HH-NMSFRA: A Heterogeneity-Aware Hybrid Protocol for Energy-Efficient Routing in Wireless Sensor Networks

Maroua Hammadi, and Mohammed Redjimi

Abstract—**When designing and implementing Wireless Sensor Networks (WSNs), where sensor nodes are restricted by battery power, energy efficiency is a fundamental challenge. In order to optimize energy consumption and enhance data delivery performance, this study suggests a new Heterogeneity-aware Hybrid NMSFRA (HH-NMSFRA) protocol that combines energy-aware node selection, multi-hop routing, and hybrid clustering approaches. By dynamically modifying the cluster head (CH) selection procedure in response to residual energy and node capabilities, the protocol takes node heterogeneity into consideration. Additionally, swarm intelligence methods like Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) are integrated for effective multi-hop routing towards the base station (BS), and reinforcement learning (RL) is used to improve the adaptive behavior of the protocol. According to simulation studies, HH-NMSFRA performs better than conventional protocols like M-LEACH, EDEEC, and NMSFRA in important performance parameters like control overhead, energy consumption, data delivery ratio, and network lifetime. In particular, HH-NMSFRA improves the data transmission ratio by 25% and extends network lifetime by up to 30% when compared to DEEC, making it a viable option for HWSNs with limited energy.**

Index terms—**HWSN, CH selection, NMSFRA, Reinforcement Learning, mobility.**

I. Introduction

Wireless Sensor Networks (WSNs) have emerged as an indispensable technology for real-time data acquisition and environmental sensing in diverse and often challenging or inaccessible areas. Their widespread adoption spans multiple application domains, including military surveillance, battlefield monitoring, environmental and climate observation, industrial automation, precision agriculture, healthcare monitoring, and smart city infrastructure [1]. These networks are composed of spatially distributed sensor nodes, each equipped with sensing, computation, and wireless communication capabilities.

Despite their utility and versatility, a critical limitation of WSNs lies in the restricted energy resources of the sensor nodes. Typically powered by compact, non-rechargeable batteries, these nodes face operational challenges once their energy reserves are exhausted. The depletion of energy in even a subset of nodes can result in reduced sensing coverage, discontinuities in data collection, and ultimately, fragmentation of the communication topology, thereby degrading the network's overall performance and reliability [2].

To tackle these energy constraints, researchers have proposed a variety of energy-efficient communication and routing strategies. Among these, cluster-based routing protocols have shown considerable promise due to their ability to reduce communication overhead and balance energy consumption. In such protocols, sensor nodes are organized into clusters, with one node within each cluster elected as the Cluster Head (CH). The CH is responsible for aggregating data from cluster members, performing local data fusion, and transmitting the aggregated data to the base station (BS). This hierarchical structure helps in reducing the number of direct transmissions to the BS, thereby conserving energy and extending network lifespan. Nonetheless, traditional cluster-based protocols such as PEGASIS (Power-Efficient Gathering in Sensor Information Systems) [3] and LEACH (Low-Energy Adaptive Clustering Hierarchy) [4] are predominantly designed under the assumption of homogeneous network settings. In these protocols, all nodes are assumed to possess identical energy and processing capabilities. This assumption becomes problematic in real-world deployments, where node heterogeneity is common. In heterogeneous WSNs, some nodes may have higher energy reserves or enhanced processing capabilities, which, if not considered in the protocol design, may lead to overburdening of certain nodes. Consequently, these high-capacity nodes deplete their energy resources prematurely, resulting in uneven energy distribution, increased latency, and reduced network lifetime.

To address these limitations, this study proposes a novel protocol named HH-NMSFRA (Heterogeneity-aware Hybrid

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Node Management and Swarm-intelligent Fault-tolerant Routing Architecture). Designed specifically for heterogeneous WSNs, HH-NMSFRA introduces a hybrid routing framework that combines the strengths of cluster-based architecture with multi-hop communication mechanisms [5]. The protocol dynamically adapts the cluster formation and cluster head selection process by considering critical parameters such as residual energy, node proximity to the BS, historical performance metrics, and node-specific roles. By doing so, HH-NMSFRA ensures equitable load distribution and avoids over-exploitation of high-capacity nodes.

Moreover, the protocol incorporates advanced swarm intelligence techniques specifically, Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) [6] to identify optimal data forwarding paths from cluster heads to the BS. These bio-inspired optimization methods mimic natural processes to solve complex routing problems efficiently and in a distributed manner. To enhance the adaptability of the system under dynamic network conditions (e.g., changing node energy levels or mobility patterns), Reinforcement Learning (RL) [7] is integrated into the routing strategy. RL enables sensor nodes to learn from past routing decisions and environmental feedback, thus refining their future choices in terms of CH selection and path formation.

The proposed HH-NMSFRA protocol is rigorously evaluated through a series of simulations conducted under varying network scenarios. Performance metrics such as network lifetime, energy consumption, packet delivery ratio, and load balancing efficiency are analyzed. The simulation results conclusively demonstrate that HH-NMSFRA outperforms conventional protocols like LEACH, SEP, and DEEC, delivering up to 30% improvement in network lifetime and a 25% increase in data transmission efficiency compared to the DEEC protocol. These findings validate the protocol’s robustness and efficacy, particularly in environments characterized by heterogeneous nodes and stringent energy limitations. As such, HH-NMSFRA represents a viable and scalable solution for enhancing the performance and sustainability of next-generation WSN deployments.

The main contributions of this research are as follows:

- We propose HH-NMSFRA, a novel heterogeneity-aware hybrid clustering and routing protocol for wireless sensor networks (WSNs) that effectively balances energy consumption and improves network longevity.
- The protocol introduces a dynamic and energy-aware cluster head (CH) selection mechanism based on residual energy, node role, and neighborhood density, ensuring fair load distribution among nodes.
- A multi-hop routing strategy is integrated with swarm intelligence techniques, namely Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), to construct energy-efficient and reliable communication paths.
- Reinforcement learning (RL) is employed to enable adaptive decision-making and enhance the protocol’s responsiveness to changing network conditions.
- Extensive simulation results are presented to validate the protocol's performance in terms of energy consumption, packet delivery ratio, network lifetime, and load balancing, demonstrating significant improvements over existing protocols such as EDEEC, M-LEACH, and NMSFRA.

The rest of the paper is organized as follows: Section II will present some related works. Section III is devoted to the proposed methodology. Simulation results are presented and discussed in Section IV, and Section V concludes this paper.

II. Related Work

In a variety of fields, including smart cities, military surveillance, health care systems, and environmental monitoring, wireless sensor networks (WSNs) [8] [9] have become essential technologies. Ensuring energy efficiency is a crucial design challenge in WSNs, particularly when sensor nodes have limited power resources [10]. In Mobile Wireless Sensor Networks (MWSNs), where node are mobile, dynamic topology changes, and varied energy capacities must be effectively controlled, the issue gets even more complicated. To address these problems, a variety of routing protocols have been proposed and some of them implemented, each focusing on a distinct area such as energy optimization, mobility management, and clustering [11].

To evenly divide energy consumption, LEACH (Low-Energy Adaptive Clustering Hierarchy), one of the fundamental routing protocols, operates by periodically selecting cluster heads randomly and rotating this role among the nodes. Although LEACH is straightforward and effective for static and homogenous networks, its lack of adaptability and restricted awareness of node location and energy cause it to perform worse in heterogeneous or mobile circumstances.

M-LEACH (Multi-hop LEACH) [12], which incorporates mobility assistance through periodic CH re-selection and handoff processes, is designed to address the shortcomings of LEACH in dynamic situations. M-LEACH is ineffective in heterogeneous WSNs because it assumes a uniform energy distribution even though it allows for node relocation.

Energy heterogeneity was specifically addressed by protocols such as SEP (Stable Election Protocol), DEEC (Distributed Energy-Efficient Clustering), and E-DEEC (Enhanced DEEC) [13]. While DEEC employed residual and average energy measures to enhance CH election, SEP suggested weighted probability for CH selection based on node energy levels. Nevertheless, many protocols exhibit performance loss during mobility and are typically optimized for static topologies.

NMSFRA (Node Mobility and Sensing Frequency Routing Algorithm) [14] was developed to close the gap between energy heterogeneity and mobility awareness. The protocol begins with cluster formation using the MS technique to ensure balanced cluster distribution, which helps equalize energy consumption across the network. It employs a dynamic fuzzy logic system for cluster head selection, adapting input parameters based on node mobility to optimize leadership roles. Additionally, the protocol accounts for link stability and incorporates a mobility model, while multi-hop routing is optimized using the NGO (Northern Goshawk Optimization) algorithm [15] to further balance cluster head (CH) energy usage and prolong network operation. To improve routing choices and CH assignments, NMSFRA integrates sensor frequency analysis with mobility prediction. Despite its improvements, NMSFRA does not take into consideration the energy capacity heterogeneity of nodes or make use of sophisticated optimization techniques that could increase network lifetime and routing stability. In response, a number of hybrid and bio-inspired metaheuristic algorithms have been studied in the field of WSN. In cluster formation and CH selection, protocols based on Particle Swarm Optimization (PSO) [15], Genetic Algorithms (GA)[16], Ant Colony Optimization (ACO) [17], and Whale Optimization Algorithm (WOA) [18] have demonstrated encouraging outcomes. Although these algorithms optimize load balancing and energy consumption, they frequently have delayed convergence and significant computational complexity.

Recently, there has been interest in the incorporation of Reinforcement Learning (RL) into WSN routing. Through interaction with the environment, nodes can learn the best policies for routing and CH selection using RL-based approaches. However, particularly in mobile and heterogeneous networks, these techniques necessitate careful adjustment of reward functions and exploration tactics.

Based on the hunting and gliding habits of pelicans, the Pelican Optimization Algorithm (POA) [19] is a relatively new bio-inspired metaheuristic. In optimization problems, it has proven to have low computational overhead and high convergence properties. Its use in WSNs is still relatively new, nevertheless [20].

In light of these advancements, the suggested Hybrid Heterogeneous NMSFRA (HH-NMSFRA) combines the advantages of the Pelican Optimization Algorithm, mobility prediction, reinforcement learning, and heterogeneity-aware routing. The goal of this hybrid protocol is to optimize network lifetime, residual energy, throughput, and packet delivery ratio (PDR) by dynamically choosing energy-efficient cluster heads in mobile and heterogeneous contexts. HH-NMSFRA overcomes significant drawbacks in both conventional and contemporary WSN protocols by utilizing the global search efficiency of POA and the adaptive learning potential of RL.

III. Proposed Methodology: Hybrid Heterogeneity-Aware NMSFRA (HH-NMSFRA)

In this paper, we propose the HH-NMSFRA (Hybrid Heterogeneity-Aware Node Mobility Supported Fault-tolerant Routing Algorithm), an improved routing protocol for mobile wireless sensor networks (MWSNs). The dynamic nature of node mobility and the unequal energy usage brought on by heterogeneous node capabilities are two significant issues in MWSNs that this protocol attempts to remedy. HH-NMSFRA optimizes energy use, enhances route stability, and prolongs network lifetime by combining a heterogeneity-aware load balancing mechanism with a hybrid protocol structure.

Traditional routing techniques usually employ a combination of proactive and reactive strategies, which limits their ability to adapt to changing network conditions. A hybrid mode-switching technique is introduced by HH-NMSFRA, which dynamically switches between proactive and reactive routing according to connection stability, energy levels, and node mobility.

Nodes, constantly, monitor and update mobility conditions (node speed), link failure rates, and energy levels in the network. Mobility-aware Switching Function (MSF) is computed at regular intervals by the base station to determine the appropriate routing mode:

$$MSF = \theta_1.V_{avg} + \theta_2.L_{fail} + \theta_3.(1 - \frac{E_{avg}}{E_{init}}) \tag{1}$$

where V_{avg} is the average node velocity, L_{fail} is the average link failure rate, E_{avg} and E_{init} represent the current and initial average energy of the network, respectively, Θ_1, Θ_2, and Θ_3 are weighting coefficients determined empirically.

If MSF exceeds a pre-defined threshold T_{switch}, the protocol switches to a reactive mode to reduce control overhead and adapt to rapid topological changes. Otherwise, it remains in proactive mode to maintain stable and energy-efficient routes.

Nodes in heterogeneous MWSNs have different communication ranges and energy attributes. Because advanced nodes are frequently chosen to be cluster heads (CHs), they are vulnerable to early energy depletion if effective regulation is not in place. This is addressed by HH-NMSFRA, which ensures equitable participation across all node types by introducing a Cluster Head Suitability Weight (W_i) for CH selection.

In proactive mode, the network maintains static routing tables that store the best routes to the sink. The proactive approach works best when the network topology is stable and mobility is low. Nodes periodically check their residual energy and select a Cluster Head (CH) based on the Cluster Head Suitability Weight (W_i):

$$W_i = \frac{E_i}{1+C_i} \tag{2}$$

where E_i is the current residual energy of node i, C_i is the count of previous rounds in which node i actes as a CH.

Nodes with the highest Wi within their vicinity are selected as CHs, thereby promoting rotational leadership and balanced energy usage across normal, advanced, and super nodes.

If $MSF > T_{switch}$, the network transits to reactive mode. In this mode, nodes no longer maintain static routing tables. Instead, nodes submit a Route Request (R_{REQ}) to their neighbors to start the route discovery process, and the neighbors forward the R_{REQ} to the sink. A Route Reply (R_{REP}) is returned to the source node when a route has been located. Once a valid route is discovered, data transmission occurs along the established path. The nodes relay packets towards the sink node, using the discovered route. After each transmission, the residual energy of the nodes is updated. Nodes with low energy are less likely to participate in future route discoveries or CH selections.

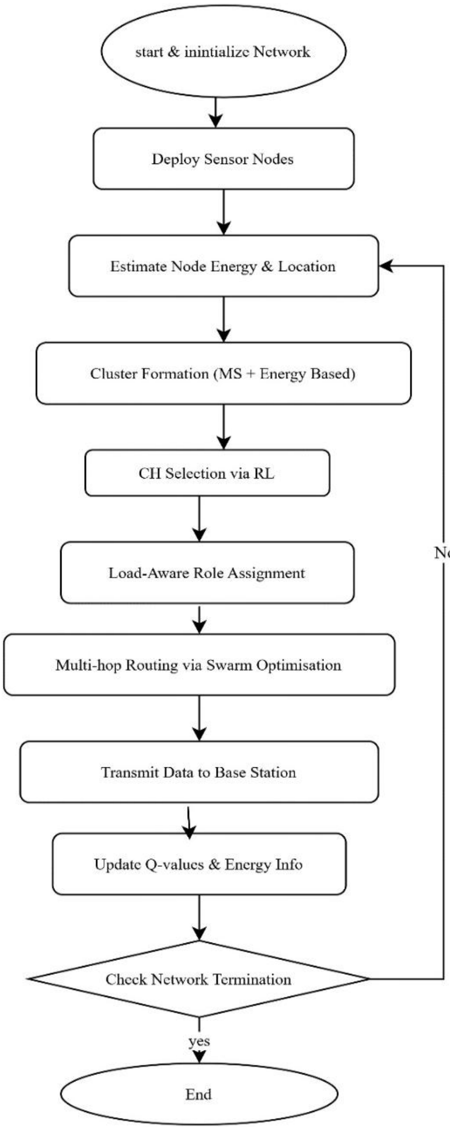

Fig.1. Flowchart of the HH-NMSFRA

To ensure fair energy distribution across nodes with varying energy capacities, energy-weighted CH selection is implemented; nodes with higher energy are more likely to become CHs, but there is a penalty for being chosen too often. the number of rounds a node has served as a CH is tracked by the penalty counter, which increases with each selection.

Each node is assigned tokens based on its energy capacity. A node must spend tokens to become a CH, which prevents energy-rich nodes from being selected too frequently. Nodes with zero tokens are skipped in the CH selection process until they accumulate more tokens after serving as non-CHs.

Once routes are established in either mode, the data transmission process continues (fig.1), with nodes forwarding data towards the sink. After each data round or at regular intervals, the MSF is recalculated to determine if the network should stay in the current mode (proactive or reactive) or switch to the other mode**.** The residual energy of all nodes is updated after each transmission, and the CH role is rotated based on the energy status and the token system (algorithm 1).

Algorithm 1**:** HH-NMSFRA Algorithm

Input:
N nodes deployed in area A
Initial energy E_0 for normal, advanced, and super nodes
Base Station location (x_{bs}, y_{bs})
Output:
Efficient multi-hop data delivery and prolonged network lifetime
1: Initialize network parameters and node energy levels
2: Classify nodes into normal, advanced, and super types based on heterogeneity
3: for each round r do
4: Compute average residual energy E_{avg} of all nodes
5: for each node i do
6: if node i is eligible to become Cluster Head (CH) then
7: Calculate CH probability:
$P_{CH}(i) = P_{opt} \times (E_{residual}(i) / E_{avg})$
8: Generate random number rand ∈ [0,1]
9: if rand < Threshold(i) then
10: Assign node i as Cluster Head
end if
end if
end for
11: Form clusters: assign each non-CH node to nearest CH
12: for each CH j do
13: Select next-hop node with:
- Higher residual energy
- Lower distance to BS
- Minimum forwarding cost
14: Transmit aggregated data using multi-hop path
end for
15: Update energy levels using radio energy model:
E_{Tx}, E_{Rx}, and aggregation costs
16: Remove dead nodes ($E_{residual} \le 0$)
17: end for

Notes:

- Popt is the optimal CH probability.
- Threshold(i) is the standard threshold function used in LEACH-like protocols.
- Forwarding cost includes both distance and inverse residual energy (weighted).

Nodes join clusters based on the intensity of the received signal and the expected link stability after the CHs have been chosen. Depending on the node density and mobility conditions, CHs combine data from member nodes and send it to the base station via single-hop or multi-hop transmission. Routing tables are kept up to date with energy and link-quality indicators on a regular basis when in proactive mode. Reactive mode favors stable and energy-rich relay nodes by employing a lightweight request-response mechanism to find routes on-demand.

Data transmission, reception, sensing, and data aggregation are the main processes of wireless sensor networks that use energy. We utilize the radio model [4], which is popular in

WSN simulations because of its ease of use and efficiency in capturing communication energy costs, to assess the efficacy of the suggested HH-NMSFRA protocol. By giving distinct beginning energy levels to different node kinds (such as normal, advanced, and super nodes), the energy model takes into consideration the heterogeneity of nodes. In a three-level heterogeneous wireless sensor network (HWSN), sensor nodes are often categorized into normal, advanced, and super nodes based on their energy capacities. Normal nodes have the lowest initial energy, advanced nodes possess moderately higher energy, and super nodes are equipped with significantly more energy than these other two types. This heterogeneity helps to balance energy consumption, enhance scalability, and extend network lifetime. Protocols designed for HWSNs typically leverage this energy variation to optimize clustering, routing, and data transmission strategies.

According to the radio model, the energy required to transmit a l-bit message over a distance d is given by:

$$E_{TX}(l,d) = \begin{cases} l.E_{elec} + l.\mathcal{E}_{fs}.d^2, & d < d_0 \\ l.E_{elec} + l.\mathcal{E}_{mp}.d^4, & d \geq d_0 \end{cases} \quad (3)$$

where $E_{TX}(l,d)$ is energy consumed in transmitting l bits over a distance d, E_{elec} is energy dissipated to run the transmitter or receiver circuitry, $\mathcal{E}_{fs}$ is freespace model amplification energy, $\mathcal{E}_{mp}$ is multipath fading model amplification energy, $d_0 = \sqrt{\mathcal{E}fs/\mathcal{E}mp}$ represents the threshold distance.

The energy required to receive an l-bit message is:

$$E_{RX}(l) = l.E_{elec}$$

Before sending the data to the base station, cluster heads aggregate them. The following model represents the energy usage for the data aggregation:

$$E_{DA}(l) = l.E_{DA} \quad (4)$$

where E_{DA} is the energy required for data aggregation per bit.

In the proposed HH-NMSFRA protocol, three types of nodes are considered, according to their initial energies:

- normal nodes that have the baseline initial energy E_0,
- advanced nodes that have $(1+\alpha).E_0$ (where α>0),
- super nodes with $1+\beta).E_0$ (where β>α).

The total initial energy of the network is given by:

$$E_{total} = N.E_0.[(1-m-b) + m.(1+\alpha) + \mathrm{b}.(1+\beta)] \quad (5)$$

where N is total number of sensor nodes, E_0 is initial energy of a normal node, m is fraction of advanced nodes, α is energy factor for advanced nodes (e.g., α=0.5 means 50% more energy), b is fraction of super nodes, β is energy factor for super nodes (e.g., β=1 means 100% more energy).

Normal Nodes: $E_0(1-m-b)$
Advanced Nodes: $mE_0(1+\alpha)$
Super Nodes: $bE_0(1+\beta)$
This heterogeneity-aware energy model ensures fair energy distribution and supports energy-aware cluster head selection in HH-NMSFRA.

The HH-NMSFRA architecture combines a heterogeneity-aware framework with a hybrid routing protocol design, which is optimized for effective data transfer and longer network lifetime in Wireless Sensor Networks (WSNs). Four functional layers make up the basic architecture:

A. The Network Initialisation Layer

Node Deployment: Sensor nodes are uniformly or randomly placed throughout the sensing region. They can be homogenous or heterogeneous in terms of energy and processing capacity.

Energy Profiling: Based on their initial energy levels, nodes are categorized into various tiers (such as normal, advanced, and super nodes).

Neighborhood Discovery: To create neighborhood tables and find potential cluster heads (CHs) in the vicinity, nodes exchange Hello packets.

B. The Hybrid Clustering and Role Assignment Layer

Heterogeneity-Aware Cluster Formation: Cluster heads are elected using a weighted probabilistic model that accounts for residual energy, node type (heterogeneity level), and proximity to the base station. A reinforcement learning mechanism (e.g., Q-learning) assists in learning the optimal CHs over time.

Hybrid Role Delegation: combines proactive clustering (for stable high-energy nodes) and reactive role switching (based on energy thresholds) and implements load-aware CH rotation to prevent premature node death.

C. Multi-hop Route Construction Layer

Swarm-Based Routing: inspired by swarm intelligence (e.g., PSO or ACO), nodes collaboratively select energy-efficient multi-hop paths toward the sink. Fault-tolerance is integrated using neural-inspired feedback to dynamically reroute in case of node failure. Hybrid Path Selection uses both link quality metrics and node-level context (e.g., buffer size, queue delay) for path selection and incorporates threshold-based fallback to ensure reliability under congestion or high load.

D. Data Transmission and Maintenance Layer

Load-Balanced Data Forwarding: traffic is distributed based on node energy levels and congestion status to ensure fair usage of network resources.

Periodic Maintenance: network health is monitored, and routing tables are updated periodically. Isolated or energy-depleted nodes are retired gracefully from routing roles.

Energy and Performance Logging: each node maintains lightweight logs of transmission success, residual energy, and participation in clustering/routing to assist in future decision-making.

The HH-NMSFRA protocol is designed for a heterogeneous wireless sensor network (WSN) environment, where nodes possess different energy capacities and computational capabilities. The system model is composed of the following elements:

The network deployment model: assumes a two-dimensional area where a fixed number of sensor nodes are randomly and uniformly distributed. The nodes may have heterogeneous energy levels and are capable of limited mobility. A centralized Base Station (BS) is located either inside or outside the sensing field. Nodes communicate using multi-hop transmission, and the deployment model is designed to support dynamic topology changes, enabling the protocol to adapt efficiently to node movement and maintain reliable routing and energy balance throughout the network. The network deployment also assumes that nodes are aware of their location, either through GPS or localization algorithms, and are capable of adjusting their transmission range. This flexible, mobility-aware deployment strategy ensures the protocol to adapt to varying node densities, energy distributions, and environmental conditions, ultimately enhancing both scalability and longevity of the WSN.

The clustering model: follows a multi-step process designed for efficiency and adaptability in mobile, heterogeneous WSNs:

- Initial Node Assessment: Each node evaluates its status based on residual energy, mobility factor, neighbor density, and distance to the base station (BS).
- Candidate CH Selection: Using a swarm intelligence algorithm (e.g., PSO), a pool of potential cluster heads (CHs) is selected by optimizing a fitness function combining energy, centrality, and stability metrics.
- Reinforcement Learning Evaluation: Each candidate node identified in the previous step uses a lightweight reinforcement learning (RL) agent to assess its own long-term suitability as a Cluster Head (CH). The agent interacts with its environment (i.e., the network conditions), using state inputs such as residual energy, mobility status, and connectivity quality. It receives rewards based on outcomes like successful data aggregation, minimal energy consumption, and communication stability. Over time, the agent learns an optimal policy to decide whether the node should accept or reject the CH role, improving CH selection adaptiveness and reliability in dynamic WSN conditions.
- Final CH Election: Nodes with the highest combined scores (from PSO and RL decisions) are elected as CHs.
- Cluster Formation: Non-CH nodes join the nearest or most suitable CH based on signal strength and energy cost. This forms dynamic, balanced clusters.
- Mobility Adaptation: Periodically or upon significant movement, clusters are re-evaluated. Nodes that move beyond a threshold trigger a local re-clustering event to maintain performance.
- Multi-hop CH Communication: CHs forward aggregated data to the BS via other CHs, selecting optimal paths.

This hybrid model ensures not only energy efficiency but also adaptability to mobility and heterogeneity in the WSN environment.

The CH selection process in HH-NMSFRA is designed to maximize energy efficiency and network lifetime by considering node heterogeneity, energy levels, and spatial factors. It combines probabilistic weighting, heterogeneity-awareness, and optionally, reinforcement learning (RL) for adaptive optimization. Each node calculates a weighted probability P_i of becoming a cluster head based on its initial and residual energy:

$$P_i = P_{opt} \frac{E_i(t)}{E_{avg}(t)} w_i \tag{6}$$

where P_{opt} is optimal probability of CH election, $E_i(t)$ is residual energy of nodes i at round t, $E_{avg}(t)$ is average residual energy of the network at round t, w_i is weight factor based on node heterogeneity. In Proactive Election, high-energy (super or advanced) nodes with strong connectivity are proactively favored for CH roles. In Reactive Rotation, nodes that have recently served as CHs reduce their CH probability in subsequent rounds to prevent early depletion. Nodes use a threshold function, $T(i)$ to determine CH candidacy:

$$T(i) = \begin{cases} \frac{P_i}{1 - P_i\left(t \bmod \frac{1}{P_i}\right)} & if\ i \in G \\ 0 & otherwise \end{cases} \tag{7}$$

where t is current round number, G is set of nodes not elected as CHs in the past $\frac{1}{P_i}$ rounds.

A lightweight Q-learning model is optionally integrated for optimizing CH selection over time, reducing redundant transmissions and handling dynamic energy-aware decisions. Each node maintains a Q-table with state-action pairs, where states represent energy and neighborhood quality, and actions correspond to the role selections (CH, relay, idle).
States: Residual energy level, number of neighbors, CH role history
Actions: Become CH, remain normal node
Reward: Based on energy efficiency, lifetime contribution, and load balancing

Each node updates its Q-values using:

$$Q(s,a) := Q(s,a) + \alpha[R + \gamma max Q(s', \alpha') - Q(s,a)] \tag{8}$$

where $Q(s,a)$ is estimated utility (Q-value) of taking action α in state s, a is learning rate (0 < α ≤ 1), controlling how much new information overrides old, R is immediate reward received after taking action α, γ is discount factor (0 ≤ ɣ < 1), reflecting the importance of future rewards, s' is next state after action, and $maxQ(s', \alpha')$ is maximum expected future reward from next state. This equation allows each sensor node to iteratively learn which actions (e.g., becoming or not becoming a cluster head) yield the best long-term performance based on the changing network environment. This allows nodes to learn the optimal frequency of CH selection and avoid overusing high-energy nodes.

IV. Simulation Setup and Performance Evaluation

This section presents the simulation setup and performance evaluation of HH-NMSFRA in comparison to some existing state-of-the-art protocols. To validate the performance of the proposed Hybrid Heterogeneity-aware NMSFRA (HH-NMSFRA) protocol, simulations were conducted using MATLAB. The simulation environment replicates a realistic mobile wireless sensor network with heterogeneous energy levels and node mobility patterns. The key parameters used in the simulation are summarized in Table I.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Simulation Area	100 m × 100 m
Number of Nodes (N)	100
Base Station Location	Center of the field
Node Types	Normal, Advanced, Super
Initial Energy (Normal)	0.5 J
Initial Energy (Advanced)	1.0 J
Initial Energy (Super)	1.5 J
Percentage of Advanced Nodes	30%
Percentage of Super Nodes	10%
Communication Range	25 m
Data Packet Size	4000 bits
Control Packet Size	100 bits
Node Mobility Model	Random Waypoint
Maximum Speed	2 m/s
Simulation Duration	Until last node dies (LND)
Transmission/Reception Energy	50 nJ/bit
Data Aggregation Energy	5 nJ/bit/signal
Free Space/Multipath Threshold	87 m
Threshold T_{switch}	0.35 (tuned experimentally)

Key parameters, including network area, node density, initial energy levels, heterogeneity proportions, radio energy model, packet size, and base-station placement, were chosen to reflect typical WSN deployment scenarios and to stress the energy management capabilities of routing protocols. For statistical robustness, each experiment was repeated for multiple independent runs and average values (with standard deviation) are reported. A sensitivity analysis was conducted for critical parameters (node density, base-station distance, and heterogeneity ratio) to demonstrate that the observed performance improvements of HH-NMSFRA are consistent across realistic operating conditions.

The proposed HH-NMSFRA protocol is evaluated against existing routing protocols, including M-LEACH, EDEEC and the baseline NMSFRA, using the following performance metrics:

- Network Lifetime (NL) is measured as the number of rounds until the first node dies (FND), half of the nodes die (HND), and the last node dies (LND).
- Stability Period is duration from network initialization to the first node death.
- Residual Energy is the total remaining energy of the network after a given number of rounds.
- Packet Delivery Ratio (PDR) represents the ratio of the number of packets successfully delivered to the base station to the total number of packets sent.
- Throughput is the total amount of data (in bits) received at the base station.
- Cluster Head Selection Fairness is the number of times each node serves as a CH to assess load balancing.
- Routing Overhead is the ratio of control packets to data packets delivered, particularly significant in reactive mode.

A. *Evaluation Strategy*

Baseline Comparison: HH-NMSFRA is compared with M-LEACH, EDEEC and standard NMSFRA under identical mobility and energy settings.

Mode Switching Analysis: The hybrid mode-switching mechanism is tested by varying node mobility to observe the impact of switching between proactive and reactive routing.

Heterogeneity Impact: The effect of node heterogeneity on energy consumption and CH distribution is evaluated by varying the ratio and energy of advanced/super nodes.

Mobility Sensitivity: The simulation is repeated with varying node speeds (from 0 to 3 m/s) to evaluate robustness under different mobility levels.

B. *Results and Discussion*

This section presents and analyzes the simulation results obtained for the proposed Hybrid Heterogeneity-Aware NMSFRA (HH-NMSFRA) protocol. The performance of HH-NMSFRA is compared with three benchmark protocols: M-LEACH, EDEEC and the baseline NMSFRA. The evaluation focuses on network lifetime, energy efficiency, packet delivery, and robustness under mobility.

Figure 2 illustrates the number of alive nodes over simulation rounds. HH-NMSFRA significantly outperforms the benchmark protocols in terms of First Node Death (FND), Half Node Death (HND), and Last Node Death (LND). FND occurs around round 780 in HH-NMSFRA, compared to 620 in NMSFRA, 570 in M-LEACH, and 450 in LEACH. LND is observed at round 1620 in HH-NMSFRA, while it occurs at

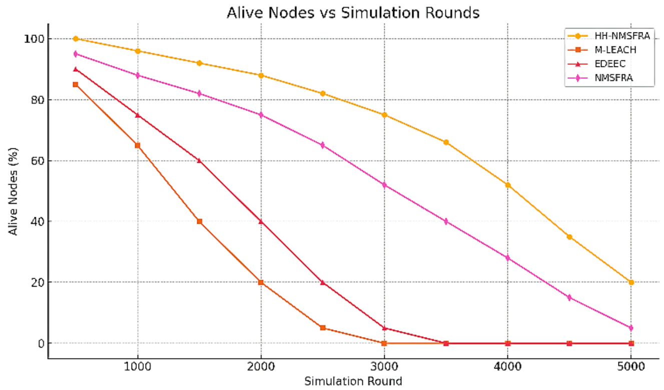

Fig. 2. Number of alive nodes over the simulation rounds

1310, 1170, and 940 for NMSFRA, M-LEACH, and LEACH respectively. The extended stability and lifetime are attributed to the hybrid routing mechanism and energy-aware CH rotation. The token system prevents overuse of high-energy nodes, ensuring balanced energy depletion. Figure 3 shows the network lifetime metrics.

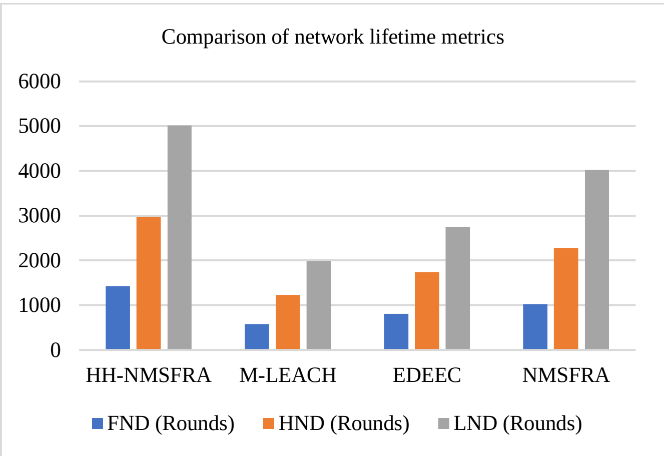

Fig. 3. Comparison of the network lifetime metrics

HH-NMSFRA shows a smoother energy dissipation curve, indicating effective load distribution. NMSFRA depletes energy faster due to less dynamic CH selection and lack of heterogeneity awareness. The heterogeneity-aware clustering and adaptive mode switching help conserve energy, especially under moderate to high mobility conditions. The token-based load balancing prevents premature energy exhaustion in advanced and super nodes. Figure 4 presents the average residual energy over time. HH-NMSFRA maintains higher energy reserves throughout the simulation.

Table II compares the PDR across all protocols. HH-NMSFRA achieves an average PDR of 96.3%, while NMSFRA, M-LEACH, and EDEEC reach 91.7%, 82.1%, and 88.4%, respectively. The use of reactive routing during high mobility enhances reliability by establishing routes based on current topology. In stable phases, proactive routing reduces delays and ensures consistent delivery. The switch between modes contributes to overall reliability.

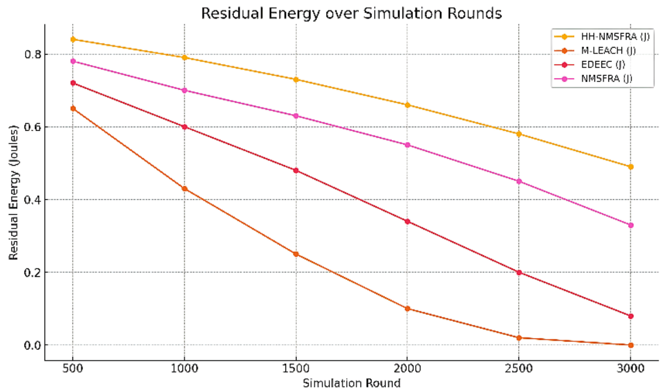

Fig. 4. Residual energy over rounds

TABLE II
COMPARISON OF PDR ACROSS PROTOCOLS.

PROTOCOL	PDR (%)
HH-NMSFRA	96.3
M-LEACH	82.1
EDEEC	88.4
NMSFRA	91.7

Table III illustrates the fairness in CH selection. In HH-NMSFRA, CH roles are distributed more evenly due to the token mechanism and energy-weighted selection. M-LEACH often favor nodes randomly, causing early deaths in certain regions. Heterogeneity-aware rotation ensures energy-rich nodes contribute more, but not excessively. This preserves fairness while maximizing network performance.

TABLE III
FAIRNESS IN CH SELECTION

PROTOCOL	CH DISTRIBUTION UNIFORMITY	LOAD BALANCING EFFICIENCY	REMARKS
HH-NMSFRA	HIGH	EXCELLENT	DYNAMIC CH SELECTION WITH LOAD-AWARENESS
M-LEACH	LOW	POOR	Random CHs lead to imbalance
EDEEC	MODERATE	FAIR	Energy-aware but lacks node distribution control
NMSFRA	GOOD	GOOD	Swarm-intelligent routing without RL

In simulations with increasing node mobility (0 to 3 m/s), HH-NMSFRA consistently maintains superior performance. NMSFRA and M-LEACH degrade significantly under high mobility due to their static routing assumptions. The Mobility Switching Function (MSF) allows HH-NMSFRA to switch routing strategies based on real-time conditions, maintaining route reliability and minimizing control overhead. HH-

NMSFRA incurs slightly higher control overhead during high mobility due to reactive route discovery. However, this is compensated by improved PDR and throughput. Table IV illustrates different metrics compared between different routing protocols.

TABLE IV
COMPARISON OF DIFFERENT METRICS

METRIC	HH-NMSFRA	NMSFRA	EDEEC	M-LEACH
STABILITY PERIOD (ROUNDS)	1450	1230	980	720
PACKETS TO BS	28000	24500	21000	17000
SCALABILITY	HIGH	MODERATE	MODERATE	LOW
MOBILITY SUPPORT	YES	YES	LIMITED	NO

The performance evaluation considers EDEEC, a single-hop heterogeneous routing protocol, alongside two multi-hop protocols, M-LEACH and NMSFRA, to provide a fair and comprehensive comparison. The inclusion of EDEEC highlights the advantages of multi-hop communication over traditional single-hop cluster-based schemes, while M-LEACH and NMSFRA serve as appropriate baselines for evaluating the enhancements introduced in multi-hop scenarios. The superior performance of the proposed HH-NMSFRA protocol demonstrates the effectiveness of its reinforcement learning-based cluster head selection, swarm intelligence-driven route optimization, and heterogeneity-aware load balancing strategies in improving energy efficiency and prolonging network lifetime.

V. CONCLUSION

This paper introduced HH-NMSFRA, a novel hybrid routing protocol designed to address the key challenges in Heterogenous Wireless Sensor Networks (HWSNs), particularly those related to energy efficiency, scalability, and fault tolerance. By integrating swarm intelligence techniques for optimal route selection, reinforcement learning for adaptive cluster head election, and a heterogeneity-aware load balancing mechanism. Simulation results show that HH-NMSFRA effectively prolongs network lifetime and enhances data delivery reliability. The proposed protocol also incorporates dynamic multi-hop communication to mitigate the energy burden on critical nodes and adapt to the varying topologies commonly found in WSN deployments. Extensive simulations and comparative analysis with established protocols such as M-LEACH, EDEEC and the baseline NMSFRA demonstrate the superiority of HH-NMSFRA in terms of residual energy preservation, number of alive nodes, packet delivery ratio, and overall throughput. The results confirm that the integration of intelligent learning and energy-aware clustering mechanisms can significantly enhance network performance under dynamic and heterogeneous scenarios. Future work will explore the deployment of HH-NMSFRA in real-time IoT applications and extend the model to incorporate mobile sink strategies, security enhancements, and intelligent data aggregation for even greater scalability and robustness.

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