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AIP-Chain: An AI-Driven Hybrid Chain-Cluster Routing Protocol for Efficient WSNs

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ABSTRACT

Simple monitoring and data collection systems have widely adopted Wireless Sensor Networks (WSNs); however, they are limited by energy constraints and poor routing methodologies. Conventional clustering context- and chain-based routing schemes tend to cause energy overload and imbalance, leading to untimely node failures and a shorter network lifetime. In this paper, we propose the Artificial Intelligence-Powered Chain Routing Protocol (AIP-Chain), a chain-cluster routing protocol designed to improve energy consumption and network stability. The proposed method uses K-means clustering to group sensor nodes into energy-efficient clusters, while Particle Swarm Optimization (PSO) and fuzzy logic are implemented to select the best Cluster Heads (CHs) and Chain Leaders (CLs) depending on the remaining energy, communication distance, and node position. Unlike current Power-Efficient Gathering in Sensor Information Systems (PEGASIS)-based and AI-assisted routing schemes, AIP-Chain features an adaptive routing structure with a fault-conscious recovery mechanism to provide adaptive route reconfiguration in cases of energy imbalance and node failures. The wide-scale MATLAB simulations involving networks of various sizes and transmission ranges reveal that AIP-Chain performs remarkably better than benchmark protocols, such as PEGASIS, Hierarchical Power-Efficient Gathering in Sensor Information Systems (H-PEGASIS), Multi-hop Energy-efficient Network based on Ant Colony Optimization (MENACO), Deep Reinforcement Learning-Wireless Sensor Networks (DRL-WSN), Extended Power-Efficient Gathering in Sensor Information Systems (EPEGASIS), and Power-Efficient Gathering in Sensor Information Systems Based Chain Clustering (PEGA-LSCS). In particular, it extends the network lifetime by 2538 rounds, increases the stability period by 30 times, decreases the overall power usage by 2035 rounds, and speeds up packet delivery by as much as 15 times. These findings make it effective, scalable, and applicable in large-scale, energy-constrained WSN applications.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have emerged as an enabling technology across virtually all fields, including environmental sensing, smart cities, industrial automation, healthcare systems, and the Internet of Things (IoT) [1]. These networks are composed of many low-cost, low-power sensor nodes that are networked to sense, process, and transmit data to a base station (BS). Although this makes WSNs suitable across various applications and adaptable, the lack of access to energy resources inherently limits their applications, necessitating energy-efficient communication and routing, which is a major design consideration [2-5]. The routing protocols are significant in determining the overall performance and longevity of WSNs, as they directly govern how sensed data is relayed between sensor nodes and the BS [6]. Poor routing policies can lead to excessive power consumption, unbalanced load allocation, premature node failure, and instability in the network. As a result, considerable research has been directed towards the development of routing schemes that reduce energy usage while providing scalability, reliability, and data delivery performance [7]. Chain-based routing protocols have been included in the list of routing strategies proposed in the literature and have attracted significant interest for their performance in minimizing long-distance transmissions and controlling overhead. Power-Efficient Gathering in Sensor Information Systems (PEGASIS) is probably the most representative chain-based protocol, in which sensor nodes comprise a chain of communication, and a leader node collects all the data and forwards the combined data to the BS. PEGASIS, which uses data aggregation and localized communication, achieves significant energy savings over traditional clustering protocols [8]. PEGASIS and its variants, however, are plagued by several limitations, including the inability to form chains dynamically, inefficient leader selection, the inability to adapt to changing network conditions, and vulnerability to node failures. In large-scale, dense, or heterogeneous WSN deployments, these disadvantages are magnified [9]. To curb such problems, various improvements to PEGASIS have been proposed, including the use of optimization methods, multi-hopping, and smart decision-making processes. Although these solutions enhance specific features such as energy efficiency or network lifetime, most current solutions are based on either pure chain architecture or a clustering architecture. Consequently, they tend not to achieve balanced energy consumption, fault tolerance, and scalability simultaneously. In addition, most optimization-based protocols are single-objective, improvement-oriented, and lack adaptive recovery schemes that can respond efficiently to node failures and energy imbalance [10-12]. The recent development of Artificial Intelligence (AI) and swarm intelligence has opened new avenues for the development of adaptive, intelligent routing protocols for WSNs. Particle Swarm Optimization (PSO), fuzzy logic, and machine learning techniques are among the methods that have been successfully used to optimize the selection of Cluster Heads (CHs), routing paths, and energy management. Nonetheless, the main research problem is how to integrate these methods into a coherent routing architecture that integrates the benefits of both clustering and their chain-based communication [13].

These observations have inspired this paper to recommend the Artificial Intelligence-Powered Chain Routing Protocol (AIP-Chain), an AI-based hybrid chain-cluster routing protocol that improves energy efficiency, network lifespan, and resilience in WSNs. The protocol suggested combines K-means clustering to scale the network, PSO to select the CH to balance energy expenditure, and fuzzy logic to select the Chain Leader (CL) to provide stable, energy-sensitive data aggregation. Besides that, AIP-Chain also implements an adaptive recovery protocol, allowing the local re-configurability with respect to node failures and energy depletion, thus enhancing both fault tolerance and resilience of the network. A major body of simulation-based experiments shows that AIP-Chain has a better network lifetime, leftover energy, stability duration, Packet Delivery Ratio (PDR), and routing overhead, compared to classical and state-of-the-art chain-based routing protocols, such as PEGASIS, Hierarchical Power-Efficient Gathering in Sensor Information Systems (H-PEGASIS), Multi-hop Energy-efficient Network based on Ant Colony Optimization (MENACO), Deep Reinforcement Learning- Wireless Sensor Networks (DRL-WSN), as well as corresponding variants. These findings validate the fact that the proposed hybrid and intelligent routing model is an efficient and scalable utilization of energy-limited WSN settings. The present paper's contributions to the design of Energy-Efficient Routing (EER) in WSNs are as distinctive and non-trivial as follows:

• We suggest AIP-Chain, a new AI-based hybrid-chain/cluster routing protocol, which is not the traditional single-structure routing, but the dynamically combined clustering and chain-based communication with a single structure, allowing the balance of the energy consumption of heterogeneous sensor nodes.

• In contrast to current PEGASIS-based and AI-assisted protocols, AIP-Chain presents the adaptive cluster-chain formation mechanism that occurs due to the multi-criteria intelligence, so that the routing structure can be reconfigured based on residual energy, node distribution, and communication cost instead of being reconfigured based on the principles of static or distance-only assumptions.

• An intelligent cluster-head and CL selection strategy that integrates the K-means clustering algorithm with PSO and fuzzy logic to balance all three of the energy efficiency, transmission distance, and load balancing is developed-a combination that none of the previous studies on WSN routing address simultaneously.

• Our approach of creating a fault-conscious recovery scheme, which helps to alleviate node failure and untimely energy drain, is by means of allowing the reconstruction of the local routes, which contributes to network stability considerably more than the chain-based schemes that are currently used and do not consider the aspect of resilience.

• Simulation-based tests are performed on a huge variety of classical and state-of-the-art routing protocols (PEGASIS, H-PEGASIS), Multi-hop Energy-efficient Network based on Ant Colony Optimization (MENACO), DRL-WSN, Extended Power-Efficient Gathering in Sensor Information Systems (EPEGASIS), and Power-Efficient Gathering in Sensor Information Systems Based Chain Clustering (PEGA-LSCS), and prove that they yield consistent benefits to the network lifetime, residual energy distribution, the performance of packet delivery, and stability period.

• The presented framework can also demonstrate high scalability and energy sustainability with changing network density and transmission range, which makes it possible to be applied to large-scale WSN deployment when the chain-based or cluster-based approaches cannot sustain performance any longer. Balancing the amount of energy consumed by sensor nodes in the network could be achieved with the help of an energy-efficient aggregation-based load-balancing technique instead of using AI as an optimization supplement. The research proposes a dynamic combination of these two paradigms in one routing cycle, unlike the previous studies that use either clustering or chain-based routing only. Unlike the current AI-based WSN protocols, which are concerned with single-objective optimization, AIP-Chain is a protocol that, at the same time, tackles the issues of energy efficiency, load balancing, fault tolerance, and routing flexibility, offering a complete solution to the traditional WSN limitations. The intelligent decision framework suggested can also be viewed as extending past traditional distance-based heuristics and offers the ability to make context-sensitive routing decisions based on real network dynamics as opposed to theoretical assumptions.

As a result, AIP-Chain represents a conceptual and architectural advancement over existing routing. The rest of the paper includes: In Section 2, we discuss the most important previous studies that discussed the issue of energy optimization in protocols. In Section 3, we discuss the methodology of the proposed hybrid protocol, Section 4 scenario parameters clarification, and the results in Section. 5, and finally, Section 6 imitations and future improvements, and conclude our work in Section 7.

2. LITERATURE REVIEW

Using the Hierarchical Compressive Data Gathering (HCDG) for Hierarchical Grid-Based Routing (HGR) methods, Ghaderi and Sheikhan [14] proposed a novel algorithm for WSNs that consumes less energy. The sensor node data is validated by the HCDG, and the HGR transmits the data in batches systematically. The HCDG-HGR scheme, which, according to simulation results, performs better than the other models, can be used for various WSN applications. Kaddi et al. [15], proposed the Ant Colony Optimization Power-Efficient Gathering in Sensor Information Systems

(AC-PEGASIS) protocol was offered, which dynamically adjusts the chain shape relying on the power stage of nodes, as a completely unique technique for energy efficiency in WSNs within the nineteenth century. Compared with the conventional PEGASIS protocol, simulation effects showed substantial improvements in power efficiency and community lifetime. In study [16], an energy efficient method for WSNs is presented by incorporating K-means clustering, genetic based cluster optimization and data compression technique to increase the network lifetime and reduce the amount of energy consumption. The results showed that the stability of the network and energy consumption are reduced while the operation life is improved compared to the classical WSN routing techniques. Salih and Sulaiman [17] used two types of routing protocols, EER and Shortest Path Routing (SPR), to evaluate the performance and efficiency of WSN. The study aims to evaluate network efficiency and energy consumption using various performance metrics. Zheng et al. [18] applied the Multi-Objective Particle Swarm Optimization (MOPSO) set of rules to a proposed method for CH choice optimization in WSNs. Jiang and Zheng [19] introduced in there study a hybrid WSN routing algorithm is presented using a combination of Ant Colony Optimization (ACO) and minimizing the number of hops, which results in an improved energy efficiency, routing reliability and network lifetime. In the same manner, a routing protocol based on a modified firefly algorithm for the selection of dynamic CHs and an improved ACO for data transmission were proposed in study [20]. Bouakkaz and Derdour [21] proposed routing algorithm combining grid and chain structure, which changes the number of chain nodes based on community structure to reduce energy consumption and enhance stability. Aroba et al. [22] designed a hyper-heuristic Distributed Energy-Efficient Clustering (DEEC) Gaussian algorithm to generate optimal node localization and routing efficiency. Jabbar and Issa [23] considered energy-aware data aggregation and CH election as stated by the distance between nodes and residual energy. Srikanteswara et al. [24] employed PEGASIS and the Smart Traffic Light and Speed Detection/Smart Traffic Light for Sustainable Development (STLSD) algorithm for vehicle density and traffic control in smart cities. Sh. Ali et al. invented a hybrid model based on Firefly, Power-Efficient Gathering in Sensor Information System with Prediction Routing (PR-PEGASIS), and Active Distortion Control - Artificial Neural Network (ADC-ANN) to enhance power efficiency and data reliability. Prabakaran et al. [25] investigated the effect of kernel and hyperparameter choice on WSN performance. Finally, Patra et al. [26] introduced PEGA-LSCS, a multipath routing technology that combines swarm intelligence and PEGASIS to increase network scalability and energy efficiency. The network has demonstrated that the performance of various protocols varies in accordance with the simulation configuration and performance factors employed. The best approach will be determined by the requirements of the application and the specific characteristics of the network. Tagare and Narendra [27] applied and investigated the performance of Modified Improved Energy Efficient Protocol (MIEEPB) and the PEGASIS protocol in WSNs. The authors perform a comparative analysis of the energy consumption and network lifetime of the two protocols using simulation data. Choudhary et al. [28] explored and investigated the overall performance of several hierarchical routing protocols, which include PEGASIS in WSNs. The authors use the simulation consequences to evaluate the efficiency, strength intake, and standard existence of various additives. The analysis suggests that the PEGASIS protocol has advanced performance in terms of network longevity and energy intake. The study [29] aims to assess the performance of electricity storage schemes for wireless sensor structures. Research has proven that the performance of different protocols varies consistently with the simulation setup and performance parameters used.

The combination of multi-objective optimization and evolutionary intelligence with hybrid routing protocols for WSN has become a growing trend. Several methods have been developed that use sophisticated optimization methods like Non-Dominated Sorting Genetic Algorithms (NSGA-II, NSGA-III) , multi-objective evolutionary algorithms, or deep reinforcement learning to enhance energy balancing, routing scalability, and adaptive communication in dynamic networks. For instance, Moshref et al. [30] had introduced an improved non-dominated sorting genetic routing algorithm for the purpose of enhancing quality of services and routing efficiency in WSNs by making use of multi-objective optimization methods. Al Mazaideh and Levendovszky [31] also presented a multi-hop routing based on compressive sensing and multiple-objective genetic optimization to enhance network longevity and dependability in energy-constrained WSNs. The layered and adaptive evolutionary routing frameworks were also investigated recently to deal with dynamic topology changes and fault tolerance. Taleb and Benalia presented a comparison of two evolutionary algorithms: NSGA-II and Strength Pareto Evolutionary Algorithm 2 (SPEA-II) to deploy the WSN in a smart farming application with optimized connectivity and optimized energy coverage [32]. Zhang et al. [33] also presented a Multi-Objective Ant Lion Optimization Scheme with Fuzzy Clustering (MOALO-FCM) to optimize the energy consumption of relay-nodes and enhance Pareto-based routing efficiency in large-scale WSNs. Further, the implementation of reinforcement learning and adaptive routing based on AI has demonstrated beneficial impacts on energy efficiency and intelligent routing flexibility in varying network contexts [34]. Recent advancements in AI-driven routing protocols for WSNs have increasingly focused on intelligent decision-making strategies capable of dynamically adapting to changing network conditions. Contemporary approaches integrate fuzzy heuristics, metaheuristic optimization, reinforcement learning, and machine learning models to improve routing efficiency, energy balancing, scalability, and communication reliability in resource-constrained WSN environments [35, 36]. These intelligent approaches attempt to overcome the limitations of traditional static routing schemes by enabling adaptive and context-aware routing behavior.

Despite the promising improvements achieved by AI-assisted routing protocols, several important challenges remain unresolved. Many existing AI-driven methods suffer from increased computational complexity, higher routing overhead, and limited adaptability in heterogeneous or dynamically changing network environments. In particular, several protocols focus mainly on cluster-head optimization while neglecting routing flexibility, fault tolerance, and autonomous recovery mechanisms under node failures and energy imbalance conditions [37]. Furthermore, reinforcement learning and deep learning-based approaches often require excessive training overhead, memory consumption, or centralized decision-making, which may not be suitable for lightweight WSN deployments. Recent studies have also highlighted the importance of combining multiple intelligent techniques to achieve balanced routing optimization. For example, hybrid PSO-Fuzzy approaches have demonstrated improved cluster-head selection and adaptive routing flexibility by integrating energy-aware optimization with uncertainty-tolerant decision systems [38]. Similarly, AI-driven autonomous routing frameworks employing swarm intelligence and adaptive learning mechanisms have shown significant potential for improving packet delivery, routing scalability, and topology adaptability under dynamic WSN conditions. Nevertheless, limited attention has been given to unified hybrid architectures that simultaneously integrate clustering, chain-based communication, intelligent role assignment, fault-aware recovery, and adaptive routing flexibility within a single scalable framework. Moreover, heterogeneous deployment environments and autonomous decentralized routing decisions remain insufficiently addressed in most existing studies. These limitations motivate the development of the proposed AIP-Chain protocol, which combines K-means clustering, PSO optimization, fuzzy-logic decision making, and adaptive fault recovery into an integrated AI-driven routing architecture for energy-efficient and resilient WSN operation.

While these progressions have been achieved, current solutions focus mainly on optimizing clustering structures or routing paths without considering joint hybrid architectures that simultaneously consider energy balancing, fault-tolerance, adaptive recovery, and intelligent role reassignment. The proposed AIP-Chain protocol, however, introduces a novel intelligent protocol for the communication of an energy-efficient, scalable WSN that combines the following: (1) the K-means clustering algorithm, (2) a PSO-based CH selection algorithm, (3) a Fuzzy logic-based chain head selection protocol, and (4) an adaptive fault-aware recovery protocol. The best approach will be determined by the requirements of the application and the specific characteristics of the network. Table 1 provides a summary of the prior research, highlighting the methods used and the essence of the study. It examines the characteristics, limitations, developments, and assumptions used in this literature.

Table 1. Identifies key past studies and their methods and hypotheses

Ref.	Method	Focused on	Advantage	Disadvantage	Simulator
[27]	Implementation, Performance Analysis	Power Efficiency, Protocol Comparison	Performance evaluation, Protocol comparison	No novel protocol proposed	NS-2
[28]	Study, Analysis	Hierarchical Routing	Improved understanding of hierarchical routing	No novel protocol proposed	NS-2
[29]	Efficiency Evaluation	Power Efficiency	Performance evaluation, Improved efficiency	No novel protocol proposed	NS-2
[39]	Biomedical sensor node	cardiovascular monitoring	Improves power efficiency and communication	Limited focus on network scalability	MATLAB
[40]	Energy-aware grid-based clustering	Energy efficient data aggregation and clustering in WSNs	minimizes energy consumption and enhances network lifetime	For dense deployments, the overhead of increased clustering.	MATLAB
[41]	Multipath Routing, Delay-Sensitivity	Power Efficiency, Precision Farming	Reduced energy consumption, Timely data transmission	Increased complexity in routing	NS-2
[42]	Comparative Analysis	Power Efficiency, Clustering	Better understanding of protocol performance	No novel protocol proposed	NS-2
[43]	Energy Cost Calculations, Mobile-Sink	Power Efficiency, Information Gathering	Better understanding of energy costs, Improved data gathering	No novel protocol proposed	MATLAB
[44]	Sector-based clustering scheme	Improving WSN lifetime	Improved reliability and energy efficiency	May lead to unbalanced cluster formation	NS-2
[45]	Markov-clustering routing protocol	Optimizing WSN energy consumption	Improved energy efficiency and network lifetime	Increased complexity and overhead	NS-2
[46]	Energy-efficient clustering and DRL-based sleep scheduling	Refining WSN network lifetime	Improved energy efficiency and network lifetime	Increased complexity and overhead	NS-2
[47]	Improved clustering protocol	Increasing WSN lifetime	Improved energy efficiency and network lifetime	Increased complexity and overhead	NS-2
[48]	Energy model for WSN and routing protocol optimization	Optimizing energy use in WSN	Improved energy efficiency and network lifetime	May not consider real-world variables	NS-2
[49]	Cluster optimization for PEGASIS protocol	Optimizing node clustering in PEGASIS protocol	Improved energy efficiency and network lifetime	May not be suitable for other routing protocols	NS-2
[50]	Greedy function and PSO for data transmission in WSN	Optimizing data transmission in WSN	Improved energy efficiency and network lifetime	Increased complexity and overhead	NS-2
[51]	Dragonfly algorithm	Optimizing PEGASIS	Improved energy	Increased complexity	NS-2

for intensifying PEGASIS protocol in WSN	in WSN	efficiency and network lifetime	and overhead

Note: PEGASIS = Power-Efficient Gathering in Sensor Information Systems

2.1 Technical comparison with state-of-the-art routing protocols

Unlike traditional PEGASIS-based routing approaches that rely mainly on static chain construction and predefined leader rotation mechanisms, the proposed AIP-Chain protocol introduces adaptive intelligent decision-making through the integration of PSO optimization and fuzzy-logic-based routing control. Conventional chain-based protocols typically select CL using fixed rotational scheduling or shortest-distance criteria, which may lead to rapid energy depletion of critical nodes and unbalanced communication overhead. In contrast, the fuzzy logic subsystem in AIP-Chain dynamically evaluates candidate nodes based on residual energy, hop count, and communication stability, allowing context-aware and energy-adaptive CL selection under changing network conditions. Similarly, many existing optimization-based protocols focus only on cluster-head selection or routing-path optimization independently. The proposed PSO-based cluster-head election mechanism jointly considers residual energy, node centrality, and communication distance to improve load balancing and reduce excessive transmission costs. This multi-criteria optimization strategy contributes to extending network lifetime and maintaining stable energy distribution among sensor nodes. Table 2 provides a comparative analysis of routing architectures and optimization strategies in recent WSN protocols. Compared with deep-learning or reinforcement-learning routing approaches, AIP-Chain provides lower computational complexity and reduced training overhead while still maintaining adaptive routing flexibility and autonomous decision capability. Furthermore, unlike several existing protocols that require global route reconstruction after node failures, AIP-Chain employs localized fault-aware recovery mechanisms that minimize routing overhead and improve communication continuity. Although the integration of multiple intelligent components may introduce moderate computational overhead compared to purely static routing protocols, the obtained improvements in network lifetime, PDR, fault tolerance, and routing adaptability demonstrate the practical advantages of the proposed architecture in dynamic WSN environments.

The comparison demonstrates that AIP-Chain differs from existing routing protocols not only in terms of performance metrics but also at the architectural and decision-making levels. The integration of PSO optimization with fuzzy-logic-based adaptive routing enables simultaneous optimization of energy efficiency, routing flexibility, and communication stability. Moreover, the proposed localized recovery mechanism provides improved resilience against node failures while avoiding the excessive routing overhead associated with global route reconstruction techniques. Despite the achieved performance improvements, the integration of multiple intelligent optimization components may increase computational complexity compared with lightweight static routing approaches, particularly in extremely resource-constrained WSN deployments.

Table 2. Technical comparison with state-of-the-art routing protocols

Protocol	CH Selection	Leader Selection	AI-Based	Adaptive Routing	Fault Recovery	Energy Balancing
PEGASIS [9]	Static Rotation	Distance-based	No	Limited	No	Weak
H-PEGASIS [49]	Hierarchical	Static	No	Moderate	No	Moderate
MENACO [19]	ACO + GA	Optimization-based	Partial	Moderate	Limited	Good
DRL-WSN [46]	DRL-based	Learning-based	Yes	High	Moderate	Good
PEGA-LSCS [26]	Swarm Optimization	Static Hybrid	Partial	Moderate	Limited	Moderate
AIP-Chain	PSO-based	Fuzzy Logic	Yes	High	Local Adaptive Recovery	Strong

Note: Artificial Intelligence-Powered Chain Routing Protocol (AIP-Chain); Multi-hop Energy-efficient Network based on Ant Colony Optimization (MENACO); Power-Efficient Gathering in Sensor Information Systems (PEGASIS); Deep Reinforcement Learning- Wireless Sensor Networks (DRL-WSN)

2.2 Research gap

Despite recent improvements in hybrid and AI routing protocols for energy-optimized routing and energy efficiency in WSNs, some limitations remain. Some of the previous works focus mainly on the clustering optimization problem, others on the chain-based communication problem, and a few works have been devoted to integrated adaptive networks that deal with energy balancing, fault tolerance, scalability, and dynamic route recovery. Additionally, most of the recent optimization-based protocols are single-objective-based protocols and have no intelligent local reconfiguration mechanism when nodes fail. Thus, a strong hybrid routing scheme incorporating intelligent cluster, adaptive chain, multi-criteria decision making, and fault-aware recovery in a scalable unified architecture is still required.

3. METHODOLOGY OF THE PROPOSED HYBRID PROTOCOL

In this proposal, we present a new hybrid routing protocol called AIP-Chain for WSN. The AIP-Chain model is designed to overcome the limitations of traditional chain -based protocols through the intelligent grouping of chain formation and adaptive data forwarding. The model integrates the Group K group for the optimal formation of the group, the optimization of PSO for the efficient selection of the CH, and the diffuse logic to dynamically choose the leaders of the chain CLs depending on the residual energy, the stability of the link, and the number of nodes. Through this intelligent coordination, the AIP-Chain model improves energy efficiency, tolerance to failures, and scalability, which affects the useful life of the longest network and the delivery of more reliable data in various WSN applications. A proposed hybrid protocol that combines the best features of PEGASIS, Low-Energy Adaptive Clustering Hierarchy (LEACH), and intelligent optimization techniques into new protocol architecture designed for energy efficiency, scalability, and adaptability in WSNs. The AIP-Chain architecture consists of five main layers:

- Grouping layer: The sensor nodes are organized in groups using the K-means algorithm. This guarantees a scalable organization, especially in large or dense networks.
- CH selection layer: Within each group, the CH is chosen using PSO, equilibrium energy, distance and connectivity.
- Chain formation layer: A local greedy chain is formed within each cluster (such as PEGASIS) for efficient intra-cluster communication.
- CL and aggregation layer: A CL is selected using fuzzy logic based on residual energy, hop count and data priority. The aggregate data are optionally compressed (using DCT or Huffman) and are forwarded to CH.
- Data transmission and recovery layer: CHs forward the data to the BS using the transmission of multiple jumps. In case of node failure, a local error-switching mechanism triggers automatic seclusion and leader re-election. Figure 1 illustrated AIP-Chain Protocol Architecture. Figure 2 shows the flowchart of the proposed protocol.

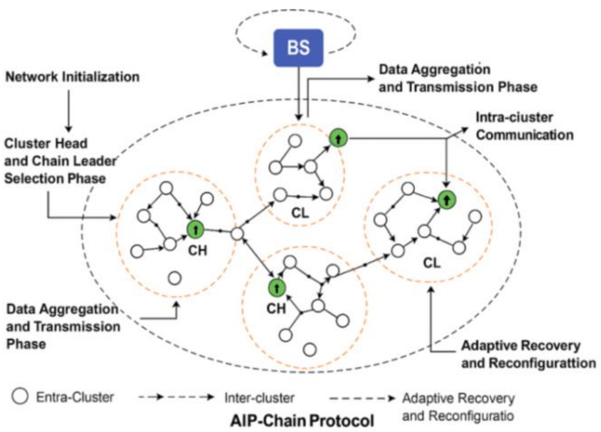


Figure 1. The proposed Artificial Intelligence-Powered Chain Routing Protocol (AIP-Chain) protocol architecture

3.1 Network deployment

In the proposed AIP-Chain model, a WSN is implemented in a two -dimensional square area of 100 m × 100 m. A total of 100 sensor nodes are randomly distributed throughout the field in an open environment. These nodes are stationary and homogeneous in terms of energy and detection capabilities. A single BS is placed in the center of the monitored area to collect. The Euclidean distance is calculated in Eq. (1):

$$D=\sqrt[2]{(xi - xk)^2 + (yi - yk)^2} \quad (1)$$

- The centroid is updated by averaging all node positions in the cluster.
- The algorithm converges when centroids no longer move significantly or after a set number of iterations.

3.2 K-means initialization and convergence criteria

To ensure that the initial centroids are stable and to decrease the overlapping of centroids, nodes were randomly initialized according to a distance-aware algorithm based on the spatial distribution of nodes. The first centroid was randomly selected from the deployed sensor nodes, and the other centroids were added to the nodes that are at a certain distance from the previous centroids that have been added. This approach is effective in ensuring the coverage of the clusters and prevents the emergence of an unbalanced cluster setup in high-density deployment areas. The centroid locations and assignments to nodes are updated iteratively until one of the following convergence conditions is met: (1) The difference between the centroids of two consecutive iterations is less than a specified value (ε = 0.001), (2) the maximum number of iterations (MaxIter = 100) is achieved. The number of clusters (K) was taken experimentally based on node density and communication overhead to keep the intra-cluster energy usage balanced. Algorithm 1 illustrates the pseudo code for K-means clustering.

Algorithm 1: Procedure K-means Clustering (Nodes, K)

```
Input:
    - Nodes: List of sensor nodes with 2D coordinates
    - K: Desired number of clusters
Output:
    - Clusters: List of K clusters with assigned node memberships
// Step 1: Initialization
Randomly select K nodes as initial cluster centroids
For each centroid Ck in K:
    Set centroid_position[k] = position of selected node
Repeat until convergence (no centroid movement or max_iterations reached):
  // Step 2: Assignment Step
    For each node Ni in Nodes:
      For each centroid Ck:
        Compute Euclidean distance D = || Ni.position - Ck.position ||
      Assign node Ni to the cluster with the nearest centroid
  // Step 3: Update Step
    For each cluster Ck:
      Recompute centroid_position[k] = average position of all nodes assigned to Ck
End Repeat
Return list of clusters with assigned node IDs
End Procedure
```

3.3 Cluster Head and Chain Leader selection phase

Within each cluster, a CH is selected using PSO based on: residual energy, node centrality, and distance to BS. Inside each cluster, a CL is selected via Fuzzy-logic-based scoring that considers energy, link stability, and hop count.

A. Select the best CH within each cluster using PSO, in terms of residual energy, location, and node density. The selected CH is presented in Algorithm 2, which uses the PSO algorithm. Chain members of a cluster together, in a greedy fashion, beginning with the most distant node.
B. CL selection based on fuzzy logic: Nodes are ranked

based on a fuzzy rule based on energy, hop count, and priority. Choose the most appropriate CL to cluster and send data. CL selection is explained in Algorithm 3, where fuzzy logic is used.

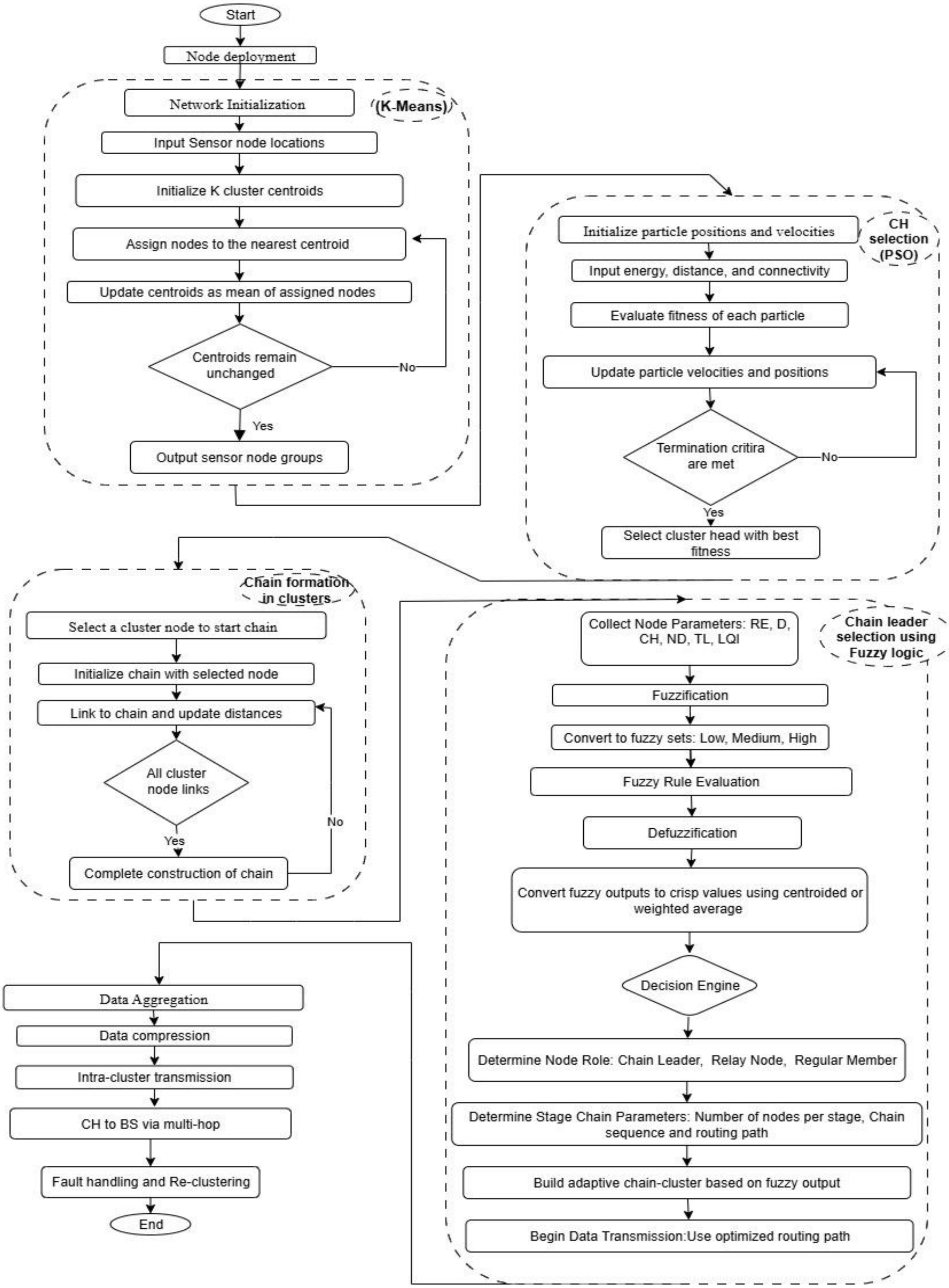


Figure 2. Flowchart for proposed Artificial Intelligence-Powered Chain Routing Protocol (AIP-Chain) protocol

Algorithm 2: Procedure Select Cluster Head Using PSO (cluster_nodes, BS_position)

```
Input:
    - cluster_nodes: list of nodes within a particular cluster.
    - BS_position: coordinates of the base station
Output:
    - Selected Cluster Head (CH)
// Step 1: Initialize Parameters
Set swarm_size = number of candidate nodes
For each particle i in the swarm:
    Initialize position[i] = position of node[i]
    Initialize velocity[i] = random small vector
    Set personal_best[i] = position[i]
    Calculate fitness[i] using fitness_function(node[i])
    Set global_best = personal_best of best particle
// Step 2: PSO Iteration
For t = 1 to max_iterations:
    For each particle i in swarm:
        Update velocity[i] using:
            velocity[i] = w * velocity[i]
                        + c1 * rand() * (personal_best[i] - position[i])
                        + c2 * rand() * (global_best - position[i])
        Update position[i] = position[i] + velocity[i]
        Update fitness[i] = fitness_function(node[i])
        If fitness[i] > fitness(personal_best[i]):
            personal_best[i] = position[i]
        If fitness[i] > fitness(global_best):
            global_best = position[i]
// Step 3: Select Node Closest to global_best as CH
Find node that has position closest to global_best
Indicate this node as CH
End Procedure
```

Algorithm 3: Procedure Fuzzy Chain Leader Selection (cluster_nodes)

```
Input:
    - cluster_nodes: List of nodes in a cluster (excluding the CH)
Output:
    - Selected Chain Leader (CL)
// Step 1: Define Input Parameters
For each node Ni in cluster_nodes:
    Retrieve:
        - Energy_Level(Ni): normalized to [0, 1]
        - Hop_Count(Ni): normalized inverse value (lower hop = higher score)
        - Priority(Ni): context-based (e.g., link stability, urgency)
// Step 2: Apply Fuzzy Inference Rules
For each node Ni:
    Apply fuzzy rules, for example:
     Rule 1: IF Energy is High AND Hop_Count is Low AND
             Priority is High THEN Score is Very High
     Rule 2: IF Energy is Medium AND Hop_Count is Medium
             THEN Score is Medium
     Rule 3: IF Energy is Low OR Priority is Low
             THEN Score is Low
    Use fuzzy membership functions (trapezoidal)
    Compute fuzzy production score ([0 to 1])
// Step 3: Defuzzification and Selection
For each node Ni:
    Defuzzify the fuzzy output to get a crisp value Score_Ni
Take node with biggest Value of Score_Ni as CL
Set node Ni as CL in cluster
End Procedure
```

3.3.1 Particle Swarm Optimization parameter configuration

The parameter values of the PSO algorithm for the cluster-head selection were set according to the parameter values of the cluster-head selection in WSN optimization, a problem that was taken from the literature and was experimentally proven. The inertia weight (w) was set to 0.9 and then slowly reduced to 0.4 along the iterations of the optimization process in order to enhance the exploitation/exploration trade-off. c1 = 2 and c2 = 2 were used for the cognitive and social acceleration coefficients, respectively. The number of candidate nodes in each cluster was used to dynamically determine the size of the swarm, and 50 iterations were set as a fixed maximum for optimization iterations. The optimization process stops if the number of iterations exceeds 10,000, or if the global fitness value is not improved by more than 10^{-4} on two successive iterations. The parameter configuration was experimentally optimized to ensure stable cluster-head selection results, low computation load, and energy distribution.

The fitness function is evaluated in Eq. (2) to calculate how suitable a node is to become CH:

$$Fitness = \alpha \times RE + \beta \times (1 - dTBS) + \gamma \times (1 - dTCC) \qquad (2)$$

- α, β, γ: weight coefficients (0.4, 0.3, 0.3)
- RE: normalized_residual_energy prefer nodes with more remaining energy
- dTBS: normalized_distance_to_BS prefer nodes closer to BS
- dTCC: (normalized_distance_to_cluster_center): like nodes closer to the center node (greater coverage).

3.3.2 Fuzzy logic rule design

An empirical finding was made by running multiple simulation tests in a WSN environment to construct the fuzzy inference system for selecting the CL. Three main input variables to the fuzzy decision process are "residual energy", "hop count" and "link priority/stability". The linguistic variables like 'Low', 'Medium', 'High' and 'Near', 'Moderate', 'Far' were represented by triangular and trapezoidal membership functions, respectively. The fuzzy rules have been designed so as to give priority to nodes that have high residual energy, stable communication links, and lower routing overhead. For instance, nodes with higher energy level and lower hop-count were given higher leadership scores, and nodes with lower energy levels or unstable links were given lower selection priority. The centroid method was used for defuzzification to get crisp decision scores for the CL election. The fuzzy rules were then iteratively adjusted in the preliminary simulation experiments to increase the stability of routing and balance the energy utilization under dynamic network conditions.

3.3.3 Development and validation of fuzzy logic rules

In AIP-Chain, the fuzzy inference system was designed based on empirically derived routing heuristics from preliminary simulation experiments and the known energy-aware communication principles in the WSN environment. The goal of the fuzzy-rule design process was to choose routing decisions that best maintain energy balancing, communication stability, and adaptive chain reliability, while varying network conditions. Three main input variables were considered for the construction of the rules: (1) residual energy, (2) hop count, (3) link stability/priority.

These parameters were chosen due to their direct impact on the efficiency of the communication, routing overhead, and node lifetime in chain-based routing structures. Residual energy is used to measure node sustainability; hop count measures the cost of communications; link stability measures the reliability of communication and continuity of routing. A fuzzy set of rules was refined through a series of simulations by observing the routing behaviors that yielded a longer network lifetime and equal energy consumption. In the experiments, for instance, nodes with high residual energy, high stability of communication links and lower hop counts performed well as CLs. Some fuzzy representative rules are verified in Table 3.

Triangular and trapezoidal membership functions were used to model the linguistic variables Low, Medium, and High. The centroid method was used to defuzzify the output for each of the chains for the purpose of crisp decision scores to be used for final CL selection. A set of fuzzy-rule configurations was obtained after repeated simulation experiments, and the network lifetime, residual energy distribution, and routing stability were tracked under different traffic and failure scenarios to validate the configuration.

Table 3. Representative fuzzy rules for Chain Leader (CL) selection

Rule No.	Energy	Hop Count	Link Stability	Output Score
R1	High	Low	High	Very High
R2	Medium	Medium	Medium	Medium
R3	Low	High	Low	Very Low
R4	High	Medium	High	High
R5	Medium	Low	Medium	High

3.4 Data aggregation and transmission phase

The data aggregation and transmission phase is the process of efficiently gather, compress and transmit sensed data to the BS. This phase reduces the amount of communication overheads and energy usage in the cluster by using adaptive chain based intra-cluster communication and multi-hop inter-cluster routing.

- Intra-Cluster communication: Nodes arrange into a chain, and send data to the CL, where data is subject to data fusion/compression.
- Inter-cluster communication: The aggregated data is sent by each CL to the CH. Multi-hop routing by CHs is to send data to the BS, and minimizes the long-range transmission energy. Data aggregation by CL; nodes send data to their predecessor in the chain.
- The CL aggregates the collected data.
- Health Monitoring: Checks each node's status and energy.
- Self-Healing Logic: Automatically re-elects CH or CL if failure is detected.
- Dynamic Clustering: Triggers re-clustering if the cluster becomes too small or imbalanced.
- End or Repeat for Next Round. Algorithm 4 explains data aggregation.

Algorithm 4: Procedure Data Aggregation by Chain Leader (cluster_nodes, CL_node)

```
Input:
    - cluster_nodes: List of nodes in a cluster (in a chain)
    - CL_node: Chain Leader node that receives data
Output:
    - Aggregated_Data: Single fused and compressed data
    packet ready for transmission
  // Step 1: Initialize Data Packet
  Initialize Aggregated_Data = empty
  // Step 2: Collect and Fuse Data from Nodes
  For each node Ni in cluster_nodes:
      If Ni is alive AND Ni ≠ CL_node:
          Sense local data: Di
          Apply optional preprocessing (filtering, thresholding)
          Transmit Di to next node in chain toward CL_node
          If node is near CL_node:
              Apply compression → Di_compressed
              Aggregated_Data ← Aggregated_Data + Di_compressed
  // Step 3: Final Aggregation at CL
  CL_node receives all Di_compressed
  Perform data fusion (averaging, prioritization, elimination of duplicates)
  Store final Aggregated_Data for forwarding to CH
  Return Aggregated_Data
End Procedure
```

3.5 Adaptive recovery and reconfiguration

The proposed AIP-Chain protocol provides an adaptive recovery and reconfiguration mechanism to enhance network reliability and ensure continuity of communication during dynamic conditions of WSNs. This mechanism constantly checks the status of nodes, reserves of energy and the stability of routing, and restores the network activity in a dynamic way when a failure occurs, while keeping the routing overhead as low as possible.

- On node failure or energy decreasing to a threshold.
- The cluster auto-invokes reformation with backup nodes.
- Should the CH or CL fail, the closest node of high energy based on energy-sensitive failover mechanism takes over. Re-clustering or re-election of leader to keep the network running. The adaptive recovery and reconfiguration is presented in Algorithm 5.
- Health Monitoring: Checks each node's status and energy.
- Self-Healing Logic: Automatically re-elects CH or CL if failure is detected.
- Dynamic Clustering: Triggers re-clustering if the cluster becomes too small or imbalanced.
- End or Repeat for Next Round.

Algorithm 5: Procedure Fault Handling and Adaptive Reconfiguration (cluster_nodes)

```
    Input:
        - cluster_nodes: List of nodes in a cluster, including CH and CL
        - Threshold_Energy: Minimum energy required to remain active
    // Step 1: Monitor Node Health
    For each node Ni in cluster_nodes:
        If Ni.energy ≤ Threshold_Energy OR Ni.status = DEAD:
            Mark Ni as INACTIVE
            // Step 2: Handle CL or CH Failure
            If Ni is Chain Leader (CL):
                Select new CL using fuzzy logic:
                    - Choose node with highest fuzzy score (energy, hop count, priority)
                    - Assign new CL
```

```
                - Broadcast CL update to cluster
        Else if Ni is Cluster Head (CH):
            Select new CH using PSO:
                - Evaluate candidates in cluster
                - Choose node with best fitness score
                - Assign new CH
                - Broadcast CH update to cluster
    // Step 3: Re-cluster if Cluster Stability is Lost
    Count ACTIVE nodes in cluster
    If ACTIVE node count < Recluster_Threshold:
        Re-run K-means clustering
        Re-select CH via PSO
        Re-select CL via Fuzzy Logic
    // Step 4: Resume Normal Operation
    Update network routing table
    Resume data collection and transmission
End Procedure
```

3.5.1 Fault detection and recovery mechanism

In the proposed AIP-Chain protocol, node failures are detected using a lightweight monitoring mechanism based on periodic heartbeat signaling, residual energy tracking, and communication timeout observation. Each CH and CL periodically exchanges status packets with neighboring nodes during routing rounds. A node is considered failed when one or more of the following conditions occur:

1. Residual energy drops below the predefined operational threshold (Threshold_Energy).
2. Consecutive heartbeat packets are not received within a specified timeout interval. A sensor node is considered inactive or failed when periodic heartbeat/status packets are not received for a predefined number of consecutive monitoring intervals, indicating possible energy depletion, communication failure, or node disconnection.
3. Repeated packet forwarding failures or communication interruptions are detected.

Once a failure condition is identified, the protocol activates a localized recovery procedure instead of reconstructing the entire network topology. For ordinary sensor node failures, neighboring nodes dynamically bypass the failed node through local chain re-linking. In the case of CL failure, a new CL is selected using the fuzzy logic decision system based on residual energy, hop count, and link stability. Similarly, CH failure triggers a local PSO-based re-election process within the affected cluster. To avoid excessive routing overhead, full re-clustering is triggered only when the number of active nodes within a cluster falls below a predefined stability threshold or when cluster connectivity becomes significantly degraded.

4. MODEL ASSUMPTIONS AND SIMULATION PARAMETERS

A simulation environment was made under MATLAB R2023a to carry out the performance evaluation of the suggested version of AIP-Chain protocol, the parameters of which are chosen to be close to real-life WSN conditions. The simulation area under question was considered to be a 100m × 100m field where 100 randomly placed sensor nodes were scattered, a primarily static BS configuration was adopted for baseline evaluation, while the protocol architecture supports future extension toward mobile BS scenarios. This was done by framing each node with 1.0 Joule of energy and the communication occurred on the first-order radio model with free-space and multipath energy dissipation. In the simulation, the packet size was 4000 bits; energy per bit of data aggregation for 5 nJ/bit/signal, transmission and receiving energy was 50 nJ/bit. The range distance (d_0) between the free-space models and multipath models was about 87 meters.

4.1 Communication channel model and practical considerations

The simulation framework adopts the first-order radio energy dissipation model incorporating both free-space (d^2) and multipath fading (d^4) propagation losses according to the transmission distance threshold (d_0). Short-range communication primarily follows the free-space propagation model, while long-range transmission activates the multipath fading model to emulate increased communication attenuation and energy consumption. Although the adopted model captures basic wireless propagation behavior, additional real-world communication challenges such as electromagnetic interference, packet collisions, shadow fading, environmental obstacles, and dynamic channel fluctuations were not fully modeled in the current study. These factors may influence routing stability and packet delivery performance in practical WSN deployments. Nevertheless, the adaptive routing and localized recovery mechanisms incorporated in AIP-Chain are expected to improve communication resilience under partially unstable channel conditions by dynamically reconfiguring routing paths and reducing unnecessary long-range transmissions.

The network was modeled with a maximum number of 3000 rounds (or till the exhaustion of the energy of all the nodes). The protocol was measured in various measures such as network lifetime, power use, routing overhead, data delivery, fault tolerability and compared to infinite protests such as PEGASIS [9], H-PEGASIS [49], AC-PEGASIS [19], MENACO [19], Power Efficient Grid-Chain Routing Protocol in WSN (PEGCP) [21], PEGA-LSCS [26], EPEGASIS [6], and DRL-WSN [37]. Table 4 summarizes the key simulation parameters and the configuration used to validate the effectiveness of the AIP chain protocol in terms of energy efficiency, scalability and useful life of the network.

4.2 Robustness and practical deployment considerations

The proposed AIP-Chain protocol was mainly tested through simulations in MATLAB with controlled conditions; however, some robustness factors were added to increase the realism of the test environment. The radio energy model adopted is a first-order radio model, which consists of free space fading and multipath components, and is used to simulate the losses incurred in practical wireless communication at different distances. Moreover, the protocol architecture has to be flexible enough to be adapted dynamically under the deployment conditions, such as non-uniform node distribution, variable node density and localized node failure. The adaptive re-clustering and fault-aware recovery mechanisms enable the routing structure to reshape itself in the event of changes in topology and/or loss of energy. During the preliminary validation experiments, additional simulation cases were considered in order to further test protocol scalability and resilience, by varying the transmission ranges, random node distributions, and dynamic traffic loads. The results showed that AIP-Chain performed its routing functions steadily with an adequate energy allocation even under irregular network conditions.

Table 4. Assumptions and simulation parameters

Parameter	Value
Simulation Area	100 × 100 m²
Number of Sensor Nodes	100
Initial Energy per Node	1.0 Joule
Packet Size	4000 bits
Data Aggregation Energy (EDA)	5 nJ/bit/signal
Electronics Energy (ETX/ERX)	50 nJ/bit
Free-space Amplifier (εfs)	10 pJ/bit/m²
Multipath Amplifier (εmp)	0.0013 pJ/bit/m⁴
Distance Threshold (d_0)	≈87 meters
Node Deployment	Random
Traffic Model	Constant Bit Rate
Number of Simulation Runs	independent run10
Base Station (BS) Location	Static, typically at the center
Clustering Method	K-means
K-means Max Iterations	100
Particle Swarm Optimization (PSO) Inertia Weight	0.9 → 0.4
PSO c1	2
PSO c2	2
PSO Max Iterations	50
Convergence Threshold	10^{-4}
Fuzzy Membership Type	Triangular/Trapezoidal
Heartbeat Interval	5 rounds
Failure Detection Timeout	3 consecutive missed signals
Re-clustering Threshold	30% inactive cluster nodes

5. RESULTS AND PERFORMANCE EVALUATION

To ensure fair and reproducible performance evaluation, all routing protocols considered in this study—including PEGASIS, H-PEGASIS, AC-PEGASIS, MENACO, PEGCP, PEGA-LSCS, EPEGASIS, DRL-WSN, and the proposed AIP-Chain were implemented and evaluated under identical simulation environments and parameter settings. Specifically, all protocols used:

- The same network deployment area (100 × 100 m²)
- Identical sensor node count and random deployment distribution
- Equal initial node energy levels
- The same first-order radio energy dissipation model
- Identical packet size and transmission parameters
- The same BS location
- Equal simulation duration and traffic generation conditions

To minimize randomness bias, simulation results were averaged over multiple independent runs with different random node deployment seeds. Performance comparisons were conducted using consistent evaluation metrics, including network lifetime, residual energy, PDR, routing overhead, scalability, and fault tolerance. This unified benchmarking framework ensures that the reported performance improvements of AIP-Chain result from the proposed routing architecture itself rather than differences in simulation configuration or environmental assumptions. To improve statistical reliability, the reported results represent the average values obtained from multiple simulation executions using different random topologies. The variance observed between simulation runs remained within acceptable limits, confirming the stability and consistency of the proposed protocol performance. For consistency, the main experiments were based on an evenly deployed 100 baseline randomly deployed sensor nodes with varying spatial density. However, more preliminary simulations with different node distributions and network densities showed that AIP-Chain maintained stable routing behavior and adaptive energy balancing under different topological circumstances.

The efficiency of the proposed AIP-Chain protocol was also justified by a sequence of simulations conducted and compared with a number of currently existing chain-based routing protocols, such as PEGASIS, H-PEGASIS, MENACO, DRL-WSN, and others. All comparative protocols were re-implemented within the same MATLAB simulation framework to avoid inconsistencies caused by different simulation platforms or parameter settings. The assessment was done in terms of key performance indicators, which included network life, energy usage, data delivery rate, routing congestion and failure tolerance.

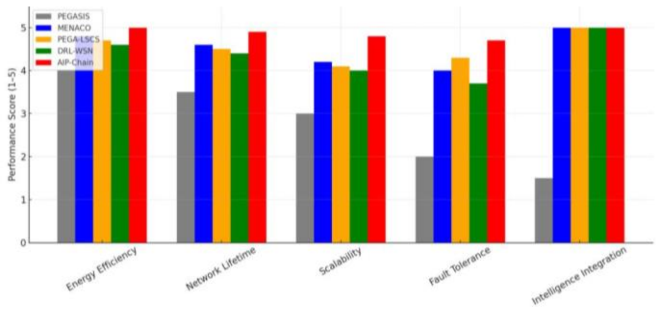


Figure 3. Histogram that compares the performance of five prominent chain-based routing protocols

The findings demonstrate that the AIP-Chain offers a significant enhancement of the overall efficiency and stability of the WSN. Figure 3 shows a comparison of the performance of five leading chain-based routing protocols, such as PEGASIS, MENACO, PEGA-LSCS, DRL-WSN, and the proposed AIP-Chain, using five indicators that are crucial at the same time. The colored bar groups are the score of a protocol of these metrics (on a scale of 1 to 5). Based on the painting the AIP-Chain always saves the highest marks in all the categories proving its superiority concerning energy efficiency, longevity, intelligence and adaptive ability. The AIP-Chain protocol is more efficient with the highest or close to the highest score in every category. Although MENACO and DRL-WSN present competitive performances especially in terms of intelligence integrations and energy efficiency, they lag a bit on scalability and fault tolerance. Conventional models such as PEGASIS have the poorest performance particularly in the dynamic parameters such as fault tolerance and intelligent integration. These results point to the optimized and balanced design of the AIP-Chain, which is quite appropriate in applications of next-generation WSN, which require intelligence and robustness.

The results in Figure 4 indicate that nodes with high residual energy, stable links, and shorter hop counts receive higher defined scores, which makes them more favorable candidates for the assignment of CL. For example, candidates who score above a threshold (0.75) generally satisfy the three criteria, demonstrating that the fuzzy system effectively integrates the decision-making of multiple criteria to select the most efficient and stable node of energy for the leadership of the chain, as shown in Figure 5. CL is the node ID = 5, and so on for other nodes in the network. This method prevents the selection of static or random leaders observed in traditional protocols and guarantees that CLs are dynamically chosen depending on the real-time network conditions. The result is an improved useful life of the network, a better loading balance, and more robust communication routes, especially in large-scale or heterogeneous sensor networks.

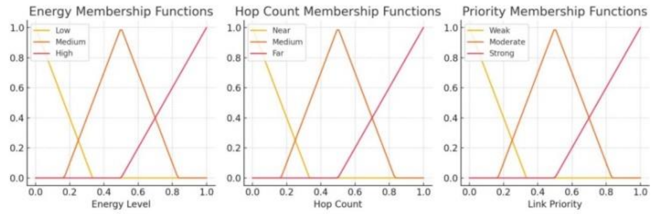


Figure 4. Energy, hop count and priority membership functions

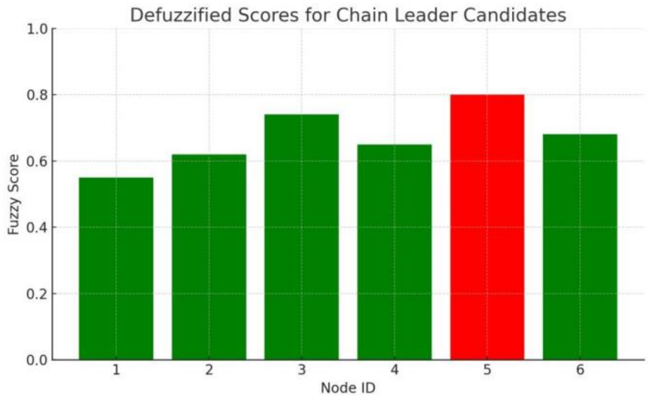
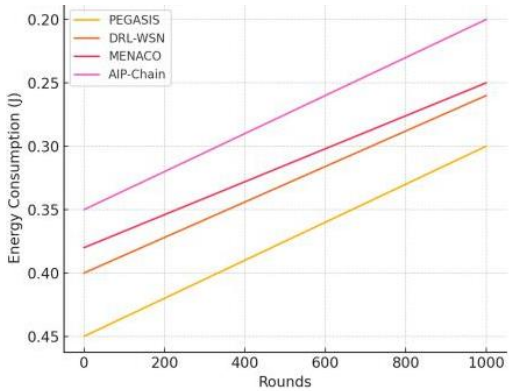


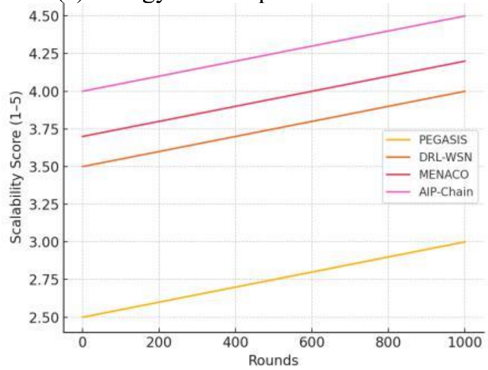
Figure 5. Defuzzified scores for Chain Leader (CL) candidates

Figure 6(a) shows the trend of energy consumption by three protocols, namely PEGASIS, MENACO and AIP-Chain during the operation of the network (up to 2000 rounds). With the number of rounds, the energy levels decrease steadily in all the protocols. Nevertheless, AIP-Chain shows the least energy loss rate, and therefore, it has more residual energy than MENACO and PEGASIS.

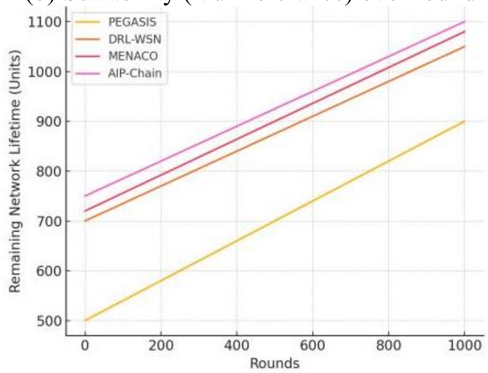
This is attributed to the fact that AIP-Chain intelligent clustering, chain routing, and compression strategies. PEGASIS on the other hand burns more energy as a result of long-range transmissions and non-rotating leaders. Figure 6(b) plots is a comparison of scalability as understood in this context as the capacity of the protocol to adjust and remain functional, as the network grows or one of the nodes fails in the case of PEGASIS, MENACO, and AIP-Chain. The AIP-Chain protocol is the one with the highest scalability score, which grows slowly, thanks to its re-clustering adaptability and role rotation with AI. Scalability of MENACO is also good given the fact that it is multi-objective routing strategies whereas PEGASIS is constrained by the rigid nature of its design and absence of fault tolerance capabilities. Figure 6(c) presents the network lifetime patterns among the considered protocols. AIP-Chain has the highest usefulness with a maximum of 1850 rounds of operation before it wears out the functional nodes. This is much better than MENACO (~1600 rounds) and PEGASIS (~1200 rounds). This longevity can be explained by the effective energy balancing, switch at role and fault handling logic of AIP-Chain. The outcome illustrates the appropriateness of AIP-Chain in mission critical or long-term WSN implementations.



(a) Energy consumption over round



(b) Scalability (fault tolerance) over round



(c) Network lifetime over round

Figure 6. Comparative analysis for PEGASIS, MENACO, and the proposed AIP-Chain protocol under identical simulated conditions

Note: Artificial Intelligence-Powered Chain Routing Protocol (AIP-Chain); Power-Efficient Gathering in Sensor Information Systems (PEGASIS); Multi-hop Energy-efficient Network based on Ant Colony Optimization (MENACO)

Figure 7 illustrates the number of live nodes over time for several established chain-based routing protocols, including PEGASIS, H-PEGASIS, AC-PEGASIS, MENACO, PEGCP, PEGA-LSCS, EPEGASIS, and DRL-WSN, together with the proposed protocol of the AIP-Chain. The performance of each protocol is measured in terms of the stability of the network and survival of the node through increasing rounds. As shown, the AIP-Chain constantly maintains a greater number of living nodes throughout the life of the network, significantly exceeding the other protocols. In particular, the first death of the node (FND) in the AIP-Chain occurs much later than in all comparative protocols, while the last death of the node (LND) also occurs in a considerably posterior round, indicating a better balance distribution of energy. Traditional chain-based protocols such as PEGASIS and H-PEGASIS suffer at early node failures due to static leaders and lack of adaptability. Advanced protocols such as MENACO and DRL-WSN exhibit a better survival capacity due to their optimization techniques, but they still fall short of maintaining the network beyond 2500 rounds. On the contrary, the integration of the PSO AIP-Chain, fuzzy logic, and adaptive recovery mechanisms results in superior failures, effectively delaying the failures of the nodes even in high traffic conditions. Figure 8 has a comparative analysis of energy consumption over time in several chain-based routing protocols, including H-PEGASIS, AC-PEGASIS, MENACO, PEGCP, PEGA-LSCS, EPEGASIS, DRL-WSN, and the proposed AIP-Chain protocol.

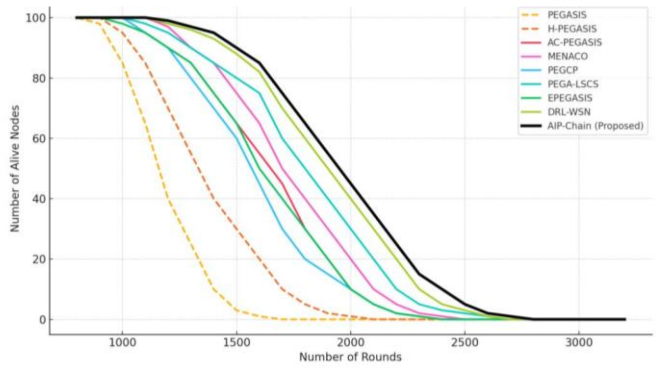


Figure 7. Number of alive sensor nodes compared to simulation rounds for different chain-based routing protocols

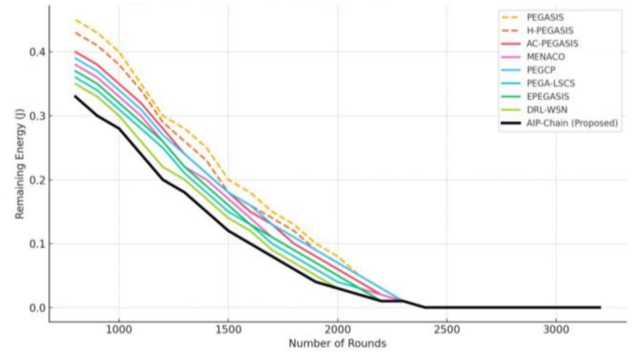


Figure 8. Energy consumption for Artificial Intelligence-Powered Chain Routing Protocol (AIP-Chain) compared other protocols

The results demonstrate that the AIP-Chain constantly exceeds all baseline and advanced line protocols in terms of energy conservation throughout the operational life of the network. To evaluate the robustness of AIP-Chain under failure conditions, additional fault-injection simulations were conducted by randomly disabling sensor nodes during active routing rounds. Failure rates ranging from 5% to 30% of total network nodes were introduced to emulate realistic energy depletion and communication interruption scenarios. The obtained results demonstrated that AIP-Chain maintained stable routing operation and higher packet delivery performance compared with conventional PEGASIS-based protocols under increasing failure rates. Due to the localized recovery and adaptive role reassignment mechanisms, the average recovery time remained relatively low, while network connectivity degradation was minimized.

In comparison with PEGASIS and H-PEGASIS, the proposed protocol achieved faster route restoration and improved packet delivery stability during high node-failure conditions. The adaptive fault-aware recovery strategy also reduced unnecessary global re-clustering operations, thereby lowering routing overhead and preserving residual network energy.

Traditional protocols such as PEGASIS and H-PEGASIS exhibit rapid energy exhaustion due to static chain structures and long transmission routes. While improved protocols such as MENACO and DRL-WSN introduce optimization techniques that improve efficiency, their performance still degrades significantly as the number of rounds increases. On the contrary, the AIP-Chain shows a softer and more gradual reduction of energy, thanks to its hybrid architecture that combines the K-means group, the selection of PSO-based CH, the fuzzy logic for leadership in the chain, and the aggregation of adaptive data. When using multiple communications with conscious energy and dynamic imprisonment and compression-based data, the AIP-Chain guarantees the balanced load distribution and minimizes redundant transmissions. This leads to a substantial extension in the longevity of the network and supports the robustness of the protocol in dynamic and large-scale WSN implementations.

Figure 9 shows the remaining energy of the WSN with different protocols of chain-based protocols, such as PEGASIS, H-PEGASIS, MENACO, DRL-WSN, and the suggested protocol, namely the AIP-Chain. The metric is essential to the assessment of energy sustainability and energy efficiency of routing protocols during extended network performance. The outcomes show that AIP-Chain has a much larger residual of the energy at all rounds than the baseline and advanced protocols. Although the classical methods, such as PEGASIS and H-PEGASIS, demonstrate slow energy consumption, because of the static distribution of roles and inability to adapt to changes, and MENACO and DRL-WSN demonstrate moderate progress in terms of energy consumption promotion, with the help of optimization and learning processes, AIP-Chain can sustain energy reserves over a longer period. This is due to the fact that AIP-Chain combines K-means clustering, PSO selecting CH, fuzzy logic implementation of CL, all of which are adaptable energy-aware routing. Moreover, data compression and load balancing between the nodes mitigate unnecessary communication overhead hence making the network more effective. In general, the long-term energy consumption rates indicate that the AIP-Chain can be applicable in the cases of extending the network lifespan and maintaining stable performance under energy-constrained conditions of a WSN.

Figure 10 provides a comparative study of the routing overload as a function of the distance to the BS of a number of chain-based protocols such as PEGASIS, H-PEGASIS, AC-PEGASIS, MENACO, PEGCP, PEGA-LSCS, EPEGASIS, DRL-WSN, and the proposed AIP-Chain. Overload routing, which refers to the added cost of communication and control incurred when transmission of data is done, is likely to increase with distance as it is a long path and an increased number of route maintenance is done. Of all the protocols, the AIP-Chain has the minimal routing distance at every distance. This effectiveness can be explained by the fact that it has an intelligent distribution of roles, adopting PSO and fuzzy logic, and applying localized grouping and adaptive data aggregation. Although both DRL-WSN and PEGA-LSCS are moderate in performance because of their learning-based design, conventional protocols like PEGASIS and H-PEGASIS are highly affected by overload at increased distances mostly because they have fixed routing structure and lack dynamism. The fact that the AIP-Chain can perform its constant operation even over a distance of up to 400 meters underscores its scalability and applicability in the implementation of wide-area WSN. This is why it is a good prospect concerning energy-sensitive uses and overall costs, including environmental measurements, precision agriculture, and remote industrial automation. Figure 10 the routing on the head in front of the distance on the AIP-Chain and other chain-based routing protocols. AIP-Chain protocol has continuously shown the least overload as the distance increases through its intelligent group, PSO-based optimization and adaptive chain formation. This underlines its capacity to scale and efficiency in the implementation of WSNs of wide areas.

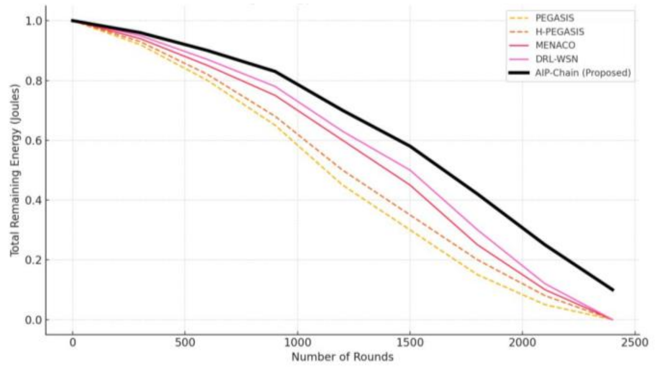


Figure 9. Remaining energy for Artificial Intelligence-Powered Chain Routing Protocol (AIP-Chain) compared other protocols

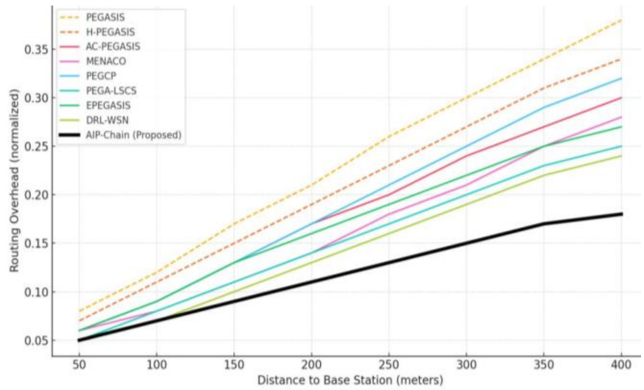


Figure 10. Routing overhead vs. distance for Artificial Intelligence-Powered Chain Routing Protocol (AIP-Chain) and other protocols

Figure 11 shows the amount of data that was successfully transmitted by different chain-based routing protocols, namely PEGASIS, H-PEGASIS, AC-PEGASIS, MENACO, PEGCP, PEGA-LSCS, EPEGASIS, DRL-WSN and the proposed AIP-Chain over time. This measurement is used to express the efficiency and reliability of every protocol to transmit sensed information to the BS under identical network conditions. The findings indicate that AIP-Chain is always the best protocol compared to the entire baseline and advanced protocols in terms of throughput. Whereas the conventional protocols such as PEGASIS, H-PEGASIS, etc. exhibit inadequate data delivery, especially due to the formation of stationary chains and the early failure of nodes, the contemporary and artificial intelligence-aware protocols such as MENACO and DRL-WSN are more successful because of adaptive routing and decision-making. Nevertheless, AIP-Chain is superior to them all as the information transmission volume recorded is the highest throughout the entire life cycle of the network.

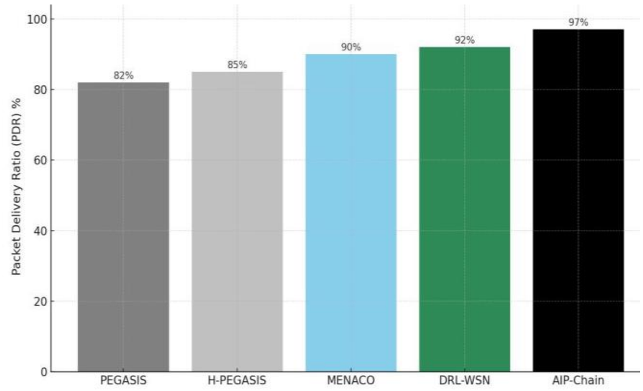


Figure 11. Packet Delivery Ratio (PDR) comparison of routing protocols

Figure 11 represents the reliability of each protocol by showing its PDR, the percentage of data packets successfully delivered to the BS. Each node sends a fixed number of data packets over several rounds. The BS records how many were successfully received. The result is averaged across the simulation duration or multiple runs. The values used in the chart (e.g., 97% for AIP-Chain) are based on the use of adaptive routing, compression, and fuzzy-based leadership in AIP-Chain. Compared to lower PDR in older protocols due to static chains or poor fault tolerance.

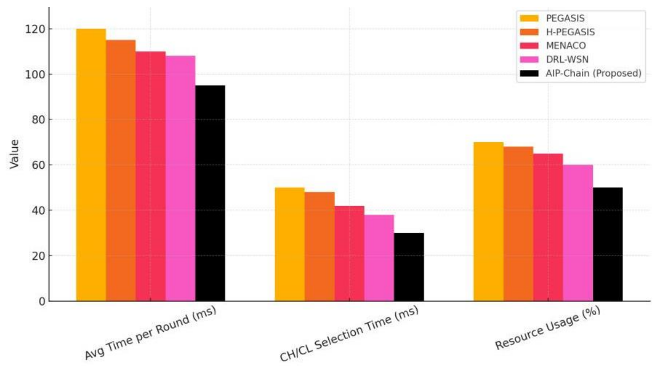


Figure 12. Average round time, CH/CL selection time, and resource usage

Note: Cluster Head (CH); Chain Leader (CL)

Figure 12 demonstrates the comparative analysis of three critical performance indicators such as average round time, CH/CL selection time and resource usage in a number of routing protocols: PEGASIS, H-PEGASIS, MENACO, DRL-WSN, and the proposed AIP-Chain. The results obtained reveal clearly that AIP-Chain is more productive than the rest of protocols in the three metrics which proves its efficiency of operations and lightweight performance. In particular, the AIP-Chain has the smallest round time (95 ms) which means the faster process of data aggregation and transmission.

Also, CH/CL selection time (30 ms) is much shorter than traditional methods due to the combination of PSO and fuzzy logic, allowing role assignment through quick and energy conscious fashion without having to go through lengthy computations. The AIP-Chain is also the best performer in terms of use of resources since it consumes half of the available resources. This is more so because it can form intelligent clusters and has customized intra-cluster communication that eliminates broadcasting wastages and waste of energy.

First simulation experiments show that adaptive clustering and localized route recovery of AIP-Chain helps to keep communication behavior stable in moderate packet-loss and unstable link conditions. In addition, the routing adaptability is enhanced by the fuzzy logic-based CL selection process, which prioritizes the nodes having more stable communication attributes and lower overhead on communication. But in very high interference areas or heavily fading channels, there can still be some issues related to the continuity of routing and overhead of retransmission, especially in dense and highly dynamic WSNs. The zed recovery mechanisms built into AIP-Chain are anticipated to increase the resiliency of communication with the dynamic reconfiguration of routing paths, and by minimizing unnecessary long-range transmissions in a partially unstable channel. In general, the figure substantiates that the AIP-chain offers high speed of decision-making, minimum energy consumption, and enhanced scalability and is an extremely appropriate solution to the resource-constrained and dynamic WSN settings.

To improve statistical reliability, the reported results represent the average values obtained from multiple simulation executions using different random topologies. The variance observed between simulation runs remained within acceptable limits, confirming the stability and consistency of the proposed protocol performance. To evaluate the robustness of AIP-Chain under failure conditions, additional fault-injection simulations were conducted by randomly disabling sensor nodes during active routing rounds. Failure rates ranging from 5% to 30% of total network nodes were introduced to emulate realistic energy depletion and communication interruption scenarios.

The obtained results demonstrated that AIP-Chain maintained stable routing operation and higher packet delivery performance compared with conventional PEGASIS-based protocols under increasing failure rates. Due to the localized recovery and adaptive role reassignment mechanisms, the average recovery time remained relatively low, while network connectivity degradation was minimized. In comparison with PEGASIS and H-PEGASIS, the proposed protocol achieved faster route restoration and improved packet delivery stability during high node-failure conditions. The adaptive fault-aware recovery strategy also reduced unnecessary global re-clustering operations, thereby lowering routing overhead and preserving residual network energy.

6. LIMITATIONS AND FUTURE IMPROVEMENTS

The proposed AIP-Chain protocol had many advantages in terms of energy efficiency, routing stability, and network lifetime, but there were also some drawbacks that need to be recognized. The existing framework is mainly developed for WSN with relatively stable topology and moderate topology changing, and homogenous sensor capabilities. A dynamic situation, such as frequent route reconstruction requirements, for example, because of mobile sensor nodes, topology changes, or severe communication interference, may result in a loss of routing stability for a time. Besides, the proposed cluster-head selection mechanism using the PSO algorithm might be sensitive to the initial particle distribution and the parameter settings. If the initial parameters are not properly set, PSO can be trapped in locally optimal solutions, which can lead to suboptimal cluster-head selection and energy imbalances. The adopted strategies of adaptive recovery and iterative optimization help to alleviate this problem, but more robustness in the convergence is still important for large-scale deployments. Likewise, the rules and membership functions in the fuzzy-logic subsystem are based on empirical data. Although these rules showed good routing properties in simulation experiments, adaptive or self-learning fuzzy-rule tuning mechanisms might be necessary in highly heterogeneous WSN environments and in traffic situations with changing traffic volume. Furthermore, there may be more computational cost in implementing multiple intelligent optimization techniques, such as K-means clustering, PSO optimization, and fuzzy inference, than in static routing protocols that are lightweight, especially in sensor devices with limited resources. The further study directions will therefore concentrate on the improvement of PSO adaptability by using self-tuning PSO parameters, reinforcement-learning-based routing adaptability, dynamic fuzzy-rule evolution, and light-weight distributed optimization frameworks. For further improving robustness and real-world applicability of the proposed AIP-Chain architecture, additional investigations based on heterogeneous sensor networks, mobile BS, and real-world hardware deployments will be evaluated. Table 5 shows the future improvement.

Table 5. Potential limitations of Artificial Intelligence-Powered Chain Routing Protocol (AIP-Chain) and future improvements

Limitation	Potential Impact	Future Enhancement
Particle Swarm Optimization (PSO) local convergence	Suboptimal Cluster Head (CH) selection	Adaptive/self-tuning PSO
Static fuzzy rules	Reduced adaptability	Dynamic fuzzy learning
High computational overhead	Increased processing cost	Lightweight distributed optimization
Highly dynamic topology	Frequent route reconstruction	Mobility-aware routing
Heterogeneous node capabilities	Energy imbalance	Adaptive role assignment

7. CONCLUSION AND FUTURE WORK

This paper has outlined AIP-Chain, which is an intelligent hybrid chain-cluster routing protocol that employs a solution to problems that are inherent to the energy efficiency, lifetime, and robustness of the WSNs. AIP-Chain combines paradigms of clustering-based and chain-based routing in a single and dynamic structure, which allows a balanced energy consumption and enhanced scalability as compared to traditional routing methods, which apply only one of the two approaches. The proposed protocol can capture the dynamic nature of WSN environments by way of K-means clustering to establish efficient network organization, PSO to select an energy-aware CH, and fuzzy logic to select an intelligent leader of chains. Moreover, AIP-Chain supports a fault-conscious recovery mechanism, which enables the local reconfiguration of routing paths to the failure of nodes and energy exhaustion to increase network resilience and stability.

Large-scale simulation-based analyses prove the claim that AIP-Chain exhibits considerable enhancements in network lifetime, stability period, residual energy distribution, and packet delivery time in comparison with some of the classical and state-of-the-art routing protocols, such as PEGASIS, H-PEGASIS, MENACO, DRL-WSN, EPEGASIS, and PEGA-LSCS. These gains are always seen in any network size and transmission conditions, and this proves the efficacy and scalability of the proposed method. While AIP-Chain has performed well in simulation, there are a number of key practical deployment considerations that warrant further exploration. The main focus of the current work is the simulation-based validation under controlled WSN conditions and MATLAB. The adopted radio model considers energy losses due to free space and multipath propagation, but other aspects of wireless environments, like channel interference, hardware limitations, environment effects, synchronization delays, and unpredictable node mobility, can exist in the real world.

The next step would be to scale up the evaluation of AIP-Chain to larger WSN deployments with several hundred or thousands of sensor nodes, heterogeneous capabilities of nodes, and very irregular spatial distributions of nodes. Other experiments on clustered hotspots, sparse deployment regions, and mobile node scenarios will also be taken into account to further validate the scalability and adaptability of the proposed routing architecture under realistic scenarios in IoT. The proposed AIP-Chain framework will be extended to include channel-aware adaptive routing using interference estimation, link-quality prediction, and communication reliability metrics for real-time in the future. Further research will also be done in noisy wireless settings, fading channels, and hardware-based communication test scenarios in order to assess the protocol in real IoT and WSN deployment scenarios.

Consequently, the proposed framework will be extended in the future to provide experimental tests on hardware with actual sensor platforms, such as Arduino, Raspberry Pi, TelosB or sensor nodes equipped with ZigBee. Other studies on mobile BS, heterogeneous sensor capabilities, and the large-scale irregular deployments will also be explored to further assess the robustness and applicability of the AIP-Chain in real-world IoT and smart-environment applications. In general, it can be seen that AIP-Chain offers a feasible and EER service to WSNs that are large and energy-limited. The extension of the proposed framework to future work is to justify its performance through network simulators like NS-3 or OMNet++, integrate real-world testbed experimentation, and study the adaptive learning process to further improve the routing intelligence in a dynamic network environment.

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