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Research Article

Hybrid Neuro-Fuzzy and Swarm Optimization-Based Energy-Efficient Routing for Large-Scale IoT Networks

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ABSTRACT

The proliferation of large-scale Internet of Things (IoT) networks has raised various concerns about energy usage, routing efficiency, scalability and lifetime. However, traditional routing protocols like LEACH, HEED, PEGASIS, and RPL can face challenges in maintaining optimal performance in dense IoT networks, as they tend to consume significant amounts of energy, have high communication overheads, and are less flexible in adapting to changing network conditions. For overcoming these issues, the current paper presents Hybrid Neuro-Fuzzy and Swarm Optimization (HNF-SO) routing protocol that combines Neuro-Fuzzy intelligence with Whale Optimization Algorithm (WOA) to improve routing decision making and global route optimization. The proposed architecture is based on hierarchical clustering network in which a Neuro-Fuzzy engine is used to calculate the energy efficiency of all considered routing candidates, to calculate the distance to the sink, to calculate the node density and to calculate the traffic load, while the WOA is used to identify the most energy-efficient cluster heads and routing paths. A large-scale IoT network scenario was used throughout the extensive simulations, and the protocol was assessed based on the energy consumption, network lifetime, residual energy, packet delivery rate (PDR), throughput, delay, and scalability. The results show that the proposed HNF-SO significantly improves the packet delivery performance, lowers the energy consumption, provides the long lifetime of the network, and can operate without any disruption even with the increase of the network size compared with the traditional routing protocols. The key contribution of this work is the development of an intelligent, scalable and energy-efficient solution for large scale deployments of IoTs by combining the algorithms of Neuro-Fuzzy decision making and swarm based optimization into a single routing framework.

1. INTRODUCTION

Internet of Things (IoT) has emerged as the core technology for connecting and interacting with a wide range of devices, sensors and intelligent systems in various areas such as smart cities, healthcare, industrial automation, transportation and environmental monitoring [1-3]. With the growing number of deployments, the number of sensor nodes in an IoT deployment has grown to hundreds or thousands of nodes spread across a wide geographical area, forming a large-scale IoT network. These networks have a huge sensing and communication capabilities, but they also pose many problems including energy consumption, routing efficiency, scalability and network lifetime [4,5].

One of these challenges is routing, which is crucial for performance and sustainability of the network. Communication operations are responsible for significant amount of energy consumption at nodes, so the poor routing decisions can quickly exhaust battery resources, cause network congestion and shorten network lifetime [6-8]. Hence, design of energy-efficient and scalable routing algorithms are still significant research challenges for contemporary IoT systems.

Recent routing protocols like LEACH, HEED, PEGASIS and RPL have been widely used to enhance the energy conservation in wireless sensor network and IoT networks [9-12]. In large scale environments, however, their performance suffers from a number of problems such as random cluster-heads, high routing overhead, scalability constraints, and unequal energy distribution. The limitations of these systems underscores the importance of developing more adaptive and intelligent routing protocols to handle dynamic network conditions.

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Recent developments in computational intelligence provide new options to overcome these limitations. The Neuro-Fuzzy systems integrate the learning ability of ANN with the uncertainty handling ability of fuzzy logic, and allow adaptive routing decisions in dynamic environments [13,14]. In the same manner, the Swarm Optimization algorithms have been proven to be effective in solving routing and cluster-head selection problems with the ability of exploring large search space efficiently [15,16]. These techniques, when combined, offer a valuable solution to enhance energy efficiency and routing performance in large-scale IoT networks.

Inspired by these challenges, the paper introduces a Hybrid Neuro-Fuzzy and Swarm Optimization-Based Energy-Efficient Routing Protocol for Large-Scale IoT Networks. The proposed framework has introduced a Neuro-Fuzzy based decision engine for routing candidates evaluation, and Whale Optimization Algorithm (WOA) for selection of optimal cluster head and communication path. The primary goals are energy saving, efficient routing, long network lifetime and scalability. The principal results of the work are given below:

1. Design and development of a Hybrid Neuro-Fuzzy decision engine for adaptive routing decisions.
2. Cluster-head and route selection using Whale Optimization (WE) for energy-efficient.
3. Design of a dynamic multi-hop communication architecture for large-scale IoT networks.
4. Scalable routing architecture with performance sustaining with growth of network.
5. Energy consumption, network lifetime, throughput, packet delivery ratio and delay for comprehensive performance evaluation against LEACH, HEED, PEGASIS, RPL and Fuzzy Routing.

The rest of this paper is organized as follows. In section 2, existing literature related to the energy-efficient routing and intelligent optimization techniques is reviewed. In this section 3, the proposed methodology is presented. The setup and evaluation metrics of the simulation are described in section 4. Experimental results are discussed in Section 5 and future directions outlined in Section 6.

2. RELATED WORK

One of the basic problems in large-scale IoT applications and WSNs is routing in energy-efficient manner, as sensor nodes have limited power supplies and network deployments are becoming more and more complex. The routing protocols have direct impact on lifetime, energy consumption, Packet Delivery Ratio (PDR) and reliability. Conventional energy efficient routing, intelligent routing and swarm intelligence-based optimization techniques are typical methods that can be categorized.

The traditional routing protocols like LEACH, HEED, PEGASIS, TEEN, and APTEEN, have been widely used to enhance energy conservation in WSNs [13-17]. LEACH uses the hierarchical clustering technique with cluster-head rotation and HEED utilizes the residual energy information for improving cluster-head selection. PEGSIS uses a chain-based communication approach to minimize the amount of communication sent, and both TEEN and APTEEN emphasize threshold-based communication approaches for event-driven applications. These protocols maximize energy utilization but, in large scale IoT deployments, they may suffer from poor scalability, communication overhead and sub-optimal cluster-head selection.

In order to alleviate these shortcomings, researchers have proposed novel routing methodologies for intelligent routing based on computational intelligence. The Fuzzy Logic Routing relies on linguistic rules to assist with routing decisions in a network with uncertain conditions, while the Neuro-Fuzzy systems integrate neural learning with fuzzy reasoning for making adaptive and energy-aware routing decisions [18,19]. Besides, machine learning and deep learning methods are also becoming more popular in predicting network conditions and optimizing routing performances. Such methods are, however, generally resource intensive and need a long training period, which could be prohibitive for resource-limited IoT devices [20,21].

Another promising potential application of swarm intelligence algorithms in IoT networks is routing optimization. The solutions of cluster-head selection, route optimization and energy management problems have been achieved by Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), Ant Colony Optimization (ACO), and Grey Wolf Optimizer (GWO) approaches, which have been proven successful in the above problems [22-25]. These algorithms are very powerful search globally and have very efficient optimization performance. However the majority of the current literature is dedicated to either intelligent decision-making or route optimization, with no effort to combine them in a single framework for routing.

To illustrate the variety of methods, some of the main routing protocols and optimization techniques found in the literature are summarized in Table 1.

TABLE I. COMPARATIVE ANALYSIS OF EXISTING ROUTING APPROACHES

Ref.	Method	Main Technique	Advantages	Limitations
[13]	LEACH	Hierarchical Clustering	Low energy consumption, simple implementation	Random cluster-head selection, poor scalability
[14]	HEED	Residual-Energy Clustering	Improved energy balancing	High control overhead
[15]	PEGASIS	Chain-Based Routing	Reduced transmission energy	High delay, scalability issues
[16]	TEEN	Threshold-Based Routing	Suitable for event-driven applications	Limited continuous monitoring
[17]	APTEEN	Hybrid Threshold Routing	Supports periodic and event-driven reporting	Increased complexity
[18]	Fuzzy Routing	Fuzzy Logic	Handles uncertainty effectively	Static rule dependence
[19]	Neuro-Fuzzy Routing	Neural Network + Fuzzy Logic	Adaptive decision-making	Increased computational cost
[20]	AI-Based Routing	Machine Learning	Intelligent route prediction	Training overhead
[21]	Deep Learning Routing	CNN/RNN/DRL	High prediction accuracy	Resource-intensive implementation
[22]	PSO-Based Routing	Swarm Optimization	Efficient cluster-head selection	Premature convergence
[23]	WOA-Based Routing	Whale Optimization	Strong global optimization capability	Parameter sensitivity
[24]	ACO-Based Routing	Ant Colony Optimization	Effective shortest-path discovery	Slow convergence
[25]	GWO-Based Routing	Grey Wolf Optimization	Good exploration–exploitation balance	Performance dependent on population size

While considerable advances have been made in routing with energy efficiency, some issues have yet to be addressed. The traditional routing protocols have a main objective of saving energy but are not adaptive and scalable when deployed in large scale. Intelligent routing methods enhance the decision making capabilities, without most of the time including a global optimization mechanism. Also, in adaptive routing, the swarm intelligence techniques often lack consideration of the dynamic network conditions. Thus, there is need for a comprehensive framework that integrates intelligent decision making and optimization methods to optimize both energy and routing reliability and scalability at the same time. To overcome these drawbacks, a routing framework combining Adaptive Neuro-Fuzzy decision-making with Whale Optimization Algorithm (HNF-WOA) based on route optimization is proposed in this study. The objective of the proposed approach is to provide energy-efficient cluster-head selection, optimized routing path, and better scalability for large-scale IoT networks.

3. PROPOSED METHODOLOGY

3.1 Overall Framework

The proposed Hybrid Neuro-Fuzzy and Whale Optimization Algorithm (HNF-WOA) framework is proposed to overcome the energy efficiency and scalability issues in large-scale Internet of Things (IoT) networks. Based on intelligent decision-making and optimization mechanisms, the framework is integrated in a single routing architecture, which optimizes network lifetime, reduces communication overhead, and improves routing reliability. It proposes a Neuro-Fuzzy inference based approach with swarm intelligence optimization to dynamically change the routing decisions based on network conditions, unlike other routing protocols which are based on energy based clustering or static routing.

First, sensor nodes are deployed throughout the monitoring region and clustered according to the geometric and connectivity features. The clustering process is designed to minimize communication overhead and enable efficient data aggregation. Then a Neuro-Fuzzy engine uses a number of network parameters, such as residual energy, distance to the sink, node density and traffic load, to find out whether a node is suitable for routing and cluster-head selection. These obtained routing scores are then fed to the Whale Optimization Algorithm (WOA).

which is used for the global optimization to determine the optimal cluster head and energy-efficient routing path. Last but not least, an optimized multi-hop communication structure is designed, where data packets are delivered within the network from the sensor nodes to the sink via intermediate cluster heads with minimal transmission energy consumption and the load distribution of the network is balanced. The combination of Neuro-Fuzzy intelligence and WOA optimization allows the framework to make adaptive routing decisions, efficiently use the resources, and increase its scalability as the network expands. Figure 1 shows the overall routing process of the proposed routing framework.

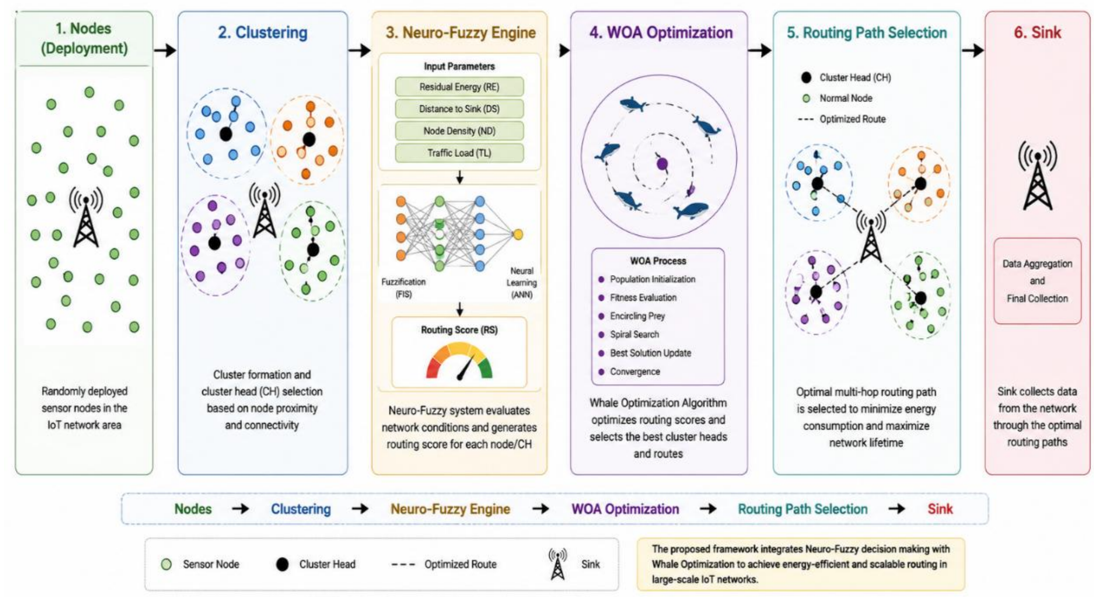

Fig. 1. Overall Architecture of the Proposed Hybrid Neuro-Fuzzy and WOA-Based Routing Framework

3.2 Network Model

The proposed Hybrid Neuro-Fuzzy and Whale Optimization Algorithm (HNF-WOA) routing algorithm is intended for large scale Internet of Things (IoT) network in which the number of sensor devices deployed in the network is very high with extended monitoring area. It is a network of a large number of sensor nodes that monitor, process and communicate with a sink node. Efficient energy management is crucial for the sustainable operation of networks and extended network lifetime in the IoT because of the restricted capability of the IoT devices in terms of computation and battery capacity.

In the proposed model, the sensor nodes are randomly distributed in the sensing field and are stationary during the simulation process. The nodes are assumed to have the same initial energy supply at deployment and have sensing, processing and wireless communication capabilities. Nodes can adapt their transmission power dynamically to suit communicating entities' distance to ensure energy efficient communication. In addition, one sink node is optimally placed in the network to gather the aggregated data sent from the cluster heads via optimal multi-hop communication paths.

The network operation is based on a hierarchical clustering scheme, where every ordinary sensor node is sending data to its cluster head and cluster heads are in charge of aggregation and sending the aggregated data to sink. This architecture minimizes the number of redundant transmissions, optimizes energy usage across nodes, and enhances scalability in large networks. The suggested routing framework also supports this process by implementing Neuro-Fuzzy intelligence to adaptively decide routing and Whale Optimization Algorithm (WOA) for an optimum selection of Cluster-head and routing. Several assumptions are made for simulation and performance evaluation to create a controlled and realistic network environment:

a) Sensor nodes are randomly distributed throughout the monitoring area.
b) All nodes remain stationary after deployment.
c) Each node is initially assigned the same amount of energy.
d) Communication links are symmetric between neighboring nodes.
e) Transmission power can be adjusted according to communication distance.
f) The sink node possesses unlimited energy resources.
a) Data packets are generated periodically by sensor nodes.
b) Cluster heads perform data aggregation before forwarding packets.
c) Multi-hop communication is employed to reduce long-distance transmission costs.

The simulation parameters used to evaluate the proposed routing protocol are summarized in Table 2.

TABLE II. SIMULATION PARAMETERS USED FOR PERFORMANCE EVALUATION OF THE PROPOSED HNF-WOA ROUTING PROTOCOL

Parameter	Value
Network Area	1000 × 1000 m²
Number of Sensor Nodes	1000
Sink Nodes	1
Initial Node Energy	2 J
Packet Size	100 bits
Transmission Range	20–50 m
Simulation Duration	1000 Rounds
Communication Model	Multi-Hop Routing
Clustering Strategy	Energy-Aware Clustering
Optimization Algorithm	Whale Optimization Algorithm (WOA)
Decision-Making Engine	Neuro-Fuzzy System
Node Deployment	Random
Mobility Model	Static Nodes
Data Aggregation	Enabled
Traffic Pattern	Periodic Sensing Traffic

The set of parameters for the simulation are chosen to simulate realistic large-scale IoT deployment scenarios where energy efficiency, routing reliability and network scalability are important performance criteria. The settings provide a suitable environment to test the proposed HNF-WOA routing framework and to benchmark its performance with the state of the art routing protocols.

3.3 Energy Consumption Model

Two of the most important issues when it comes to the performance and longevity of large-scale Internet of Things (IoT) networks are energy consumption and battery life. The major challenge is that sensor nodes are usually battery-powered devices with limited energy sources, and if they are consuming too much energy in transmitting or receiving data, they will decrease the life of the network and decrease the overall performance of the system. Unlike sensor networks, communication tasks in wireless sensor networks and IoT networks require a lot of energy. Thus, designing energy-aware routing mechanisms needs an accurate energy consumption model that can estimate the energy consumption used for packet transmission and reception.

A well-known First Order Radio Energy Model (FOREM) is used to assess the energy efficiency of the proposed Hybrid Neuro-Fuzzy and Whale Optimization Algorithm (HNF-WOA) routing protocol. Many studies on energy-efficient routing have used this model due to its simplicity and ability to reflect the energy requirements of wireless communication. The model assumes that the energy consumption is a function of packet size and transmission distance..

3.3.1 Transmission Energy Model

Transmission conditions on the channel depend on the energy that is used when sending a data packet of k bits of information over a distance d. If the transmission distance is less than a specified threshold distance (d_0) the free space propagation model is used. If there is no other option, the multipath fading model is used. The energy needed for a k-bit packet to be transmitted to a distance d is:

$$E_{Tx\,(k,d)} = \begin{cases} EK_{elec} + k\varepsilon_{fs} d^2 & d < d_0 \\ EK_{elec} + k\varepsilon_{mp} d^4 & d \geq d_0 \end{cases} \quad (1)$$

where:

- $ETx(k,d)E\_\{Tx\}$ = transmission energy consumption (J)
- k= packet size (bits)
- $Eelec$= electronic energy consumption (J/bit)
- εfs= free-space amplifier coefficient
- εmp = multipath fading amplifier coefficient
- d = transmission distance (m)
- d_0= threshold distance (m)

The threshold distance is computed as:

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (2)$$

This threshold determines whether the free-space or multipath fading model should be used during energy estimation.

3.3.2 Communication Energy Calculation

In addition to transmission energy, sensor nodes consume energy during packet reception and data aggregation processes. The reception energy is independent of communication distance because no signal amplification is required at the receiving side. Therefore, the energy consumed for receiving a k-bit packet is expressed as:

$$ERx(k) = kEelec \qquad (3)$$

where:

- $ERx(k)$ = energy consumed during packet reception (J)
- $Eelec$ = electronic energy required for packet processing

Since the proposed HNF-WOA framework employs a cluster-based communication architecture, cluster heads perform data aggregation before forwarding information toward the sink node. Data aggregation reduces redundant transmissions and improves overall communication efficiency. The aggregation energy is calculated as:

$$\mathrm{E_{DA}(k)} = K\mathrm{E_{DA}} \qquad (4)$$

where:

- $\mathrm{E_{DA}(k)}$= aggregation energy consumption (J)
- $\mathrm{E_{DA}}$ = aggregation energy consumed per bit

To support intelligent cluster-head selection and route optimization, the remaining battery energy of each sensor node is continuously monitored. The residual energy of node i after communication operations is calculated as:

$$\mathrm{E_{Residual}^{(i)}} = \mathrm{E_{Initial}^{(i)}} - \left(\mathrm{E_{Tx}^{(i)}} + \mathrm{E_{Rx}^{(i)}} + \mathrm{E_{DA}^{(i)}} \right) \qquad (5)$$

where:

- $\mathrm{E_{Residual}^{(i)}}$= remaining energy of node iii
- $\mathrm{E_{Initial}^{(i)}}$= initial battery energy
- $\mathrm{E_{Tx}^{(i)}}$ = transmission energy consumed
- $\mathrm{E_{Rx}^{(i)}}$ = reception energy consumed
- $\mathrm{E_{DA}^{(i)}}$ = data aggregation energy consumed

Nodes with higher residual energy are considered more suitable for cluster-head responsibilities because they can sustain communication activities for longer periods and contribute to balanced energy utilization throughout the network.

3.3.3 Energy-Aware Routing Decision

In the proposed routing scheme for HNF-WOA, the energy status of all the sensor nodes is constantly monitored. At each routing round the residual energy is analyzed by the Neuro-Fuzzy decision engine along with other network parameters like distance to the sink, node density and traffic load. Then, the Whale Optimization Algorithm is used to determine the best routing configuration that can reduce the energy cost of the communication and maximize the network lifetime. The proposed routing framework introduces energy-aware clustering, intelligent decision-making and swarm-based optimization to ensure balanced energy consumption, minimize communication overhead, and significantly prolong the operational life of large-scale IoT networks.

Communication energy consumption is estimated in the First-Order Radio Energy Model in this study and the parameters used in this model are summarized in Table 3 to ensure realistic estimation of communication energy consumption. These are the parameters used to evaluate energy-efficient routing protocols in WSNs and IoT networks and serve as a common ground for comparisons. The chosen values are those for the energy needed to run radio electronics, the power needed for signal amplification in the case of free space propagation versus multipath propagation, and the energy needed for data aggregation processes carried out at cluster heads. These parameters are then used for calculating the transmission energy, reception energy, remaining energy and optimization metrics of the routing during the simulation.

TABLE III. RADIO ENERGY MODEL PARAMETERS

Parameter	Description	Value
$Eelec$	Electronic Energy Consumption	50 nJ/bit
fs	Free-Space Amplifier Energy	10 $pJ/bit/m^2$
mp	Multipath Amplifier Energy	0.0013 $pJ/bit/m^4$
EDA	Data Aggregation Energy	5 nJ/bit
$Initial\ Energy$	Initial Battery Energy per Node	2 J
d_0	Threshold Distance	Computed using Eq. (2)

3.4 Cluster Formation Phase

The proposed HNF-WOA framework uses a hierarchical clustering mechanism, which is introduced to enhance the scalability and energy efficiency of the large-scale IoT networks. Clustering involves dividing the sensor nodes into groups and aggregating data at the interior of the cluster and then forwarding it to the sink. This way, there is less communication over long distances, load balancing and network lifespan is increased.

Once nodes are deployed, they find neighbours using discovery process and gather network information such as residual energy, connectivity, local node density, etc. Based on these parameters, the cluster-head candidates are identified and sent to the Neuro-Fuzzy decision engine to evaluate them further. Secondly, the most appropriate cluster heads are identified by using the Whale Optimization Algorithm to form balanced and energy-efficient cluster heads. The overall procedure of the cluster formation is summarized in Table 4.

TABLE IV. CLUSTER FORMATION PHASES IN THE PROPOSED HNF-WOA FRAMEWORK

Phase	**Process**	**Input Parameters**	**Output**
Phase 1	Node Deployment	Sensor Nodes, Network Area	Distributed Nodes
Phase 2	Neighbor Discovery	Node ID, Residual Energy, Coordinates, Communication Range	Neighbor Table
Phase 3	Connectivity Analysis	Neighbor Information	Connectivity Matrix
Phase 4	Density Estimation	Neighbor Count	Node Density Profile
Phase 5	Candidate Evaluation	Residual Energy, Density, Connectivity	Cluster Head Candidates
Phase 6	Cluster Creation	Candidate Nodes and Neighbor Lists	Cluster Membership Lists
Phase 7	Cluster Head Selection	Candidate Set	Selected Cluster Heads
Phase 8	Cluster Verification	Cluster Size and Connectivity	Final Clusters

The output of the cluster formation phase is cluster membership information, neighbor tables, connectivity profiles, node density information and cluster-head candidate sets. These outputs will be fed into the Neuro-Fuzzy routing engine and Whale Optimization module which are used for intelligent cluster-head selection and route optimization. The proposed framework achieves significant energy and connectivity cost reduction, load balancing of sensor network, and the overall scalability of large-scale IoT systems by clustering sensor nodes into energy-aware and connectivity-aware groups. Figure 2 shows the proposed HNF-WOA based cluster formation process by considering node deployment, neighbour discovery, connectivity analysis, density estimation, candidate evaluation, cluster-head selection, and cluster formation.

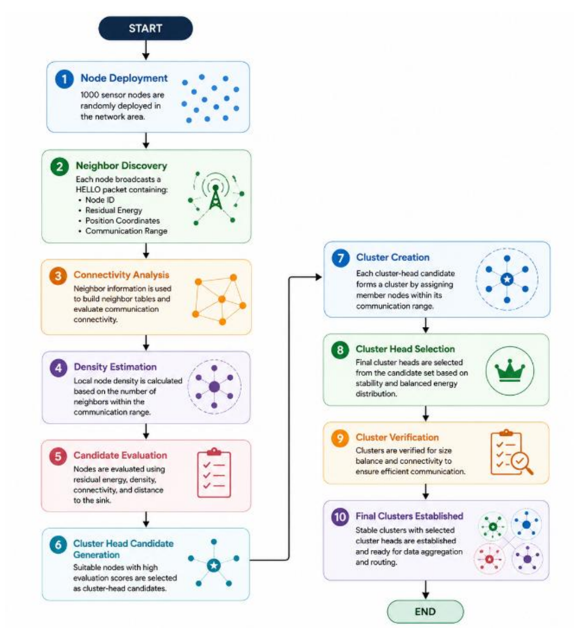

Fig. 2. Cluster Formation Process

3.5. Neuro-Fuzzy Routing Engine

The Neuro-Fuzzy Routing Engine is the part of the proposed HNF-WOA framework responsible for making intelligent decisions. It fuses the adaptive learning ability of Artificial Neural Networks (ANNs) and uncertainty-handling ability of Fuzzy Inference Systems (FIS) to assess candidate nodes' quality for routing and cluster-head selection. The proposed engine takes into account multiple network properties to compute an overall routing score, whereas traditional routing algorithms are based on a single property.

The routing decision process comprises of four steps: Input acquisition, Fuzzification, Neuro-Fuzzy Inference, and Routing score generation. The four network parameters used as decision inputs are residual energy (RE), distance to the sink (DS), node density (ND), and traffic load (TL). All these parameters together give a complete picture of the status of the nodes and the environment of the network. In the fuzzification stage, numerical inputs are mapped to linguistic variables to make intelligent decision making possible. Table 5 summarizes the linguistic representations used for each of the parameters.

TABLE V. LINGUISTIC VARIABLES USED IN THE NEURO-FUZZY ROUTING ENGINE

Input Variable	Linguistic Values
Residual Energy (RE)	Low, Medium, High
Distance to Sink (DS)	Near, Moderate, Far
Node Density (ND)	Sparse, Moderate, Dense
Traffic Load (TL)	Low, Medium, High

Subsequently, the fuzzy inference system evaluates a set of IF–THEN rules that represent desirable routing behaviors under different network conditions. Sample routing rules adopted in the proposed framework are presented in Table 6.

TABLE VI. SAMPLE NEURO-FUZZY ROUTING RULES

Residual Energy	Distance to Sink	Traffic Load	Routing Decision
High	Near	Low	Excellent
High	Moderate	Medium	Very Good
Medium	Near	Low	Good
Medium	Far	High	Fair
Low	Far	High	Poor

The neural network part continuously refines and optimizes the inference process to enhance the accuracy and adaptability of routing. Neuro-Fuzzy engine computes a routing score (RS) based on evaluated rules and learned network conditions which indicates the suitability of each of the candidate nodes for routing and cluster-head responsibilities. The nodes that have higher routing score are more suitable to be chosen for cluster-head and to participate in the routing. The scores are then passed to Whale Optimization Algorithm (WOA) that is used for global optimization of the cluster head and routing paths for maximum energy efficient cluster head.

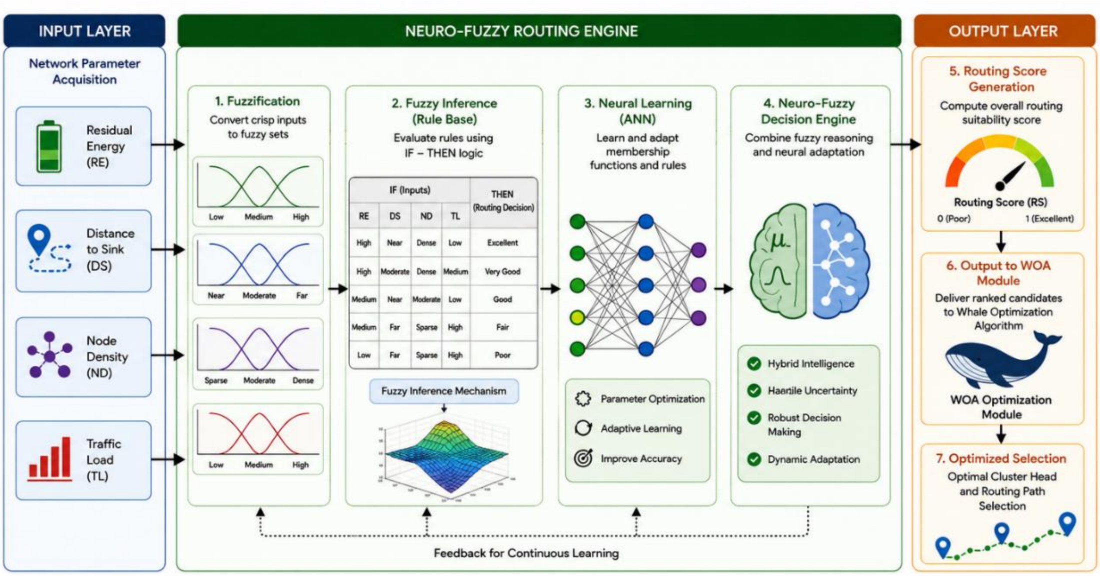

Fig. 3. Neuro-Fuzzy Routing Engine Architecture

3.6. Whale Optimization Module

In large scale IoT networks, the intelligent routing candidate's evaluation by the Neuro-Fuzzy routing engine is not enough for finding the most energy efficient cluster heads and communication paths. Thus, the proposed framework is based on Whale Optimization Algorithm (WOA) for global optimization. WOA is an algorithm based on swarm intelligence technique of humpback whales' bubble-net hunting behaviour. The algorithm is well-known for its exploration-exploitation trade-off in search process, which is suitable for solving complex routing optimization problems. The proposed HNF-WOA approach is to use the generated candidate nodes by the Neuro-Fuzzy engine, and look for the optimum routing configuration in order to maximize the energy efficiency and at the same time the reliability of the communication performance.

Residual energy, distance to the sink, node connectivity, and traffic load are some factors that are taken into account during the optimization process. WOA looks at candidate solutions and improves them iteratively until the most satisfactory cluster head set and routing paths are found, based on these parameters. The optimization process used in the proposed framework involves multiple consecutive steps, as shown in Table 7.

TABLE VII. WHALE OPTIMIZATION STAGES IN THE PROPOSED HNF-WOA FRAMEWORK

Stage	Description	Output
Population Initialization	Generate candidate cluster heads and routing paths	Initial Population
Fitness Evaluation	Assess candidate quality using network metrics	Fitness Scores
Encircling Prey	Move candidates toward the best solution	Updated Population
Spiral Search	Refine local search around promising solutions	Improved Candidates
Best Route Selection	Identify the most suitable routing solution	Optimal Candidate
Position Update	Generate new candidate solutions	New Search Space
Convergence Verification	Check stopping criteria	Final Optimized Solution

The output of the WOA module comprises optimal cluster-head set, optimized multi-hop routing paths and energy-aware communication structure. These outputs are then being used while transmitting these data, to save energy, network loads and network life. The operational flow of Whale Optimization Algorithm is shown in Fig. 4, where the candidate generations, fitness evaluation, route optimization and optimization towards the optimum routing solution in the proposed HNF-WOA framework is presented.

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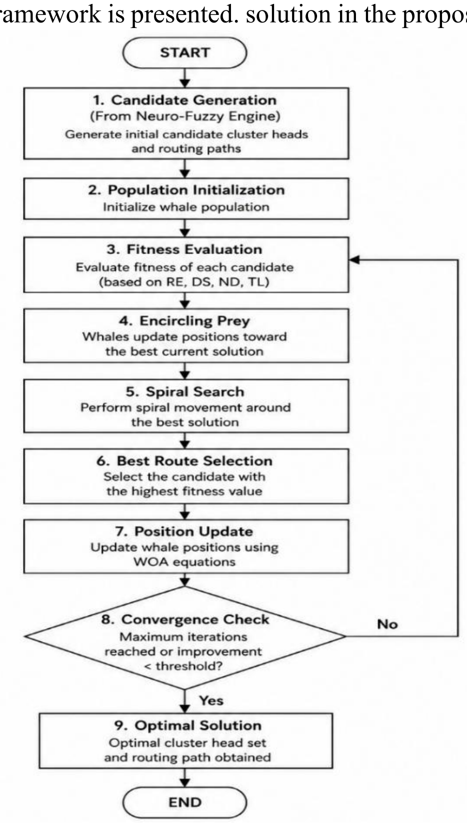

Fig. 4. Whale Optimization-Based Route Optimization Flowchart

3.7. Hybrid Routing Algorithm

The proposed Hybrid Neuro-Fuzzy and Whale Optimization Algorithm (HNF-WOA) aims to combine the intelligent decision making with global optimization within a single routing mechanism. The Neuro-Fuzzy engine first proposes a set of candidate nodes to consider based on the residual energy, distance to the sink, node density and traffic load, creating a set of routing scores that indicate the suitability of the candidate nodes. Later, the Whale Optimization Algorithm (WOA) is used to determine the most energy-efficient cluster heads and routing paths based on these scores. Then the optimized routing configuration is used for multi-hop data transmission, which guarantees energy balance and longer network lifetime.

Algorithm 1. Hybrid Neuro-Fuzzy and WOA Routing Algorithm

Input: Sensor Nodes, Residual Energy, Distance to Sink, Node Density, Traffic Load
Output: Optimal Cluster Heads and Routing Paths

Begin
1. Deploy sensor nodes in the network area.
2. Perform neighbor discovery and construct neighbor tables.
3. Form clusters based on connectivity and density information.
4. Collect network parameters:
    - Residual Energy
    - Distance to Sink
    - Node Density
    - Traffic Load
5. Execute Neuro-Fuzzy evaluation.
6. Generate routing scores for all candidate nodes.
7. Initialize Whale Optimization population.
8. Evaluate candidate fitness values.
9. Perform route optimization using WOA.
10. Update candidate positions and search for better solutions.
11. Select optimal cluster heads.
12. Establish optimal multi-hop routing paths.
13. Perform data transmission.
14. Update node energy levels.
15. Repeat optimization until network termination.

End

The proposed HNF-WOA routing algorithm is a single algorithm that combines the clustering mechanism, Neuro-Fuzzy decision-making process and Whale Optimization-based route optimization. First, sensor nodes are clustered and then candidate nodes are selected by the Neuro-Fuzzy engine on various network parameters. The routing scores generated are then optimized using the Whale Optimization Algorithm to find the best routing path and cluster heads. Lastly, the chosen paths are used to transmit data multi-hop to the sink node. The overall operating flow of the proposed routing structure is shown in Figure 5.

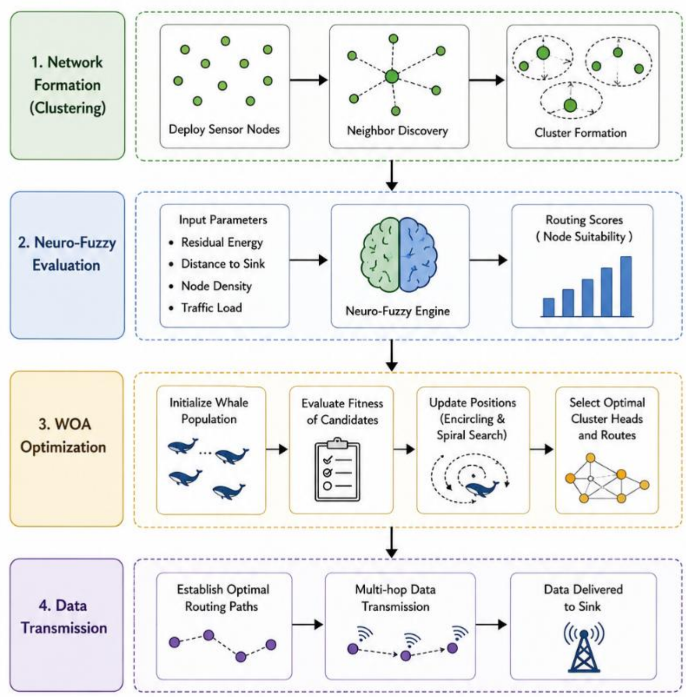

Fig. 5. Hybrid Neuro-Fuzzy and WOA Routing Algorithm Workflow

3.8. Multi-Hop Data Transmission

In order to minimize the energy consumption and enhance the efficiency of communication in massive IoT networks, the proposed HNF-WOA framework adopts a multi-hop transmission mechanism. Sensor nodes send information to the cluster head that is closest to the sensor. The cluster head collects the received information, and it will send the information to one or more relay cluster heads until it reaches the sink. This hierarchical communication structure Reduces long-distance transmissions, equalizes the energy consumption of nodes, and enhances network scalability. Optimized routing paths obtained from Whale Optimization Algorithm are used to get the most energy-efficient forwarding paths. In Figure 6, hierarchical structure of communication is designed where the data transmission takes place from the sensor nodes to the cluster heads and further from cluster heads to the relay cluster heads to the sink node.

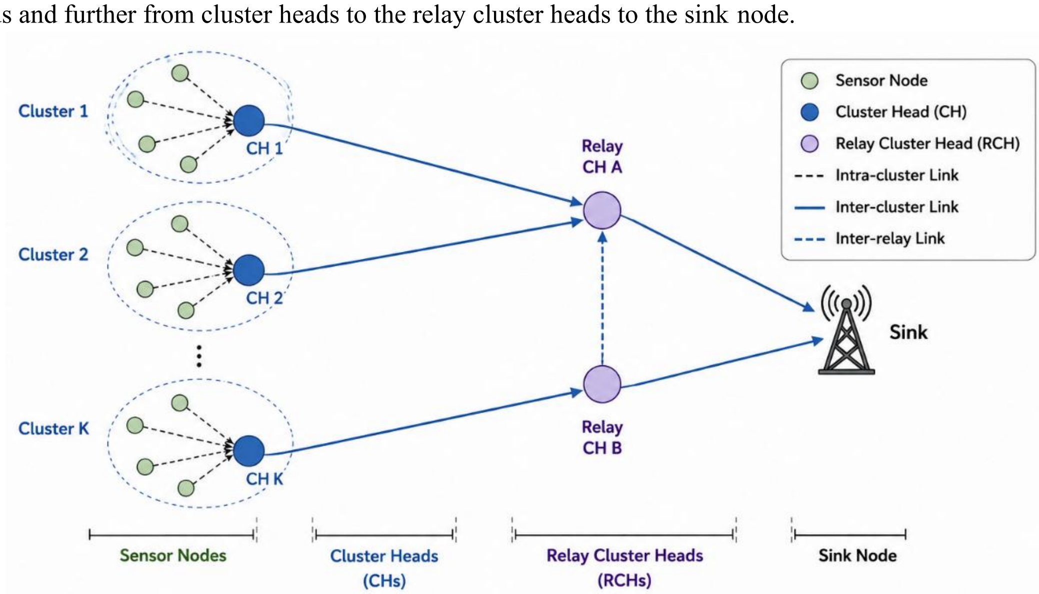

Fig. 6. Multi-Hop Routing Architecture

4. EXPERIMENTAL SETUP

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4.1 Authors and Affiliations

A comprehensive simulation environment was set up to assess the effectiveness of the proposed Hybrid Neuro-Fuzzy and Whale Optimization Algorithm (HNF-WOA) routing scheme. The proposed protocol has been designed and simulated in MATLAB R2024a platform, which is a flexible platform for modelling large-scale IoT networks, clustering mechanisms, intelligent routing algorithms, and optimization techniques. The simulation environment was set up to represent realistic IoT communication scenarios with many sensor nodes spread over a wide geographical area.

Several commonly used network performance metrics were used to evaluate the performance of the proposed routing scheme. Among these metrics are energy consumption, network lifetime, throughput, packet delivery ratio (PDR), end-to-end delay, residual energy, dead nodes, and scalability performance. These measures collectively assess the protocol's effectiveness in enhancing communication efficiency, optimizing energy usage, and ensuring network reliability. The proposed approach was evaluated through simulation using a number of well-known routing protocols that are widely used in IoT and wireless sensor networks. The clustering-based routing protocols are LEACH, HEED, PEGASIS, the chain-based routing protocols are RPL, and the intelligent routing protocols are Fuzzy Routing.

In this study, the simulation parameters, performance measures, and benchmark protocols are summarized in Table 8.

TABLE VIII. EXPERIMENTAL SETUP AND EVALUATION PARAMETERS

Category	Parameter	Description
Simulation Environment	Software Platform	MATLAB R2024a
Simulation Environment	Network Type	Large-Scale IoT Network
Simulation Environment	Routing Strategy	Hybrid Neuro-Fuzzy + WOA
Performance Metric	Energy Consumption	Total communication energy consumed during simulation
Performance Metric	Network Lifetime	Number of operational rounds before node depletion
Performance Metric	Throughput	Successfully delivered packets per unit time
Performance Metric	Packet Delivery Ratio (PDR)	Ratio of successfully received packets to transmitted packets
Performance Metric	End-to-End Delay	Average packet transmission delay
Performance Metric	Residual Energy	Remaining energy available in network nodes
Performance Metric	Dead Nodes	Number of nodes that exhausted their energy resources
Performance Metric	Scalability Factor	Protocol performance under increasing network size
Benchmark Protocol	LEACH	Cluster-based energy-efficient routing protocol
Benchmark Protocol	HEED	Residual-energy-based clustering protocol
Benchmark Protocol	PEGASIS	Chain-based energy-efficient routing protocol
Benchmark Protocol	RPL	Routing protocol for low-power and lossy networks
Benchmark Protocol	Fuzzy Routing	Intelligent fuzzy logic-based routing protocol

5. RESULTS AND DISCUSSION

5.1. Energy and Network Lifetime Performance

The energy efficiency is one of the most critical performance metrics of IoT routing protocols as it affects the lifetime of a network and sustainability of communication. The proposed HNF-WOA framework has a continuous balance process between energy consumption, intelligent cluster-head selection and optimized multi-hop routing. As a result, the energy consumption is evenly spread throughout the network, minimising the likelihood of network nodes failing prematurely.

For the assessment of energy-related performance, the overall energy consumption, energy remaining in the network, network lifetime and energy-related dead nodes were studied during the entire simulation period. The results show that the proposed protocol has a higher residual energy level and extended network lifetime over the conventional routing protocols. Moreover, less nodes are turned off because of exhausted batteries, which shows the effectiveness of the proposed optimization strategy. This qualitative comparison is presented in the form of a graph showing the energy consumption behavior of the studied routing protocols during the simulation time, as shown in Figure 7. As well as the corresponding numerical results are summarized in Table 9.

The proposed Hybrid Neuro-Fuzzy and Whale Optimization Algorithm (HNF-WOA) routing framework was tested using extensive simulations, and its performance has been compared with various benchmark routing protocols such as LEACH, HEED, PEGASIS, RPL and Fuzzy Routing. The performance of energy efficiency, network lifetime, routing performance and scalability were evaluated. The results obtained show the efficiency of using Neuro-Fuzzy decision making together with Whale Optimization for intelligent and energy-efficient routing in large-scale IoT systems.

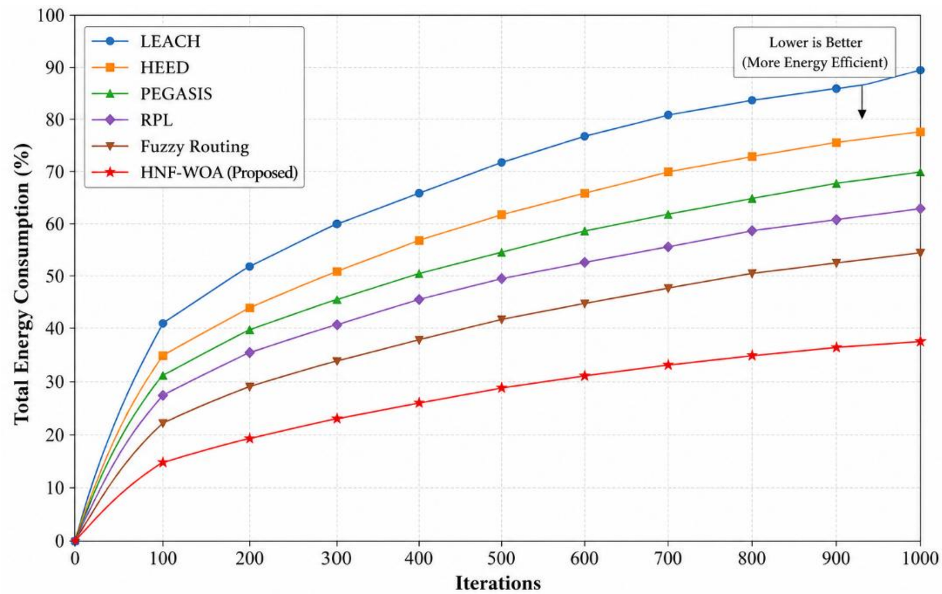

Fig. 7. Energy Consumption Comparison of Routing Protocols

TABLE IX. ENERGY AND LIFETIME PERFORMANCE COMPARISON

Protocol	Energy Consumption (%)	Residual Energy (%)	Dead Nodes	Network Lifetime (Rounds)
LEACH	42	58	105	760
HEED	37	63	94	810
PEGASIS	35	65	87	835
RPL	31	69	80	890
Fuzzy Routing	25	75	60	950
HNF-WOA (Proposed)	**18**	**82**	**42**	**1080**

The proposed HNF-WOA protocol achieved the lowest energy consumption (18%) compared with LEACH (42%) and HEED (37%). This improvement is attributed to intelligent cluster-head selection and optimized multi-hop routing provided by the integration of Neuro-Fuzzy inference and WOA optimization.

5.2. Routing Performance Analysis

In addition to energy efficiency, reliable packet delivery and communication quality are essential requirements for large-scale IoT networks. Therefore, the routing performance of the proposed protocol was evaluated using throughput, packet delivery ratio (PDR), and end-to-end delay metrics. The Neuro-Fuzzy decision engine improves routing quality by selecting suitable forwarding nodes according to network conditions, while the Whale Optimization Algorithm identifies efficient communication paths. As a result, the proposed protocol achieves higher throughput and packet delivery performance while simultaneously reducing communication delay. Figure 8 presents the overall routing performance comparison among the evaluated protocols, and the quantitative routing results are summarized in Table 10.

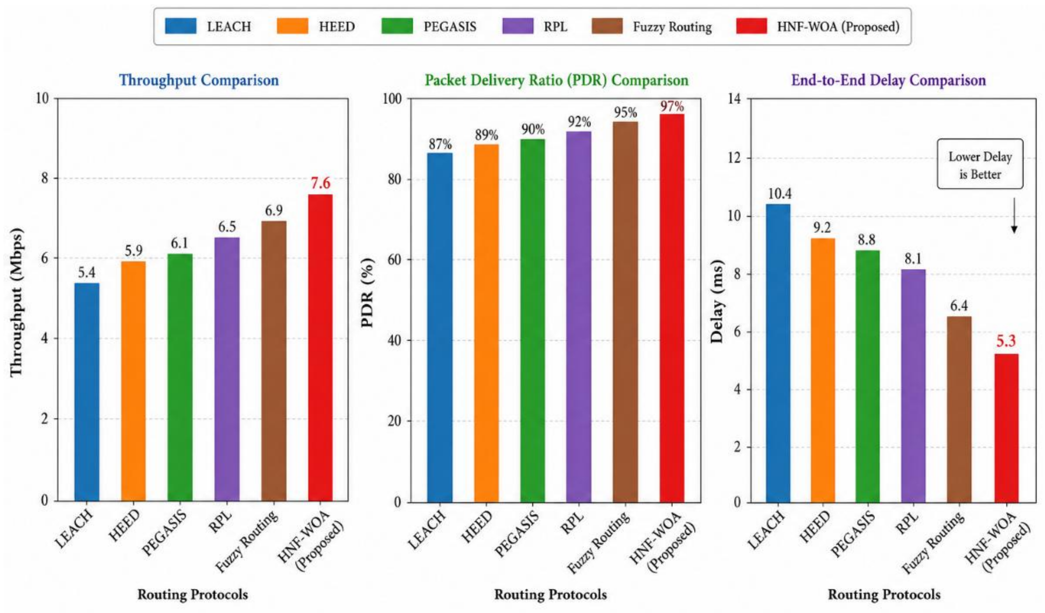

Fig. 8. Routing Performance Comparison

TABLE X. ROUTING PERFORMANCE COMPARISON

Protocol	Throughput (Mbps)	PDR (%)	Delay (ms)
LEACH	5.4	87	10.4
HEED	5.9	89	9.2
PEGASIS	6.1	90	8.8
RPL	6.5	92	8.1
Fuzzy Routing	6.9	95	6.4
HNF-WOA (Proposed)	**7.6**	**97**	**5.3**

The results presented in Table 10 demonstrate the superiority of the proposed HNF-WOA routing protocol in terms of communication performance. The proposed framework achieved the highest throughput of 7.6 Mbps and the highest packet delivery ratio (PDR) of 97%, indicating more reliable and efficient data transmission compared with the benchmark protocols. Furthermore, HNF-WOA achieved the lowest end-to-end delay of 5.3 ms, which reflects the effectiveness of the Neuro-Fuzzy decision engine and Whale Optimization Algorithm in selecting optimal routing paths. These improvements confirm that the proposed protocol can enhance communication quality while maintaining efficient network operation in large-scale IoT environments.

5.3. Scalability and Comparative Analysis

To assess scalability, the proposed protocol was evaluated under different network sizes ranging from 200 to 1000 sensor nodes. The results demonstrate that the HNF-WOA framework maintains stable performance as the network size increases. This behavior is primarily attributed to the cluster-based architecture, intelligent Neuro-Fuzzy decision-making, and global optimization performed by the Whale Optimization Algorithm.

The scalability evaluation confirms that the proposed framework remains effective in dense IoT deployments and can support large-scale communication scenarios without significant degradation in routing performance. Figure 9 illustrates the scalability performance of the proposed routing framework under varying network sizes. Then, A final overall comparison is presented in Table 11.

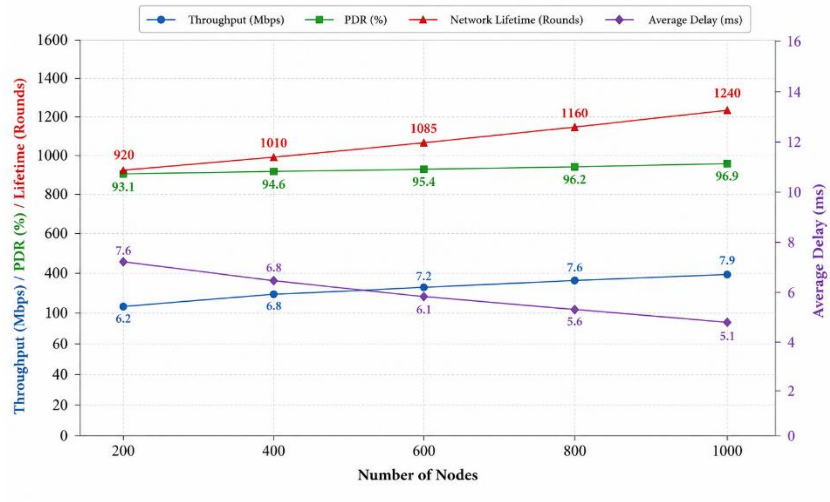

Fig. 9. Scalability Performance of the Proposed HNF-WOA Framework

TABLE XI. OVERALL COMPARATIVE PERFORMANCE ANALYSIS

Protocol	**Energy Efficiency (%)**	**PDR (%)**	**Delay (ms)**	**Network Lifetime (Rounds)**
LEACH	58	87	10.4	760
HEED	63	89	9.2	810
PEGASIS	65	90	8.8	835
RPL	69	92	8.1	890
Fuzzy Routing	75	95	6.4	950
HNF-WOA (Proposed)	**82**	**97**	**5.3**	**1080**

Table 11 provides an overall comparison of the evaluated routing protocols using the most important network performance metrics. The proposed HNF-WOA framework consistently outperformed LEACH, HEED, PEGASIS, RPL, and Fuzzy Routing across all evaluation criteria. Specifically, it achieved the highest energy efficiency (82%), the highest packet delivery ratio (97%), the lowest communication delay (5.3 ms), and the longest network lifetime (1080 rounds). These results demonstrate that the integration of Neuro-Fuzzy intelligence with Whale Optimization effectively balances energy consumption, improves routing reliability, and enhances scalability. Consequently, the proposed framework represents a robust and energy-efficient routing solution for large-scale IoT deployments. The obtained results validate the research hypothesis that combining adaptive Neuro-Fuzzy decision-making with swarm-based optimization can simultaneously improve energy efficiency and routing performance. Unlike existing approaches that focus on either intelligent routing or route optimization individually, the proposed HNF-WOA framework integrates both capabilities within a unified architecture, resulting in improved network lifetime, reduced delay, and enhanced scalability for large-scale IoT networks.

6. CONCLUSION

This study presented a Hybrid Neuro-Fuzzy and Whale Optimization Algorithm (HNF-WOA) routing framework for enhancing energy efficiency in large-scale Internet of Things (IoT) networks. The proposed approach combines the intelligent decision-making capability of Neuro-Fuzzy systems with the global optimization strength of the Whale Optimization Algorithm to achieve efficient cluster-head selection and routing path optimization. Through intelligent clustering, adaptive routing decisions, and optimized multi-hop communication, the proposed framework successfully reduced energy consumption, balanced network load, prolonged network lifetime, improved packet delivery performance, and maintained low communication delay. Furthermore, the scalability analysis demonstrated that the proposed routing protocol remains effective under increasing network sizes, making it suitable for large-scale IoT deployments. Overall, the integration of Neuro-Fuzzy intelligence and swarm-based optimization provides a robust and energy-aware routing solution capable of addressing the challenges associated with dense and resource-constrained IoT environments. Future research may extend the proposed framework by incorporating Federated Learning-based routing mechanisms for decentralized intelligence, Deep Reinforcement Learning techniques for dynamic routing adaptation, Edge Computing integration to support real-time decision-making, and secure routing frameworks that enhance data confidentiality, authentication, and resilience against cyberattacks in next-generation IoT networks.

Conflicts of Interest

The authors declare no conflict of interest.

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