual energy, node density, sink node distance, and node mobility.
- Deep Q-Learning (DQL) algorithm based on reinforcement learning for adaptive and intelligent route selection, which can optimize routing paths continuously based on energy consumption, end-to-end delay, and link stability.
- The proposed protocol also aims to minimize redundant data transmissions and control overhead while ensuring reliable and low-latency communication.
- The proposed IEARP-AI protocol aims to evaluate its performance using simulations with and compare its performance with other existing state-of-the-art routing protocols in terms of improved network lifetime, packet delivery ratio, scalability, adaptability, and robustness.

2. RELATED WORKS

Nguyen et al. [6] proposed an energy-efficient routing protocol called EE-AIRP, in which AI technology is used for efficient decision-making regarding the selection of the cluster head as well as the routing path based on significant factors like the amount of residual energy, the density of the nodes, the distance of communication, etc. However, the EE-AIRP protocol assumes a static network topology, i.e., the sensor nodes as well as the Sink node are static in the entire network during the entire round. In addition, the EE-AIRP protocol assumes a high computational complexity. Furthermore, the EE-AIRP protocol is not very suitable for sensor nodes.

The energy-efficient data aggregation and routing protocol with the help of artificial intelligence for the improvement of network lifetime for WSNs has been proposed by Chakravarthy et al. [7]. In the proposed protocol, artificial intelligence is used for the optimization of data aggregation, cluster formation, and routing with the help of the residual energy of the nodes, distance between the nodes, and traffic load. The proposed protocol also prevents the transmission of redundant data and optimizes the energy usage of the nodes. Nevertheless, despite the efficiency of the proposed protocol, there might be issues of complexity and overhead of the proposed AI-based protocol, which might pose a challenge for the efficient use of the energy-efficient sensor nodes.

Al-Shukrawi et al. [8] proposed an algorithm for the energy management system for WSNs based on Q-learning. This algorithm has shown improvements in terms of energy consumption, packet delivery ratio, and network lifetime. This paper intends to show the application of reinforcement learning for the management of wireless sensor networks. The difficulty in training the model might pose a problem in the application of the proposed system.

A protocol for optimization in terms of energy, with the help of AI, has been proposed by Haider et al. [9], considering the optimization of the routing protocol in wireless sensor networks with the help of UAVs, where the data collection is performed with the help of unmanned aerial vehicles, thus reducing the

distance and cost of transmission. The protocol assists in the efficient usage of energy with the intelligent selection of the cluster head and the greedy communication. However, the usage of the route planning of the UAV may not be efficient.

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Kaur and Kang [11] have proposed a rank-based secure routing mechanism in M-WSNs through a DNN technique. In this routing mechanism, it can be noticed that the routing paths in the network are classified according to certain parameters such as energy consumption, quality of service (QoS), security, etc. This intelligent routing technique can enhance the reliability of information transfer in the network along with the network lifetime, especially considering the mobile nodes in the network. It can be mentioned that the training process of this intelligent routing technique can be considered a hindrance to this technique due to the high computations involved in this process.

Sheikh and Joshi have proposed an “Improved Smart Energy Based Routing Approach for IoT enabled Wireless Sensor Networks” [12]. This proposed work is intended for improving the protocol by optimized routing techniques, which include energy consumption and QoS for a longer lifetime in the network. This proposed protocol is based on smart energy management and routing techniques, which are applicable for static networks only. However, this protocol does not include mobility aspects in WSNs. This proposed work comes under the category of improving energy-efficient and intelligent routing for IEARP-AI.

Li et al. [13] proposed an energy-aware routing architecture for WSNs with a key focus on careful path selection and stability for the entire network. They proposed the MPHR-RL algorithm, which represents a combination of reinforcement learning with multipath routing, in which it dynamically selects routes for saving energy. The proposed optimization model decides on cost-based optimal solutions to equally distribute the utilization of the sensor nodes' energy. This method avoids wasting energy due to frequent route failure and its retransmissions. Simulation results exposed that their approach tends to improve network lifetime, packet delivery ratio, and routing reliability compared to traditional algorithms. As such, this work points to a substantial reinforcement learning contribution to the energy-efficient routing of WSNs.

Tawfeek et al. [14] proposed an improved routing scheme for Wireless Sensor Networks based on Ant Colony Optimization. Their MACOA relies on pheromone-based decisions for the purpose of homogeneously distributing energy consumption among nodes and reducing unnecessary packet transmissions. The main objective is to minimize energy wasting while preserving network connectivity with high packet delivery ratio under changing network conditions. Simulation results show that MACOA extends the network lifetime compared to standard ACO and other benchmark protocols to load balancing and reduced routing failures due to changing node residual energies.

In this way, this paper represents another example of how swarm intelligence techniques can contribute to energy-aware routing policies in scenarios characterized by stringent resource constraints.

Reinhardt [15] proposed reinforcement learning-driven IoT sensor network routing with improving energy efficiency. This system finds an efficient route concerning the remaining energy in a node and the quality of the links. It ensures adaptive decisions and thus routes may be updated on the fly depending on the current conditions of the network. It helps to distribute energy consumption more uniformly among sensor nodes. In simulation, longer network lifetime and reduced packet loss were achieved using this approach. In general, this work depicts how reinforcement learning can enable smarter routing in wireless sensor networks based on IoT.

In another research work, Zeng et al. [16] proposed a threshold-driven K-means sector clustering approach for improving efficiency in clustering as well as energy usage in a WSN. The proposed method combines a threshold-driven technique with a standard K-means clustering process, which enhances the dynamic cluster formation process while eliminating unneeded processes. As a result, the network is divided into several sectors, which improves communication with decreased distance as well as uniform distribution of the nodes within a cluster. The research promotes sector-based intelligent clustering for large-scale WSN.

In another research by Akram et al [17], they proposed a clustering and routing protocol for wireless sensor networks called EEMLCR, which primarily targets the optimization of energy usage using machine learning. According to the proposed protocol, it employs ML techniques to optimize the selection of cluster heads while determining routing paths by considering the remaining energy, distance, and network traffic density. The routing protocol offers better reliability for packet transfer while reducing end-to-end delay. The proposed protocol demonstrates remarkable improvements in network lifetime and energy efficiency compared to other clustering and routing schemes through extensive simulations, which proves the potential of machine learning for effective wireless sensor network communication.

Srinivasan et al [18], proposed an energy-efficient, hierarchical clustering scheme for dynamic data fusion in WSNs intended for smart farming. The proposed technique organizes sensor nodes into hierarchical clusters in order to minimize redundant transmissions and optimize data aggregation. A dynamic data fusion process at the cluster heads minimizes data communication overhead and thereby reduces energy consumption. The algorithm is adaptable to altering conditions and varying data rates of generation. Longer life, reduced energy expenditure, and reliable delivery of data are achieved in experiments. This work emphasizes the impact of intelligent clustering combined with data fusion in large-scale farming monitoring applications.

3. PROPOSED AI ALGORITHM COMBINATION FOR IEARP-AI

3.1 PHASE 1: CLUSTERING PHASE

The Cluster phase consists of the grouping sensor nodes into distinct clusters, a technique designed at modifying communication overhead and conserving energy resources. In this case, the sensor nodes engage in the process of exchanging localization data that entails the use of factors like energy level, mobility, and neighbor density [19]. Clustering ensures that there is scalability in the network structure while reducing the requirement for distant communication by promoting intra-cluster communication.

Initially, the clustering phase is characterized by a node information exchange process. In this process, each sensor node broadcasts a Hello message at regular intervals. This message comprises critical data, including the residual energy of the node, its unique identifier, geographical coordinates, mobility factor, and the count of neighboring nodes. The reception of these messages permits each node to construct a neighbor table, which contains updated information regarding proximate nodes. This table serves as a foundation for evaluating the feasibility of potential clustering configurations. After this exchange, the initial formation of cluster will be taken place which is predicted for an assessment of node proximity and the connectivity of the network.

In the process of network clustering, nodes connect with the nearest potential Cluster Head (CH) nodes by calculating a clustering fitness score. This score comes from weighing all nodes, leading to the finalization of clusters. During this process, the clusters adjust dynamically. This adjustment happens through regular updates of neighbor information, which accounts for changes in network topology. The cluster maintenance protocol ensures the strength of the clustering system. This protocol requires nodes to continuously monitor the CH's status and energy levels. If a CH fails or experiences a significant energy drop, a re-clustering procedure starts. This involvement is crucial for maintaining network stability and prolonging the overall operational lifespan of the network.

For the Mathematical Model for Clustering Suitability, let E_i = residual energy of node i , d_{ij} = Euclidean distance between node i and potential CH j , E_{max} = maximum initial energy and d_{max} = maximum transmission range and α, β = weighting factors, where $\alpha + \beta = 1$

The clustering suitability score S_{ij} of node i toward CH candidate j is defined as:

$$S_{ij} = \alpha \left(\frac{E_i}{E_{max}} \right) + \beta \left(1 - \frac{d_{ij}}{d_{max}} \right) \quad (1)$$

A node joins the cluster of the CH candidate that maximizes the suitability score:

$$CH^* = \arg \max (s_{ij}) \quad (2)$$

Algorithm 1: Clustering Phase

Input: N = set of sensor nodes, Position, ResidualEnergy, Mobility, NeighborCount

Output: Clusters {C1, C2, ..., Ck}

Begin

```

1: For each node i ∈ N do
2:   Broadcast Hello message containing:
3:     NodeID, ResidualEnergy, Position, Mobility,
       NeighborCount
4: End for
5: For each node i ∈ N do
6:   Build Neighbor Table with information received
7:   Compute Cluster Suitability Score:
8:     Score_i = w1*(ResidualEnergy_i/E_max) +
       w2*(1/Distance_to_CH) + w3*(1/Mobility_i) +
       w4*(NodeDegree_i/MaxDegree)
9: End for
10: For each node i ∈ N do
11:   If Score_i is highest among neighbors then
12:     CandidateCH_i = True
13:   Else
14:     Join cluster of neighbor with highest Score
15:   End if
16: End for
17: Finalize clusters when all nodes have a CH assigned
18: Periodically update clusters to adapt to node mobility and
   energy changes
19: End

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3.2 PHASE 2: CLUSTER HEAD SELECTION PHASE (FUZZY-PSO)

The cluster head (CH) selection phase is an important aspect for achieving network stability and energy efficiency. In order to solve problems arising from heterogeneity of energy resources, node mobility, and changing topology, a novel Fuzzy-Particle Swarm Optimization algorithm (Fuzzy-PSO) has been developed for the purpose of optimum selection of CHs. This is made possible due to the combination of fuzzy and PSO algorithms in decision making.

Initially, fuzzy logic is used to evaluate the suitability of each node to act as a CH by considering multiple input parameters, including residual energy, node degree, average distance to neighboring nodes, and mobility factor. These parameters are modeled using linguistic variables and membership functions to capture imprecise and nonlinear relationships inherent in wireless sensor networks.

A fuzzy inference system based on Mamdani reasoning evaluates a predefined rule base and produces a CH suitability index through centroid-based defuzzification. Nodes with higher fuzzy scores are considered more appropriate candidates for CH roles. Next, Particle Swarm Optimization (PSO) is applied to improve the CH selection process. In PSO, each particle

represents a potential CH configuration, and the initial population is generated from nodes with high fuzzy suitability scores.

The fitness of each particle is computed based on energy efficiency, intra-cluster communication cost, node connectivity, and mobility stability. Through iterative updates of particle velocity and position, guided by personal best and global best solutions, PSO converges toward an optimal CH set that balances energy consumption across the network.

The hybrid Fuzzy-PSO mechanism ensures that CHs are selected not only based on local optimality but also on global network performance. By minimizing communication overhead, reducing frequent CH re-election, and accommodating node mobility, the proposed approach achieves stable cluster formation, enhanced energy balance, and prolonged network lifetime. This phase significantly contributes to improving the scalability and robustness of the overall routing framework.

3.2.1 Mathematical Fitness Formulation:

The PSO fitness function is defined as:

$$Fit = w_1 \left(\frac{E_i}{E_{max}} \right) + w_2 \left(\frac{ND_i}{ND_{max}} \right) + w_3 \left(1 - \frac{D_i}{D_{max}} \right) - w_4 \left(\frac{M_i}{M_{max}} \right) \quad (3)$$

where, E_i = residual energy of node i , ND_i = node degree, D_i = average distance to neighbors, M_i = mobility factor, and $w_1 + w_2 + w_3 + w_4 = 1$

Algorithm 2: Fuzzy-PSO Cluster Head Selection

Input: Clustered nodes, fuzzy parameters

Output: Optimal Cluster Heads

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1: For each node i in cluster do
2:   Evaluate fuzzy inputs (RE, ND, D, MF)
3:   Compute fuzzy CH suitability score
4: End for
5: Initialize PSO particles using top fuzzy-ranked nodes
6: Compute fitness value for each particle
7: Update pbest and gbest
8: While stopping criterion not met do
9:   Update velocity and position of particles
10:  Recalculate fitness values
11:  Update pbest and gbest
12: End while
13: Select nodes corresponding to gbest as CHs

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3.3 PHASE 3: AI-BASED ROUTE SELECTION PHASE

After the optimal cluster heads (CHs) are selected, an AI-driven routing method is used to set up efficient and reliable communication paths between clusters and the base station. This stage aims to intelligently initialize routes by taking into account several network factors such as the remaining energy of cluster heads, link quality, hop count, and traffic load. These factors together shape how well routing works and how long the network lasts. By using learning-based decision-making, the model adjusts its routing decisions to match changing network conditions and helps prevent poor routing choices that might result from uneven energy use or weakening links.

Initially, each CH collects local routing information from neighboring CHs, such as remaining energy levels, signal-to-noise ratio or packet reception rate as indicators of link quality, current traffic load, and hop distance to the base station.

These parameters form the input feature set for the AI routing model. Based on this information, the model evaluates multiple candidate paths and predicts the most energy-efficient and reliable routes for inter-cluster data forwarding. The learned routing policy prioritizes paths that minimize energy consumption and transmission cost while maintaining strong link stability and balanced traffic distribution.

Furthermore, the AI-based routing framework enables an improvement in decision making through constant learning from information provided back by the network in terms of successful data packet transmission and energy variations on the path of the routes. In effect, this ensures that packet loss does not occur, congested and depleted nodes are avoided, and there is an effective utilization of resources for routing. Through optimal route choices between clusters, there is improved throughput, reduced delay, and increased network lifetime.

3.3.1 AI-Based Routing Cost/Reward Function:

The routing decision is guided by a reward function defined as:

$$R = \lambda_1 \left(\frac{E_{CH}}{E_{max}} \right) + \lambda_2 (LQ) - \lambda_3 \left(\frac{HC}{HC_{max}} \right) - \lambda_4 \left(\frac{TL}{TL_{max}} \right) \quad (4)$$

where

E_{CH} = residual energy of the CH

LQ = link quality metric

HC = hop count to base station

TL = traffic load

$$\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 = 1$$

The route with the maximum reward value is selected for data forwarding.

Algorithm 3: AI-Based Inter-Cluster Route Selection

Input: Selected CHs, routing parameters

Output: Optimal inter-cluster routes

- 1: For each CHi do
- 2: Gather neighbor CH information (Energy, LQ, HC, TL)
- 3: Generate candidate routing paths
- 4: Evaluate paths using AI routing model
- 5: Compute reward value for each path
- 6: Select route with maximum reward
- 7: End for
- 8: Update routing table at each CH
- 9: Periodically re-evaluate routes based on network feedback

3.4 PHASE 4: AI-BASED ROUTE UPDATE PHASE

In order to deal with network dynamics like mobility of nodes, energy loss, and changes in the traffic pattern, an approach based on artificial intelligence for updating the path has been utilized to ensure that the network remains reliable as well as energy efficient. The proposed methodology differs from the static

routing scheme in that it keeps track of various parameters of the network.

During network operation, the cluster heads keep monitoring the latest information about the routing metrics in their neighboring cluster heads and analyze the efficiency of existing routes. The results of the analysis are inputted into the AI system for learning based on past and present information, thereby predicting possible degradation or breakdown of the routes. If any substantial deterioration of the existing route occurs, such as low energy levels, link instability, and congestion, the AI system initiates a partial route update instead of total rerouting.

Moreover, the intelligent routing algorithm for updating routes depend on selecting reliable and balanced routes by changing the routing process to prevent overloaded or critical nodes in terms of energy from being used. The suggested method avoids disruption in the routing process due to congestion, leading to minimal packet drop and low latency in transferring information to the base station. Thus, this stage improves the robustness and longevity of the network, adding value to the previously discussed process of route selection.

3.4.1 Route Update Decision Metric:

The route update decision is governed by the following condition:

$$U = \mu_1 \Delta E + \mu_2 \Delta LQ + \mu_3 \Delta C \quad (5)$$

where, ΔE = change in residual energy, ΔLQ = change in link quality and ΔC = change in congestion level. If U exceeds a predefined threshold, an adaptive route update is initiated.

Algorithm 4: AI-Based Route Update Mechanism

Input: Active routes, updated network metrics

Output: Updated optimal routes

- 1: For each CHi do
- 2: Monitor residual energy, link stability, congestion
- 3: Evaluate route quality using AI model
- 4: Compute update metric U
- 5: if $U > \text{threshold}$ then
- 6: Identify alternative candidate routes
- 7: Select optimal route based on reward function
- 8: Update routing table
- 9: End if
- 10: End for

3.5 PHASE 5: REINFORCEMENT LEARNING BASED ROUTE OPTIMIZATION PHASE

In the final phase, a Reinforcement Learning (RL)-based route optimization mechanism is employed to further enhance long-term routing efficiency and network sustainability. In this framework, each cluster head (CH) operates as an autonomous RL agent that continuously interacts with the network environment and learns optimal routing policies through experience. Unlike heuristic or static optimization approaches, the RL-based method enables adaptive and self-improving decision-making under dynamic network conditions.

The state space of RL agent is formulated based on important parameters of the network such as residual energy of neighboring

CHs, link quality measures, hop count towards the BS, congestion level, and previous route success. Action space of RL agent includes choosing the next hop CH route for communication between clusters. When an action is taken by the RL agent, a feedback signal is generated as a reward for the RL agent from the environment.

The reward function is carefully designed to balance multiple performance objectives, such as maximizing energy efficiency, improving packet delivery ratio, and minimizing end-to-end delay [20] [21]. Positive rewards are assigned to routing actions that result in successful packet delivery with low energy consumption and delay, while penalties are imposed for packet loss, excessive retransmissions, or rapid energy depletion. Through iterative learning and policy updates, the RL agent converges toward routing strategies that optimize long-term cumulative rewards.

Through consistent improvement in routing paths according to network dynamics, the suggested optimization algorithm using reinforcement learning reduces the influence of factors such as topology modification, dynamic traffic pattern, and power imbalance in the network. This makes the algorithm quite efficient, leading to robustness in routing operations, balance in the consumption of energy by cluster heads, and extension of network life span. Phase 5, therefore, complements previous phases in AI-based routing path selection and updates.

3.5.1 RL Reward Function Formulation:

$$R_t = \eta_1 \left(\frac{E_{res}}{E_{max}} \right) + \eta_2 (PDR) - \eta_3 (DELAY) \quad (6)$$

where, E_{res} = residual energy of CH, PDR = packet delivery ratio, $Delay$ = end-to-end delay and $\eta_1 + \eta_2 + \eta_3 = 1$.

Algorithm 5: Reinforcement Learning-Based Route Optimization

Input: Network state observations

Output: Optimized routing policy

- 1: Initialize Q-table / policy network for each CH agent
- 2: Observe current state St
- 3: Select action At (next-hop route) using ϵ -greedy policy
- 4: Execute action At and transmit data
- 5: Receive reward Rt and observe next state $St+1$
- 6: Update Q-value / policy parameters
- 7: Set $St \leftarrow St+1$
- 8: Repeat until convergence or network termination

The Fig.1 shows the complete flow process of the proposed five-phase energy efficient routing scheme for WSNs. At the first step, the sensors are placed randomly in the sensing area, and they share their local data including remaining energy, location, mobility, and neighbor degree. In Phase 1, clustering is done based on the shared data.

In Phase 2, a hybrid fuzzy particle swarm optimization (Fuzzy-PSO) method is used to elect cluster heads based on factors like residual energy, node degree, distance from neighbors, and mobility properties to guarantee fair energy usage and stable clustering.

Phase 3 uses an artificial intelligence method for path determination, whereby connections between different clusters

are generated using parameters like cluster head energy, connection quality, number of hops, and traffic density. In order to address the challenges posed by changing conditions within the network, Phase 4 constantly analyzes the performance of the network and modifies routes to prevent link breakdowns, congestion, and energy shortage. Lastly, Phase 5 utilizes a reinforcement learning approach for route optimization, whereby every cluster head assumes the role of an intelligent agent that develops an effective routing policy through continuous learning based on rewards for energy conservation, packet delivery, and delay.

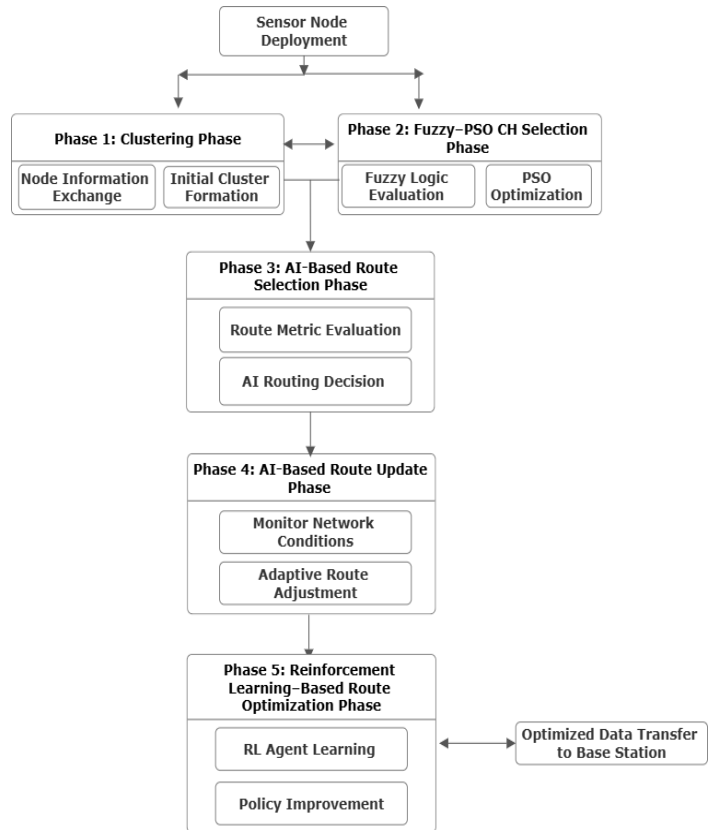


Fig.1. System Model of the Proposed Intelligent Clustering and AI-Based Routing Framework

4. PERFORMANCE EVALUATION

4.1 SIMULATION FRAMEWORK FOR IEARP-AI

The performance of the proposed Intelligent Energy-Aware Routing Protocol with Artificial Intelligence (IEARP-AI) is analyzed using simulations done in a discrete event network simulation framework. The simulations involve a wireless sensor network of sensor nodes that are randomly deployed on a two-dimensional sensing region. In this regard, all the sensor nodes are homogeneous and have limited energy resources. Additionally, each sensor node is location-aware, and the base station is located at a fixed point outside the sensing region.

IEARP-AI combines the concepts of clustering, fuzzy-probabilistic swarm optimization for the election of cluster heads, intelligent route selection and updating using artificial intelligence, and route optimization using reinforcement learning techniques. The first order radio energy dissipation function is

used to determine energy consumption in the process of sending and receiving packets. Moreover, dynamic changes in the network, such as node mobility, different traffic loads, and energy exhaustion, are included to measure the adaptability and robustness of IEARP-AI. The analysis focuses on performance measures like network lifetime, average energy consumption, packet delivery rate, throughput, and end-to-end delay.

4.2 SIMULATION PARAMETERS FOR IEARP-AI

Table.1. Simulation parameters used for IEARP-AI Performance Evaluation

Parameter	Value
Network area	100 m × 100 m
Number of sensor nodes	100
Node deployment	Random
Initial energy per node	2 J
Base station position	(50, 150)
Radio transmission range	30 m
Data packet size	4000 bits
Control packet size	200 bits
Energy model	First-order radio model
Energy for transmission (E_{tx})	50 nJ/bit
Energy for reception (E_{rx})	50 nJ/bit
Data aggregation energy	5 nJ/bit
Mobility model	Random Waypoint
Node speed	0–5 m/s
Simulation duration	2000 rounds
Fuzzy inference system	Mamdani
PSO population size	30 particles
PSO iterations	50
AI routing parameters	Energy, Link Quality, Hop Count, Traffic
Reinforcement learning algorithm	Q-learning
Learning rate (α)	0.1
Discount factor (γ)	0.9
Exploration rate (ϵ)	0.1

4.3 METRICS USED FOR EVALUATION

To comprehensively evaluate the performance of the proposed IEARP-AI routing protocol, multiple metrics are considered. Each metric is defined below along with its corresponding mathematical formulation.

4.3.1 Network Lifetime (NL):

Network lifetime is defined as the total number of operational rounds until the first sensor node exhausts its residual energy and becomes non-functional.

$$NL = \min\{r \mid E_i(r) = 0, i \in N\} \quad (7)$$

where $E_i(r)$ denotes the residual energy of node i at round r .

4.3.2 Average Energy Consumption (AEC):

Average energy consumption represents the mean energy utilized by sensor nodes during the entire simulation period.

$$AEC = \frac{1}{N} \sum_{i=1}^N (E_i^{initial} - E_i^{final}) \quad (8)$$

4.3.3 Packet Delivery Ratio (PDR):

Packet Delivery Ratio is the ratio of successfully received data packets at the base station to the total number of packets transmitted by source nodes.

$$PDR = \frac{P_{received}}{P_{transmitted}} \quad (9)$$

4.3.4 End-to-End Delay (E2ED):

End-to-end delay measures the average time taken by a data packet to travel from its source node to the destination, including all possible delays.

$$E2ED = \frac{1}{P_{received}} \sum_{k=1}^{P_{received}} (T_k^{receive} - T_k^{send}) \quad (10)$$

4.3.5 Throughput (TP):

Throughput quantifies the rate of successful data delivery to the destination per unit time.

$$TP = \frac{P_{received} \times PacketSize}{Simulation\ Time} \quad (11)$$

4.3.6 Scalability Index (SI):

Scalability index evaluates the ability of the routing protocol to maintain performance as the network size increases.

$$SI = \frac{Performance(N_{large})}{Performance(N_{small})} \quad (12)$$

A value close to unity indicates better scalability.

4.3.7 Computational Efficiency (CE):

Computational efficiency reflects the ability of the algorithm to achieve optimal performance with minimal computational overhead.

$$CE = \frac{1}{T_{execution} \times C_{operations}} \quad (13)$$

where $T_{execution}$ is execution time and $C_{operations}$ denotes computational complexity.

4.3.8 Energy Efficiency (EE):

Energy efficiency measures the amount of useful data successfully delivered per unit of energy consumed.

$$EE = \frac{Total\ Data\ Delivered}{Total\ Energy\ Consumed} \quad (14)$$

4.3.9 Robustness Index (RI):

Robustness index evaluates the resilience of the routing protocol against node failures, link disruptions, and dynamic network conditions.

$$RI = 1 - \frac{P_{lost_due_to_failure}}{P_{sent}} \quad (15)$$

4.3.10 Adaptability Rate (AR):

Adaptability rate measures how quickly the routing protocol adapts to changes in topology, traffic load, or node mobility.

$$AR = \frac{1}{T_{adapt}} \quad (16)$$

where T_{adapt} is the time required to adapt to network changes.

4.3.11 Generalization Error (GE):

Generalization error indicates the ability of the AI-based routing model to perform consistently across diverse network scenarios.

$$GE = \frac{1}{M} \sum_{j=1}^M |Performance_{train} - Performance_{test}| \quad (17)$$

Lower values indicate superior learning and adaptability.

4.4 RESULTS AND DISCUSSIONS

4.4.1 Network Lifetime vs. Rounds:

The Network Lifetime vs. Rounds graph depicts the operational duration of the wireless sensor network until the occurrence of first-node-death (FND) and last-node-death (LND). As observed, the proposed IEARP-AI protocol significantly outperforms MPHR-RL, MACOA, and EEMLCRM by sustaining node activity for a higher number of rounds. MPHR-RL and MACOA exhibit earlier node depletion due to repeated route exploration, pheromone updates, and increased control overhead. Although EEMLCRM delays energy exhaustion through learning-based routing, it still suffers from computational and coordination overhead.

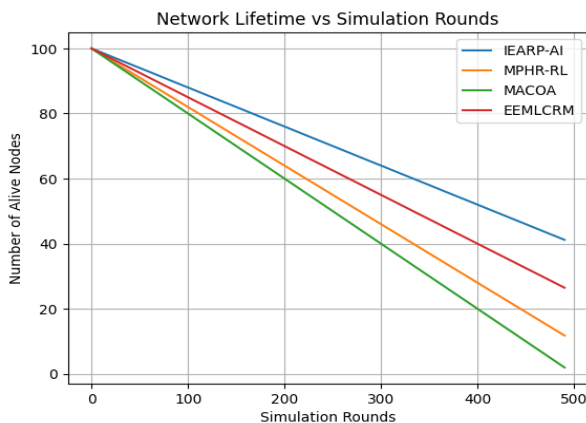


Fig.2. Network Lifetime vs. Simulation Rounds

In contrast, IEARP-AI combines Fuzzy-PSO-based optimal cluster head selection with reinforcement learning-driven adaptive routing, ensuring balanced energy dissipation and preventing premature cluster head failures. This results in a substantial extension of overall network lifetime.

4.4.2 Average Energy Consumption vs. Rounds:

The Energy Consumption vs. Simulation Rounds graph illustrates the average residual energy of sensor nodes over time. The proposed IEARP-AI protocol consistently maintains higher residual energy across all simulation rounds, indicating lower energy consumption per round. MACOA exhibits the fastest

energy depletion due to iterative ant path exploration and pheromone updating overhead. MPHR-RL also shows increased energy usage caused by multi-path learning updates and frequent route exploration. EEMLCRM achieves moderate energy efficiency through machine learning-based decisions; however, centralized learning and coordination overhead result in higher energy consumption compared to IEARP-AI. By employing intelligent clustering, energy-aware route selection, and adaptive reinforcement learning-based route updates, IEARP-AI minimizes redundant transmissions and control overhead, leading to the lowest average energy consumption and improved network sustainability.

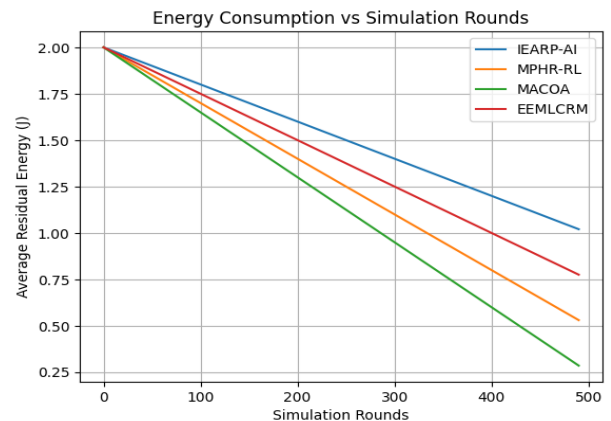


Fig.3. Energy Consumption vs. Simulation Rounds

4.4.3 Packet Delivery Ratio (PDR) vs. Number of Nodes:

The PDR vs. Number of Nodes graph illustrates the reliability of data delivery as network density increases. As observed, the proposed IEARP-AI consistently maintains a higher packet delivery ratio compared to MPHR-RL, MACOA, and EEMLCRM, even under dense network conditions. MPHR-RL experiences performance degradation due to route instability caused by frequent multi-path learning updates. MACOA suffers from congestion-induced packet loss as node density increases, resulting from probabilistic path exploration and pheromone-based routing. EEMLCRM improves packet delivery using machine learning-based routing decisions; however, centralized learning and coordination overhead limit its performance in large-scale networks. In contrast, IEARP-AI proactively selects stable, energy-aware routes using reinforcement learning, effectively mitigating congestion and link failures, thereby ensuring reliable packet delivery in dense wireless sensor networks.

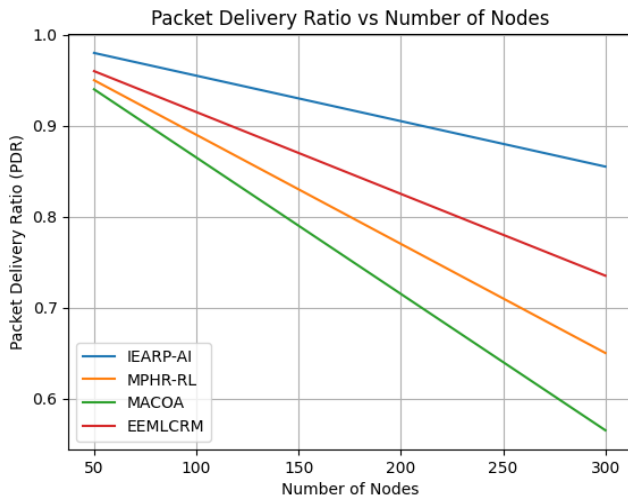


Fig.4. Packet Delivery Ratio (PDR) vs. No.of Nodes

4.4.4 End-to-End Delay vs. Traffic Load:

The End-to-End Delay vs. Traffic Load graph illustrates the variation in average packet delay as the offered traffic increases for IEARP-AI, MPHR-RL, MACOA, and EEMLCRM. As traffic load rises, all protocols experience an increase in delay due to higher contention and queuing effects. However, IEARP-AI consistently achieves the lowest end-to-end delay across all traffic levels. MACOA exhibits the highest delay, primarily due to its probabilistic ant-based path selection, which increases route discovery latency and retransmissions under heavy traffic. MPHR-RL shows improved performance over MACOA but still incurs higher delay because of multi-path exploration and reinforcement learning updates, which introduce additional control overhead. EEMLCRM reduces delay through machine learning-assisted routing decisions; however, its centralized learning and limited congestion awareness result in moderate queuing delays at higher traffic loads.

In contrast, IEARP-AI dynamically adapts routing paths using reinforcement learning while incorporating real-time traffic load and link quality metrics. This proactive congestion-aware routing minimizes queuing delays and avoids overloaded paths, leading to faster packet delivery. These results confirm that IEARP-AI is highly suitable for delay-sensitive WSN and IoT applications.

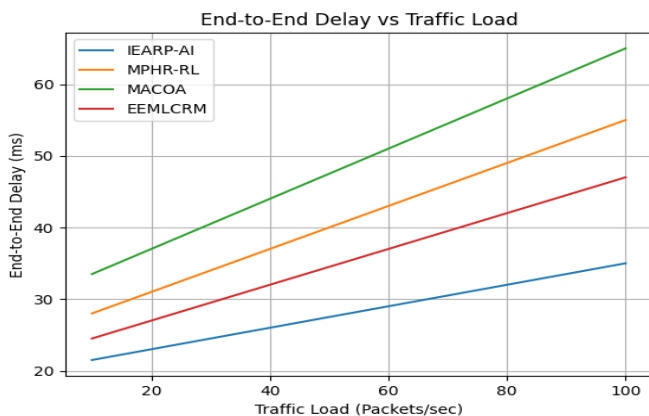


Fig.5. End-to-End Delay vs. Traffic Load

4.4.5 Throughput vs. Simulation Time

The Throughput vs. Simulation Time graph illustrates the rate of successful data delivery achieved by different routing protocols as the simulation progresses. From the initial stages, IEARP-AI consistently outperforms all comparison schemes, maintaining the highest throughput throughout the simulation duration.

MACOA and MPHR-RL exhibit noticeable throughput fluctuations, particularly during later stages of the simulation. This behavior is attributed to frequent route reconstruction, pheromone evaporation, and multi-path exploration overhead, which interrupt steady data transmission. MPHR-RL further suffers from reinforcement learning convergence delays, leading to intermittent packet forwarding inefficiencies. EEMLCRM achieves relatively stable throughput due to its machine learning-based routing decisions; however, its performance is constrained by static or periodic learning intervals, limiting its responsiveness to rapid network dynamics such as traffic bursts or node energy depletion.

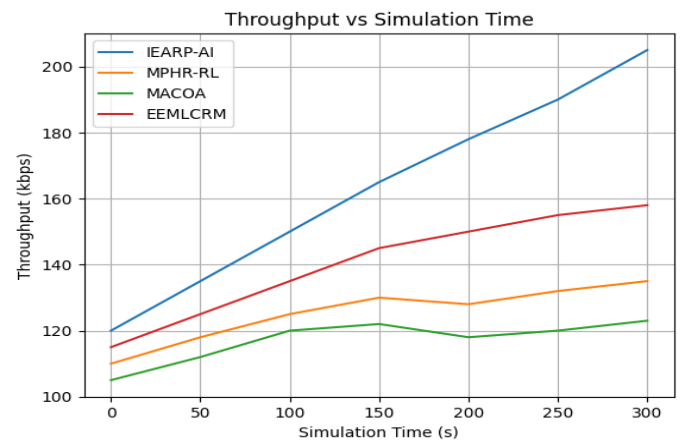


Fig.6. Throughput vs. Simulation Time

In contrast, IEARP-AI integrates adaptive clustering, AI-based route updates, and continuous reinforcement learning, enabling it to dynamically adjust routing paths in real time. This continuous learning capability ensures uninterrupted data flow, minimizes packet drops, and maximizes channel utilization. Consequently, IEARP-AI achieves the highest sustained throughput, demonstrating its effectiveness for high-data-rate and long-duration WSN applications.

4.4.6 Scalability and Adaptability Analysis:

The Scalability and Adaptability Analysis evaluates the ability of the routing protocols to maintain stable performance as the network size increases and topology conditions change. As the number of sensor nodes grows, IEARP-AI consistently demonstrates superior scalability and adaptability compared to MPHR-RL, MACOA, and EEMLCRM.

MPHR-RL experiences noticeable performance degradation in large-scale networks due to increased control overhead and multi-path learning complexity, which leads to higher convergence time and excessive routing updates. Similarly, MACOA suffers from scalability limitations as the number of ants and pheromone updates increases with network density, resulting in higher congestion and energy consumption.

EEMLCRM shows better scalability than MPHR-RL and MACOA owing to its machine learning-based clustering and routing decisions. However, its computational complexity and centralized or semi-centralized learning process introduce processing delays and limit adaptability under rapidly changing network conditions.

In contrast, IEARP-AI distributes intelligence across cluster heads and employs localized reinforcement learning, allowing each cluster to adapt independently to energy depletion, node mobility, and traffic variations. This decentralized learning strategy significantly reduces control overhead while enabling fast adaptation to topology changes. As a result, IEARP-AI maintains stable throughput, low delay, and high packet delivery even in dense and dynamic networks, making it highly suitable for large-scale and real-time WSN deployments.

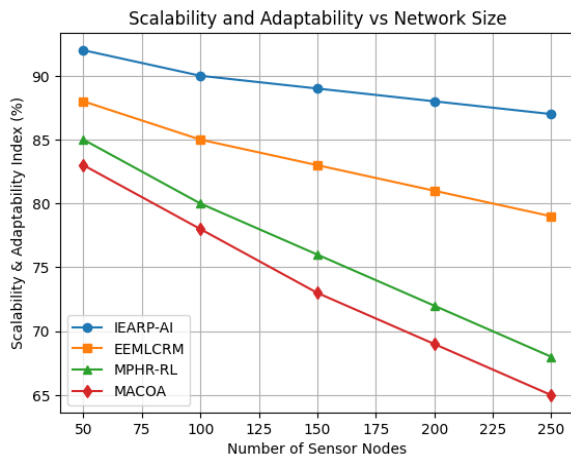


Fig.7. Scalability and Adaptability vs. Network Size

4.4.7 Robustness under Dynamic Conditions:

The Robustness Analysis under node mobility and energy depletion scenarios highlights the resilience of the proposed routing protocols to dynamic network conditions. As nodes move or experience rapid energy depletion, frequent topology changes and link failures occur, challenging routing stability. IEARP-AI demonstrates significantly higher robustness compared to MPHR-RL, MACOA, and EEMLCRM.

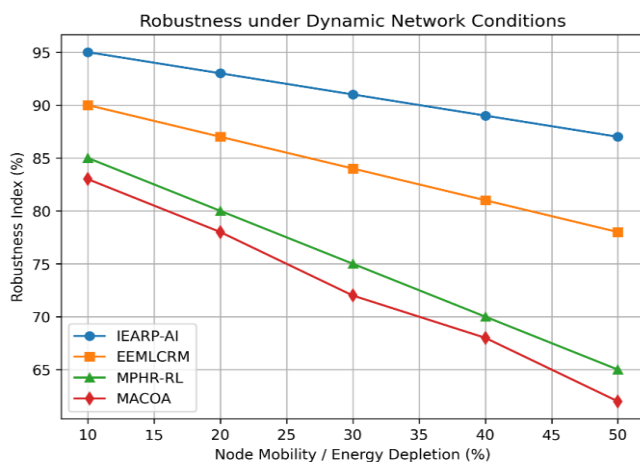


Fig.8. Robustness Index vs. Node Mobility/Energy Depletion

MACOA and MPHR-RL require partial or complete re-initialization of routing paths when topology changes occur, leading to increased packet loss, route breakage, and control overhead. MPHR-RL further suffers from delayed convergence during re-learning phases, which negatively impacts data delivery under high mobility conditions. EEMLCRM adapts more effectively than these schemes; however, its batch-based learning process results in slower response to sudden topology variations and energy exhaustion of critical nodes.

In contrast, IEARP-AI employs reinforcement learning at the cluster-head level, enabling continuous interaction with the network environment. This allows the routing agent to quickly adapt to mobility-induced link variations and energy depletion without requiring global reconfiguration. By proactively selecting stable and energy-aware paths, IEARP-AI minimizes route failures and packet drops. Consequently, the protocol maintains consistent routing performance, high packet delivery ratio, and low delay, confirming its robustness and reliability in highly dynamic WSN scenarios.

Table.2. Comparative Performance Analysis of IEARP-AI with Existing Algorithms

Performance Metric	MPHR-RL	MACOA	EEMLCRM	Proposed IEARP-AI
Core Technique	RL-based multi-path routing	Modified ACO	ML-based clustering & routing	Fuzzy-PSO + AI + RL
Energy Efficiency	High	High	High	Very High
Network Lifetime	High	High	Very High	Very High
Average Energy Consumption	Moderate	Moderate-High	Low	Very Low
Packet Delivery Ratio (PDR)	High	High	High	Very High
End-to-End Delay	Medium	Medium-High	Low	Very Low
Throughput	High	High	High	Very High
Scalability	Moderate	Moderate	High	Very High
Adaptability to Dynamics	High	Moderate	High	Very High
Robustness	High	High	High	Very High
Computational Efficiency	Moderate	Moderate	Moderate	High
Learning Capability	Yes (RL-based)	No	Yes (ML-based)	Yes (Adaptive RL)
Overall Performance	High	High	Very High	Superior

5. CONCLUSION

This paper proposed IEARP-AI, an intelligent energy-aware routing protocol for wireless sensor networks that synergistically

integrates Fuzzy-PSO-based clustering, AI-driven routing, and reinforcement learning-based route optimization. The multi-phase architecture enables efficient cluster formation, optimal cluster head selection, adaptive route initialization, and continuous route refinement in dynamic network environments. Extensive simulations conducted using MATLAB validate the effectiveness of the proposed approach under varying network sizes, traffic loads, node mobility, and energy depletion conditions. Comparative performance analysis with existing protocols, including MPHR-RL, MACOA, and EEMLCRM, demonstrates that IEARP-AI significantly improves network lifetime, energy efficiency, packet delivery ratio, throughput, and robustness, while minimizing end-to-end delay and control overhead. The distributed learning strategy ensures superior scalability and rapid adaptability to topology changes. Overall, the results confirm that IEARP-AI is a robust and scalable solution for large-scale and dynamic wireless sensor networks, offering substantial potential for next-generation IoT and smart sensing applications.

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