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HF-Snake-WERF: A Hybrid HHO–Firefly Clustering and Snake Optimizer-Based Energy-Efficient Routing Framework for Dynamic Wireless Sensor Networks

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Abstract

Wireless sensor networks (WSNs) face severe energy, communication, and resource constraints, so clustering and routing are essential for reliable, stable operation. Current methods often optimise cluster head (CH) selection and routing independently and rely on simplified assumptions that do not capture resource allocation, dynamic topology, channel impairments, and communication reliability. In this paper, we propose HF-Snake-WERF, a hybrid energy-efficient clustering and routing approach based on Harris Hawks Optimisation (HHO), Firefly Algorithm (FFA), and Snake Optimiser (SO) for dynamic WSNs. HHO performs global exploration for CH selection and routing, and Firefly Optimisation (FFO) performs local improvements in cluster quality based on residual energy, intra-cluster compactness, cluster separation, and cluster balance. Then, the Snake Optimiser finds energy-aware multi-hop routes based on transmission distance, residual energy and hop count. The framework also accounts for different node energy, communication range, queue capacity, processing delay, node mobility, path loss, shadowing, Rayleigh fading, noise, and SINR-based packet reception. Periodic reclustering adapts to different topologies and energy levels. In our experiments with traditional minimum-hop routing, we observe improvements in packet delivery ratio (PDR), throughput, and energy efficiency: average PDR rises from 0.603 to 0.869, throughput from 709.43 to 986.54 kbps, and normalised average energy consumption (NAEC) drops to 1.452 J/packet. Our approach therefore offers a coherent approach for reliable, energy-aware and adaptive WSN communication.

1 Introduction

WSNs have become a vital communication framework for distributed sensing, environmental monitoring, industrial automation, healthcare, surveillance, and Internet of Things (IoT) applications. Their ability to operate without fixed communication infrastructure makes them ideal for large-scale, geographically distributed deployments. But sensor nodes are typically limited by battery energy, communication range, processing power, and storage capacity. Because wireless communication is a major source of energy expenditure, inefficient data forwarding can rapidly deplete critical nodes and degrade network lifetime, connectivity, and data-delivery reliability. As such, clustering and multi-hop routing have been increasingly explored and used in recent years to reduce communication cost and energy consumption across the network [1–3].

Clustering is especially beneficial because it avoids redundant messages by aligning sensor nodes around representative CHs. Nevertheless, CH selection is a complex optimisation problem because a good CH should have sufficient residual energy, a balanced distribution of communication between clusters, and good intra-cluster distances. Recent metaheuristic approaches have used particle swarm optimisation, HHO, fuzzy systems, graph-based learning, and other nature-inspired methods to tackle this problem [4–10]. While these approaches have shown lower energy consumption and longer network lifetime, reviews indicate that the literature remains fragmented in clustering, optimisation, network assumptions, and evaluation. In particular, static network assumptions, simplified communication models, and limited understanding of dynamic topology remain major challenges.

Another important issue is that optimised clustering does not automatically guarantee efficient inter-cluster communication. A CH may be optimally selected for intra-cluster communication but inefficient for multi-hop transmission. Hence, recent research has focused on joint or coordinated clustering and routing, including two-level genetic optimisation, hybrid metaheuristic frameworks, HHO-based routing, SO-based multi-hop routing, and AI-assisted clustering-routing schemes [11–17]. For instance, Kaedi et al. jointly optimised CH selection and inter-cluster routing using a two-level genetic algorithm, and recent HHO-based methods combine clustering and routing objectives to improve network lifetime and energy efficiency. Wang et al. also showed the growing interest in SO-based multi-hop routing.

Despite these advances, several limitations remain. First, many existing methods implement either one optimisation or a single optimisation process for clustering and routing, which may not allow humans to fully exploit global and local search patterns. Second, routing primarily relies on distance and residual energy and does not account for realistic channel impairments, interference, SINR, queueing, and processing effects. Third, the optimisation process does not integrate dynamic mobility and periodic topology reconstruction. In the years 2025–2026, some work has been conducted to tackle dynamic clustering, multi-objective optimisation, adaptive routing, and heterogeneous deployment, but simultaneously, global clustering, local cluster exploration, node refinement, energy-aware multi-hop routing, heterogeneous node resources, dynamic mobility, channel reliability, and periodic reclustering are not fully understood [18–25].

To address these limitations, we propose the Hybrid HHO-FF and Snake-based Wireless Energy-efficient Routing Framework (HF-Snake-WERF). The proposed framework uses HHO for global exploration of cluster-head configurations, FFO for local refinement by considering residual energy, intra-cluster compactness, cluster separation, and cluster-size balance, and SO-based multi-hop routing that considers distance, residual energy, and hop count. Unlike simple static-based routing approaches, HF-Snake-WERF considers heterogeneous node properties (distance, mobility, path loss, shadow fading, Rayleigh fading, noise) and packet reception based on SINR, queue capacity, processing time, packet transmission, energy depletion, and periodic reclustering.

1.1 Contribution

The main contributions of HF-Snake-WERF are as follows:

- A two-level HHO-FF optimisation approach for global exploration and local refinement of CH configuration
- SO-based energy-aware multi-hop routing approach after optimised clustering;
- Heterogeneous node resource-based network resource optimisation (as well as realistic communication conditions in the network) and dynamic reclustering (as mobility-induced topology changes take place)
- Highly refined network performance is evaluated by energy consumption, throughput, delay, PDR, residual energy, and network lifetime.

Our framework aims to move beyond a single optimisation of clustering or routing to an energy-efficient WSN architecture that is more effectively and dynamically adaptive.

2 Related Work

2.1 Energy-Aware Clustering and Cluster-Head Optimisation

Early work from 2021 to 2023 focused on improving CH selection and cluster formation. Alharbi et al. [1] proposed an improved clustering and routing protocol for large-scale IoT-based WSNs, leveraging transmission range, residual energy, node connectivity, and alternative routing paths to improve network lifetime. Their work is particularly relevant because it recognised that clustering and routing should not be treated entirely separately. Panchal and Singh [2] designed EEHCHR to address uneven CH energy consumption and hierarchical routing. Reddy et al. [3] combined Glowworm Swarm Optimisation with Ant Colony Optimisation for energy-efficient clustering and routing, demonstrating the potential of hybrid swarm intelligence to optimise WSN.

Zhang et al. [4] proposed energy-aware affinity propagation clustering, considering residual energy and network load balancing during clustering, while employing an inter-cluster relay strategy for multi-hop communication. Interestingly, their energy-threshold reclustering mechanism aimed to avoid the high overhead of frequent reconstruction. Feng et al. [5] looked at heterogeneous WSN clustering with a Bamboo Forest Growth Optimiser, while Lakshmanna et al. [6] proposed a better metaheuristic-driven energy-aware clustering-routing scheme for IoT-assisted WSNs. These works show the shift from simple distance-based CH selection to resource-aware, optimisation-driven clustering.

More recent work has also used HHO and related metaheuristics. Hu et al. [7] proposed a collaborative HHO and fuzzy-logic-based cluster routing protocol in which residual energy, distance to the base station, and neighbouring-node information guide CH selection. An HHO-based IEEE conference study [8] similarly used HHO to cluster and TORA for routing. Xue et al. [9] combined k-medoids/improved artificial bee colony clustering with HHO-based cross-layer routing. These approaches validate HHO's effectiveness for WSN optimisation but also show that HHO is often used as the primary optimiser rather than just part of a global-to-local optimisation sequence.

Other developments focus on learning- and graph-based CH selection. Saadati et al. [10] used Graph Neural Networks with coverage metrics for dense WSN clustering, while Wilson et al. [11] incorporated a binarised spiking neural network with Honey Badger optimisation for multi-objective CH selection and energy-aware routing. These works show that research is moving beyond traditional metaheuristics toward data-driven and hybrid intelligent optimisation. However, these approaches can add computational complexity and tend to focus mainly on CH optimisation or a specific application scenario rather than the global-local routing architecture. Table 1 summarises energy-aware clustering and CH optimisation techniques discussed above.

Table 1
Summary of energy-aware clustering and CH optimisation studies

Ref.	Year	Main technique	Primary focus	Main limitation relative to HF-Snake-WERF
[1]	2021	Improved clustering + routing	Range/energy-aware clustering	Limited optimization depth
[2]	2021	EEHCHR	Hierarchical energy balancing	CH/routing optimization remains relatively structured
[3]	2021	GSO + ACO	Hybrid clustering/routing	Primarily metaheuristic optimization
[4]	2022	Energy-aware affinity propagation	CH and relay selection	Centralized clustering; limited mobility treatment
[5]	2022	Bamboo Forest Growth Optimizer	Heterogeneous clustering	Focus mainly on clustering
[6]	2022	Metaheuristic energy-aware routing	IoT-assisted WSN	Optimization-oriented rather than realistic dynamic channel modeling
[7]	2024	Collaborative HHO + fuzzy logic	CH selection and routing	HHO remains primary optimizer
[8]	2023	HHO + TORA	Clustering and routing	Limited hybrid global-local refinement
[9]	2023	K-IABC + HHO	Cross-layer clustering/routing	More complex integrated design
[10]	2024	GNN + coverage metrics	Dense-network clustering	Learning complexity; static clustering emphasis
[11]	2024	BzSpNN + Honey Badger	Multi-objective CH selection	Specialized intelligent architecture

The literature shows that energy-aware CH selection is now well established. However, the approaches we reviewed show that we still need optimisation strategies that separate global exploration from local refinement while connecting the clusters to an independently optimised multi-hop routing layer. This is the first important motivation for our HHO–FF architecture in HF-Snake-WERF.

2.2 Hybrid Metaheuristic and Joint Clustering–Routing Approaches

Another direction focuses on clustering and routing optimisation. Alharbi et al. [1] already noted that clustering and routing separately can limit energy and lifetime improvements in some research. Kaedi et al. [12] addressed this issue more directly through a two-level genetic algorithm, where one optimisation level chooses CHs and the other determines the multi-hop routing between CHs. This study is

particularly relevant to the present study as it shows the importance of considering the downstream routing consequences in CH selection.

Chaurasia et al. [13] proposed MOCRAW, which employs Dragonfly Algorithm-based optimisation with local and global search components for CH selection and routing. They aim to analyse node density, residual energy, CH-to-BS distance and inter-cluster relationships. Vellaichamy et al. [14] investigated multi-criteria clustering together with a bio-inspired optimisation strategy for energy-efficient routing. El Khediri et al. [15] proposed a hybrid metaheuristic combining Artificial Bee Colony and Ant Colony Optimisation for energy-efficient cluster routing. These studies demonstrate that hybridisation can enhance exploration and exploitation, and that energy distribution is better than with a single optimisation method.

The dual-phase optimisation paradigm has been particularly visible in recent work. Roberts et al. [16] proposed a two-stage Sailfish Optimisation–Spotted Hyena Optimisation framework with one algorithm for clustering and CH selection and another for routing. Wang et al. [17] implemented a multi-hop clustering and routing protocol based on Enhanced SO and Golden Jackal Optimisation. This work is particularly relevant to HF-Snake-WERF because it uses SO for energy-efficient multi-hop routing. Wang et al. [18] proposed a Spider Wasp Optimiser framework that combines CH selection and inter-cluster routing and also proposed relay points and K-means grouping to handle long-distance forwarding and load imbalance.

Recent HHO-based studies also point to the appeal of hybrid optimisation. Hu et al. [7] employed collaborative HHO with fuzzy logic, while Wang et al. [19] combined quantum-based HHO with deep reinforcement learning for clustering and adaptive routing. Their work shows that energy efficiency and routing quality vary in dynamic WSNs. These approaches show that current research is moving toward hybrid optimisation and learning-based routing, but the optimisation combinations and objectives differ substantially from the HHO-FF-Snake sequence proposed here. Table 2 summarises hybrid routing approaches discussed in this section.

Table 2
Hybrid and joint clustering-routing studies

Ref.	Year	Clustering	Routing	Key contribution	Limitation relative to HF-Snake-WERF
[1]	2021	Energy/connectivity based	Alternate paths	Joint treatment of clustering and routing	Limited metaheuristic refinement
[3]	2021	Glowworm Swarm	ACO	Hybrid swarm optimization	Does not use global-local HHO–FF sequence
[6]	2022	Metaheuristic	Energy-aware routing	IoT-assisted routing	Limited realistic dynamic-channel modeling
[12]	2022	GA level-1	GA level-2	Simultaneous CH and routing optimisation	Single optimisation family
[13]	2023	Dragonfly	Levy-based routing	Local/global search	Different optimisation architecture
[14]	2023	Multi-criteria	Bio-inspired routing	Multi-criteria routing	Limited dynamic communication modeling
[15]	2024	ABC/ACO hybrid	Cluster routing	Hybrid metaheuristic search	Does not separate HHO global and FF local search
[16]	2024	SFO	SHO	Dual-phase optimization	Different optimisation mechanisms
[17]	2024	Enhanced Snake/other optimizer	Multi-hop	Snake-based routing	Snake is not integrated with HHO–FF CH optimisation
[18]	2025	SWO	K-means + Dijkstra	Joint CH/inter-cluster routing	Joint optimisation rather than hierarchical global-local optimisation
[19]	2025	Quantum HHO	D3QN-PER	Adaptive intelligent routing	Higher learning complexity

The key observation in this category is that joint optimisation is becoming the dominant research direction, but most existing studies either use the same optimisation family for both stages or merge the stages into a single optimisation formulation. HF-Snake-WERF instead deliberately separates the responsibilities: HHO explores the CH search space globally, FF refines the promising CH region locally, and SO independently addresses multi-hop routing. This separation creates a more interpretable optimisation hierarchy.

2.3 Intelligent, Adaptive, Multi-Objective and Dynamic Routing

The third category represents the latest trends in intelligent and adaptive WSN routing. Kandris et al. [20] studied hierarchical energy-efficient routing and highlighted the continuing need for energy sustainability in LEACH-derived protocols. Prashanth and Manjunatha [21] also studied energy-efficient routing for heterogeneous WSNs and highlighted the importance of considering node resources when planning for energy-efficient routing. These studies are relevant to HF-Snake-WERF because the proposed network explicitly models heterogeneous node characteristics.

Zhang et al. [22] proposed an Artificial Bee Colony-based multi-hop clustering strategy, while Behzadi et al. [23] developed a multi-objective energy-efficient clustering strategy based on improved Binary Dragonfly Optimisation and fuzzy inference. Wang et al. [18] utilised Spider Wasp Optimisation for joint CH and inter-cluster routing. These studies now incorporate multiple goals such as energy, distance, load balance, and network lifetime, rather than a single shortest-path criterion.

The literature has advanced further in 2025–2026 towards AI-assisted and adaptive methods. Zhang and Liu [24] combined reinforcement learning and metaheuristic energy-aware clustering. Hoque et al. [25] proposed NCRDAP, an AI-driven clustering, routing and data aggregation framework. Goel et al. [26] proposed an adaptive hybrid optimisation for WSN clustering. Saroit and Tarek [27] developed an energy-driven K-means-based LEACH strategy that replaces Euclidean distance with an energy proxy. These developments indicate that current WSN research is increasingly focused on adaptive optimisation, intelligent decision-making, and more meaningful energy metrics.

The 2026 literature is particularly important for positioning the present study. Madhankumar et al. [28] proposed a multi-objective clustering and routing framework that is based on GrayLag Goose Optimisation with residual energy, node degree, distance, and delay. Prince et al. [29] addressed unequal clustering and CH rotation with a mobile data collector to solve the energy-hole problem. Niranjana and Kumareshan [30] combined fuzzy clustering, adaptive optimisation, trust-based routing and deep learning for secure, energy-efficient WSN operation. These studies, summarised in Table 3, indicate that recent work is moving toward multi-objective, adaptive, heterogeneous, and application-aware WSN architectures.

Table 3
Recent intelligent, adaptive and multi-objective approaches

Ref.	Year	Approach	Main objectives	Key limitation relative to HF-Snake-WERF
[20]	2023	LEACH-based hierarchical routing	Energy sustainability	Primarily hierarchical protocol analysis
[21]	2023	Heterogeneous cluster routing	Energy efficiency	Limited hybrid optimization
[22]	2025	Artificial Bee Colony	Multi-hop clustering	Different metaheuristic mechanism
[23]	2025	Dragonfly + fuzzy logic	Multi-objective clustering	Mainly clustering-centric
[24]	2025	RL + HHO	Adaptive routing	Learning overhead
[25]	2025	AI clustering/routing/data aggregation	Energy, lifetime, reliability	More complex AI architecture
[26]	2026	Adaptive hybrid optimization	Energy-efficient clustering	Focus primarily on clustering
[27]	2026	Energy-driven K-means LEACH	Energy/lifetime	Conventional LEACH structure
[28]	2026	GrayLag Goose optimization	Energy + delay + clustering/routing	Different optimisation strategy
[29]	2026	Unequal clustering + MDC	Energy-hole mitigation	Requires mobile data collector
[30]	2026	Fuzzy + adaptive optimisation + deep learning	Secure energy-efficient routing	Security-focused and more complex

Despite considerable progress in energy-efficient clustering and routing for WSNs, several important limitations remain. Most previous studies focus on cluster-head (CH) selection through individual or hybrid metaheuristic strategies, but few provide a well-defined optimisation process that separates global exploration from local refinement and exploits both. Also, clustering and routing are usually treated as weakly coupled and independent processes and cannot exploit the effects of CH quality, residual energy, network distance to the CH, and even multi-hop routing decisions. Many previous studies rely on simplistic network assumptions, e.g., homogeneous nodes, static topologies, ideal wireless links, and distance-based communication models, which may not reflect the reality of WSNs with varying energy resources, mobility, path loss, fading, interference, and link quality. Furthermore, routing is often dominated by distance or residual energy, and it does not consider communication delay, queue conditions, SINR, packet delivery reliability, or transmission-related energy consumption. Dynamic reclustering remains unexplored, especially when network conditions and node energy change over time. Furthermore, although machine learning and meta-heuristic optimisation have become increasingly common in recent years, integrating these techniques into a single optimisation framework for energy

balancing, reliable multi-hop routing, realistic communication, and network reconfiguration remains lacking.

These gaps indicate the need for a more unified, real-world optimisation framework and strategies that can jointly improve clustering quality, routing efficiency, network reliability, and network lifetime. These limitations motivate a hybrid, adaptive, and energy-aware clustering and routing framework that addresses the interdependent nature of CH selection and multi-hop communication. Rather than focusing on a single optimisation strategy based on competition between search mechanisms, HHO performs a global search for promising CH configurations, and the FFA refines them locally. The resulting cluster structure can then be integrated with a SO-based multi-hop routing mechanism to determine the energy-efficient communication routes between clusters. More importantly, our framework evaluates network decisions in a heterogeneous node environment and under more realistic communication conditions, including path loss, fading, interference, SINR, transmission energy, queueing, and processing delay. The periodic reclustering can further help to adapt the network structure to node energy and topology as well. So, the main motivation is not simply to combine multiple metaheuristic algorithms but to make a coherent optimisation approach where the optimised clustering is a key point for adaptive, reliable and energy-efficient routing, with the ultimate goal of reducing the energy cost and communication delay of the network while improving packet delivery, throughput, residual energy balance and overall network lifetime.

3 Methodology

3.1 Overview of the Proposed HF-Snake-WERF Framework

We propose a Hybrid HHO-FF and Snake-based Wireless Energy-efficient Routing Framework (HF-Snake-WERF), shown in Fig. 1, to improve communication performance and energy efficiency in a mobile WSN. Our framework uses three optimisation layers: HHO for global cluster-head selection, FF-based local refinement to improve the cluster-head configuration from HHO, and SO to determine energy-aware multi-hop paths between source and destination CHs. The entire simulation is based on a heterogeneous network with sensor nodes differing in initial energy, transmission range, queue capacity, processing time, and mobility speed.

The implementation considers a network which contains 1000 sensor nodes in a 300 m × 300 m square sensing area. The simulation runs for 500 frames, with a reformation interval of 20 frames per cluster. The network generates 120 bytes (960 bits) of data and transmits it at 81,920 bits/s. The data is sent with a path loss of 3.0, a reference distance of 1 m, a reference path loss of 50 dB, a shadowing standard deviation of 4 dB, a noise power of − 100 dBm, and an SINR acceptance threshold of -52 dB. The transmission power is 0 dBm. The heterogeneous nature of the network is introduced by assigning each node an initial energy between 1 and 5 J, a transmission range between 60 and 100 m, a queue capacity of 5–24 packets, a processing delay between 0.5 and 3 ms, and a mobility speed between 1 and 5 m/s. Table 1 summarises these parameters.

Our main goal of HF-Snake-WERF is not to optimise the clustering or routing, but to create a sequential communication process in which the cluster configuration determines the selection of communication points, the routing mechanism determines the multi-hop path, and the transmission path directly affects delay, packet delivery, interference, and energy consumption. To provide a fair benchmark, we compare the optimised mechanism with a standard clustering scheme, both using the same node initialisation, mobility trace, physical-layer parameters, traffic generation mechanism, and energy model. Thus, performance differences primarily reflect the clustering and routing strategies, not network conditions. Table 4 shows the parameters used in the study with abbreviations, respective meanings, and initial values.

Table 4
Simulation and Optimisation Parameters Used in the Proposed WSN Framework

Parameter	Symbol	Value/Setting	Purpose
Network width	W	300 m	Horizontal network dimension
Network height	H	300 m	Vertical network dimension
Number of nodes	N	1000	Total sensor nodes deployed
Initial energy	E_i	Randomly distributed between 1–5 J	Heterogeneous initial energy of each node
Packet size	L_p	960 bits	Size of transmitted data packet
Data rate	R_b	81,920 bits/s	Wireless transmission rate
Packet time	T_p	0.1 s	Packet activity duration initialised in the implementation
Communication range	R_i	Randomly distributed between 60–100 m	Node-specific maximum communication range
Simulation duration	T_{sim}	500 frames	Total simulation period
Reclustering interval	T_{re}	20 frames	Frequency of cluster reconstruction
Time-step parameter	Δt	1 frame	Simulation update interval
HHO population size	N_{HHO}	25	Number of Harris Hawks used for global exploration
HHO iterations	I_{HHO}	40	Number of HHO optimisation iterations
FF population size	N_{FF}	20	Number of FF agents used for local refinement
FF iterations	I_{FF}	40	Number of local-refinement iterations
FF attractiveness	β_0	1	Initial FF attractiveness coefficient

Parameter	Symbol	Value/Setting	Purpose
Light absorption coefficient	γ	1	Controls attractiveness reduction with distance
Snake population size	N_{SO}	20	Number of candidate routing paths
Snake iterations	I_{SO}	40	Number of routing optimisation iterations
Maximum hops	$H_{\max}$	6	Maximum allowable routing path length/intermediate-hop setting
Transmission power	P_{tx}	0.052 W	Energy consumption during transmission
Reception power	P_{rx}	0.059 W	Energy consumption during reception
Idle power	P_{idle}	0.003 W	Energy consumption during idle operation
SINR transmit power	P_{dBm}	0 dBm	Transmit power used in SINR calculation
Path-loss exponent	n	3.0	Controls signal attenuation with distance
Reference distance	d_0	1 m	Reference distance for path-loss calculation
Reference path loss	PL_0	50 dB	Path loss at the reference distance
Shadowing standard deviation	σ_{sh}	4 dB	Models log-normal shadow fading
Noise power	P_N	−100 dBm	Receiver noise floor
SINR threshold	Γ_{th}	−52 dB	Minimum SINR required for successful packet reception
Speed of light	c	3×10^8m/s	Propagation-delay calculation
Queue capacity	Q_i	Randomly distributed between 5–24 packets	Maximum queue length at each node
Processing delay	$D_{\mathrm{proc},i}$	Randomly distributed between 0.5–3 ms	Node processing latency

Parameter	Symbol	Value/Setting	Purpose
Mobility speed	v_i	Randomly distributed between 1–5 m/s	Node movement speed
Random seed	S	42	Ensures reproducible heterogeneous-node initialization
Numerical stability constant	ϵ	10^{-6}	Avoids division by zero in calculations

The proposed methodology is organised so that each stage's output becomes the next stage's input. Consequently, the complete workflow maintains a consistent relationship between node characteristics, clustering decisions, routing decisions, energy consumption, packet delivery, and network lifetime.

3.2 Heterogeneous WSN Initialisation

The first step of HF-Snake-WERF establishes the heterogeneous wireless sensor network. A set of N sensor nodes is deployed in a two-dimensional rectangular monitoring region. Each sensor node is assigned a position, initial energy, node characteristics and communication parameters. Table 5 indicates different node characteristics with respective significance and notations. The network heterogeneity is incorporated through different node characteristics, rather than treating all sensor nodes as the same computational and communication entities. This matters because available energy, processing capability, communication behaviour, and cluster-head suitability can vary between nodes. Let the i-th sensor node be represented by Eq. 1 as:

$$\mathcal{N}_i = (x_i, y_i, E_i, \tau_i)\,,\ i = 1,2,\ldots,N$$

1

where x_i and y_i denote the spatial coordinates of node i, E_i represents its residual energy, and τ_i denotes its heterogeneous node type or associated node characteristic. The first stage of initialisation is important because all subsequent clustering and routing decisions depend on the initial spatial distribution and resource availability of the nodes. A heterogeneous initialisation also allows the proposed framework to check whether the optimisation process can focus on resource-rich nodes without wasting too much energy on individual nodes.

Table 5
Heterogeneous node characteristics

Node characteristic	Representation	Significance
Node identifier	i	Uniquely identifies a sensor
Position	(x_i, y_i)	Determines communication distance
Residual energy	E_i	Represents available energy
Node type	τ_i	Represents heterogeneous characteristics
Communication capability	C_i	Determines communication suitability
Processing capability	Q_i	Represents processing capacity
Mobility state	M_i	Determines node movement
Cluster membership	c_i	Indicates the assigned cluster
Routing state	r_i	Represents the selected forwarding relationship

3.3 Heterogeneous Communication and Processing Characteristics

After network deployment, each node is represented by the communication and processing parameters used in the implementation. This stage avoids the assumption that all nodes contribute equally to network operation. Nodes with more residual energy and better communication skills are more suitable for cluster-head and forwarding responsibilities. However, assigning the same tasks to the same node may exhaust its energy early. Therefore, the proposed optimisation considers resource availability while planning the network structure. For a node i, a normalised resource representation can be expressed with the following mathematical Eq. 2 as:

$$\rho_i = \omega_E \frac{E_i}{E_{\max}} + \omega_C C_i + \omega_Q Q_i$$

2

where $E_{\max}$ is the maximum available energy, C_i denotes the normalised communication capability, Q_i denotes the normalised processing capability, and $\omega_E, \omega_C, \omega_Q$ are weighting coefficients. The

resource representation is important because it provides a common basis for comparing heterogeneous nodes. The nodes with favourable resource conditions can thus be considered stronger candidates for cluster-head or relay responsibilities.

3.4 Wireless Channel and SINR Modelling

Wireless communication is affected by propagation distance, received signal strength, background noise and interference from simultaneous transmissions. Therefore, HF-Snake-WERF also uses a channel model and signal-to-interference-plus-noise ratio (SINR) calculation before assessing communication quality. For a transmitter $i$and receiver j, the received signal strength depends on the transmission power and the propagation characteristics of the communication channel. The resulting communication quality is represented through SINR as given in Eq. 3:

$$\Gamma_{ij} = \frac{P_i G_{ij}}{\sum_{k \neq i} P_k G_{kj} + N_0}$$

3

where P_i is the transmission power of node i, G_{ij} is the channel gain between nodes i and j, $P_k G_{kj}$ represents interference generated by another transmitting node k, and N_0 is the noise contribution. SINR is important because distance alone does not fully describe wireless link quality. A short link can still perform poorly if interference is high. Therefore, we use SINR in routing and packet delivery to make the proposed framework more communication-aware.

3.5 Node Mobility Modelling

The proposed network supports node mobility by updating mobile node positions during the simulation. Mobility changes the topology dynamically and therefore changes the distances between sensor nodes, available communication links, cluster membership, and routing paths.

At simulation time t, the position of node i can be represented using Eq. 4:

$$p_i(t) = [x_i, (t)\, y_i(t)]$$

4

The code updates the position according to the implemented mobility mechanism. The updated position affects further distance calculations and communication decisions. The mobility stage matters because a routing path that is optimal at one instant may become inefficient or unavailable after nodes move. HF-Snake-WERF therefore does not assume a permanently static topology and incorporates dynamic reorganisation during simulation.

3.6 Baseline Distance-Constrained Clustering

Before implementing the proposed optimisation, establish a baseline clustering. The baseline approach uses the communication-distance constraint to form initial clusters. For two nodes $i$and j, their Euclidean separation is calculated using Eq. 5:

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}$$

5

Here, d_{ij} represents the physical distance between nodes i and j, while x_i, y_i, x_j, y_j denote their respective coordinates. A node is considered a candidate member of a cluster as long as the distance between the node and its candidate CH satisfies the communication-range constraint. The baseline clustering is important for two reasons. First, it provides a feasible initial network organisation. Second, it provides a reference against which the optimised HF-Snake-WERF clustering and routing decisions can be compared.

3.7 Initial Range-Based Cluster Formation

After the baseline distance calculation, we create initial clusters based on the communication proximity. Each sensor node is assigned to the appropriate cluster-head candidate when the candidate is within communication range. This process establishes a preliminary relationship between CHs and ordinary sensor nodes. But proximity alone may not necessarily provide an energy-efficient configuration. A close node could have low residual energy or poor communication. So, the initial clustering provides a starting solution that HHO and FF optimisation then improve.

3.8 Multi-Objective Cluster-Head Fitness Function

Cluster-head selection is a multi-objective optimisation problem. The objective is not simply to select the nearest nodes but to select nodes that provide a good combination of residual energy, communication distance, cluster balance, and communication quality. The general fitness formulation used by HF-Snake-WERF can be expressed using Eq. 6 as:

$$F_{\mathrm{CH}} = \lambda_1 * D_{\mathrm{cl}} + \lambda_2 * E_{\mathrm{cost}} + \lambda_3 * B_{\mathrm{cl}} + \lambda_4 * I_{\mathrm{link}}$$

6

where D_{cl} represents the clustering-distance cost, E_{cost} represents the energy-related cost, B_{cl} represents cluster imbalance, I_{link} represents the communication/interference-related cost, and $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ are the corresponding objective weights. The goal is to minimise F_{CH}. A lower fitness value indicates a more desirable cluster-head structure. Table 6 lists the essential behaviour of the parameters involved in CH optimisation.

Table 6
Components of the cluster-head optimisation objective

Component	Meaning	Desired behaviour
D_{cl}	Cluster-member distance	Minimize
E_{cost}	Energy expenditure	Minimize
B_{cl}	Cluster imbalance	Minimize
I_{link}	Interference/communication penalty	Minimize
F_{CH}	Overall cluster-head fitness	Minimize

This multi-objective design matters because it prevents a single criterion from dominating the clustering decision. The resulting cluster-head configuration is expected to be more energy-efficient and communicate better than distance-based clustering.

3.9 HHO for Global Cluster-Head Optimisation

HHO is our first optimisation layer for cluster-head selection. HHO is designed to explore the candidate space globally and prevent cluster-head clustering from becoming too locally attractive but globally inefficient. Each HHO search agent represents a possible cluster-head solution. The quality of each solution is evaluated using F_{CH}. In each iteration, the hawks update their candidate positions based on the current best solution and HHO exploration/exploitation.

The general search-agent representation is given by Eq. 7:

$$X_h^{(q)} = \left[x_{h,1}^{(q)}, x_{h,2}^{(q)}, \ldots, x_{h,D}^{(q)}\right]$$

7

where $X_h^{(q)}$ denotes the h-th HHO candidate at iteration q, and D represents the dimensionality of the encoded cluster-head solution. The best solution obtained during HHO is retained as the globally optimal cluster-head candidate. HHO is important in HF-Snake-WERF because it can search a large solution space and provide a high-quality candidate before local refinement.

3.10 FF-Based Local Refinement

Although HHO provides global exploration, the solution may still have small inefficiencies. Hence, the proposed framework uses the FFA as a local refinement mechanism. In the FF stage, the candidate solutions are evaluated according to their fitness. A less attractive FF moves towards a more attractive

candidate, and the attraction decreases with the distance between the candidates. The attractiveness between two candidate solutions can be thought of as given by Eq. 8:

$$\beta_{ab} = \beta_0 e^{-\gamma d_{ab}^{\hspace{0.17em}2}}$$

8

where β_{ab} is the attraction between fireflies $a$and b, β_0 is the maximum attraction, γ controls the decrease in attraction, and d_{ab} represents the distance between their solution representations. The FF stage is significant because it performs a fine-grained search around the promising region identified by HHO. Thus, HHO performs global exploration, and FF performs local exploitation. The final cluster-head configuration obtained after this stage is denoted by Eq. 9:

$$\mathcal{C}^* = \mathrm{FA}\left(\mathrm{HHO}\left(\mathcal{C}_0\right)\right)$$

9

where $\mathcal{C}_0$ is the initial cluster-head configuration and $\mathcal{C}^*$is the optimised configuration.

3.11 Optimised Cluster-to-Node Mapping

Once the optimised CHs are obtained, ordinary sensor nodes are mapped to their most suitable CHs. The mapping is done based on the communication constraints and the optimised cluster-head locations. For each ordinary node i, we evaluate candidate CHs j based on distance and communication feasibility. The chosen CH should be feasible and efficient in terms of communication range. This step is important because one cannot optimise cluster-head positions alone. The final network structure depends on how efficiently all ordinary nodes are connected to the optimised heads.

3.12 SO for Energy-Aware Multi-Hop Routing

After clustering, the SO determines efficient multi-hop routes. This optimisation stage is based on the cluster and inter-cluster communication structure generated by the previous stages. A routing candidate is a sequence of forwarding nodes connecting a source node to a destination or sink. The routing objective includes communication distance, energy consumption, link quality, and other penalties implemented in the simulation. A generalised routing cost can be expressed using Eq. 10 as:

$$F_{\mathrm{route}} = \mu_1 * D_{\mathrm{path}} + \mu_2 * E_{\mathrm{path}} + \mu_3 * Q_{\mathrm{link}} + \mu_4 * I_{\mathrm{path}}$$

10

where D_{path} is the total path distance, E_{path} represents path energy cost, Q_{link} represents the link-quality penalty, I_{path} represents interference-related cost, and $\mu_1, \mu_2, \mu_3, \mu_4$ are routing-objective weights. The SO searches for the route with the smallest overall routing cost. This is important because shortest-distance routing is not necessarily the most energy-efficient route. A slightly longer route may provide considerably better residual energy and link quality.

3.13 Source-Destination Traffic Generation

Once the routing topology is determined, the simulation generates source-destination communication pairs according to the traffic-generation procedure. For every communication pair, the source generates packets that are forwarded through the chosen multi-hop path. Each transmission updates the relevant energy, delay, and packet-delivery parameters. The traffic stage is important because the proposed framework is evaluated under actual communication activity rather than only on the static quality of the clustering configuration.

3.14 Per-Hop Communication Delay

We calculate communication delay for each hop along a chosen routing path. The transmission component depends on packet size and data rate, while other delay components depend on the implementation. The transmission delay of a packet over a link can be expressed as given in Eq. 11:

$$T_{ij}^{\mathrm{tx}} = \frac{S_p}{R_d}$$

11

where S_p is the packet size in bits and R_d is the data transmission rate in bits per second. For a route having L communication hops, the total transmission delay is obtained by accumulating the hop-level delays and other delay components used in the simulation. The delay stage matters because a routing method that minimises energy consumption but introduces excessive communication delay may not suit real-time or delay-sensitive wireless applications.

3.15 Queue and Energy Consumption Modelling

During the simulation, packet transmission and reception consume node energy. The residual energy of each node is then updated after the communication. For a node i, its residual energy after a communication operation can generally be represented as Eq. 12:

$$E_i^{\mathrm{new}} = E_i^{\mathrm{old}} - E_i^{\mathrm{tx}} - E_i^{\mathrm{rx}}$$

12

where E_i^{tx} and E_i^{rx} represent the energy consumed by transmission and reception, respectively. Queue-related operations affect packet waiting and forwarding behaviour. Overloaded nodes can experience additional delay and may become energy bottlenecks. Hence, considering the queue behaviour gives a more realistic evaluation of routing performance. The energy stage is central to HF-Snake-WERF because the network lifetime is directly determined by the rate at which sensor nodes consume their available energy.

3.16 Interference-Aware Packet Delivery

Packet transmission is also evaluated via communication quality and interference conditions. A packet is successfully delivered when the communication conditions match those described in the simulation. SINR allows for packet delivery to reflect both desired signal strength and simultaneous interference. Therefore, the framework does not assume that every geometrically feasible transmission will succeed automatically. This stage matters because packet loss directly affects throughput, delay, and network utilisation. HF-Snake-WERF uses interference in routing evaluation to find efficient and reliable paths.

3.17 Synchronised Baseline and Optimised Simulations

A fair experimental comparison requires the baseline and proposed methods to work in the same network conditions. So, the normal/baseline and optimised simulations are synchronised with the same environmental and traffic conditions. We use the same initial network dimensions, node population, node characteristics, traffic conditions, packet parameters, and simulation duration wherever possible. The main difference between these two configurations is the clustering and routing optimisation method. This synchronisation shown in Table 7 is essential because differences in network conditions should not be mistaken for improvements in either network.

Table 7
Synchronisation between baseline and proposed simulations

Experimental factor	**Baseline**	**HF-Snake-WERF**
Network dimensions	Same	Same
Number of nodes	Same	Same
Initial node positions	Same	Same
Initial energy	Same	Same
Packet characteristics	Same	Same
Data rate	Same	Same
Mobility conditions	Same	Same
Channel conditions	Same	Same
Traffic generation	Same	Same
Simulation duration	Same	Same
Clustering	Baseline distance-based	HHO + FF
Routing	Baseline routing	Snake-optimised routing
Energy accounting	Same	Same
Performance metrics	Same	Same

3.18 Dynamic Reclustering

Wireless sensor networks with mobile nodes change their topology over time. Thus, the initial cluster configuration cannot necessarily remain optimal throughout the entire simulation. HF-Snake-WERF therefore allows for dynamic reclustering. When network conditions change sufficiently, the optimisation procedure can recalculate cluster-head and cluster-member relationships. The new configuration reflects changes in node location, residual energy, communication distance, and network connectivity. Dynamic reclustering is important because it prevents the routing structure from becoming obsolete as the network evolves. It also allows nodes to redistribute communication responsibilities and reduces the risk of premature node failure.

3.19 Performance Evaluation Metrics

The proposed and baseline approaches are evaluated across multiple performance indicators. These are communication effectiveness, energy efficiency, delay, reliability & network longevity. These metrics are integrated on the same basis, rather than focusing on accuracy to achieve accuracy-like performance measures (i.e., a single performance measure).

3.20 Throughput Measurement

Throughput is calculated from the amount of successfully transmitted information and the elapsed simulation time. In the implementation, the packet size is converted into bits and divided by the elapsed time. The throughput can therefore be represented as Eq. 13:

$$\Theta = \frac{N_{\mathrm{del}} S_p}{T_{\mathrm{elapsed}}}$$

13

where N_{del} denotes the number of successfully delivered packets, S_p is the packet size in bits, and T_{elapsed} is the corresponding elapsed time. The resulting quantity is the bit rate, usually expressed in bits per second.

3.21 Network Lifetime Estimation

Network lifetime is an important indicator of energy-efficient wireless sensor network operation. It is determined from the evolution of active and failed nodes during simulation. The lifetime can be analysed using the time at which nodes start to fail and the time for the network to reach the failure condition. The proposed HF-Snake-WERF would avoid node failures by distributing clustering and routing responsibilities more efficiently. The lifetime analysis is particularly useful for showing whether the combined HHO-FF clustering and Snake routing mechanisms sustain network operation. Table 8 shows network lifetime indicators used in this study for evaluation.

Table 8
Network-lifetime indicators

Indicator	Description
First Node Death (FND)	Time at which the first sensor node becomes inactive
Intermediate node death	Evolution of node failures during operation
Last Node Death (LND)	Time at which the final operational node becomes inactive
Alive-node ratio	Proportion of nodes remaining operational
Residual energy	Energy remaining in the network

3.22 Complete Operational Sequence of HF-Snake-WERF

The proposed framework operates through a sequential optimisation process as governed by Algorithm 1. First, the algorithm initialises the heterogeneous sensor network. The algorithm establishes the positions, energies, communication properties, and mobility parameters. The algorithm then determines the wireless channel and SINR conditions. Next, the algorithm constructs a distance-constrained baseline cluster structure. Candidate CHs are evaluated by the multi-objective cluster-head fitness function. HHO searches globally for CHs, and FF then localises the best solution within the cluster-head search space. The optimised CHs then associate regular sensor nodes. Once the cluster structure is set up, traffic-generation procedures define the source-destination communication requirements. The SO searches for energy-aware multi-hop paths. During packet transmission, it continuously monitors delay, energy consumption, queue behaviour, interference, SINR, and packet delivery. Node positions and network states are updated according to the mobility and simulation mechanisms. When needed, the network is re-clustered to account for topology and energy changes.

Algorithm 1. HF-Snake-WERF: Hybrid HHO–FF and Snake-Based Wireless Energy-Efficient Routing	
Input	Network dimensions, Nsensor nodes, initial energy, node heterogeneity, communication range, channel parameters, mobility parameters, packet parameters, and optimisation parameters.
Output	Optimised clusters, energy-aware multi-hop routes, packet-delivery results, delay, throughput, energy consumption, and network-lifetime measures.
1	**Initialise the network**: *Deploy Nheterogeneous sensor nodes and assign their positions, residual energy, node characteristics, and communication parameters.*
2	**Model the wireless environment**: *Calculate inter-node distances, channel conditions, and SINR values for feasible communication links.*
3	**Update mobility**: *Generate/update node positions according to the implemented mobility model to obtain the current network topology.*
4	**Form initial clusters**: *Apply the communication-distance constraint to generate feasible initial cluster configurations.*
5	**Evaluate cluster-head candidates**: *Calculate the multi-objective cluster-head fitness using distance, energy, cluster balance, and communication/interference-related criteria.*
6	**Apply HHO**: *Initialise HHO candidate solutions and perform global exploration of the cluster-head search space. Retain the best cluster-head configuration obtained from HHO.*
7	**Apply FF refinement**: *Use the HHO-derived solution as the starting point for FF-based local search and obtain the refined cluster-head configuration.*
8	**Map cluster members**: *Associate ordinary sensor nodes with suitable optimised CHs subject to communication constraints.*
9	**Generate traffic**: *Establish source-destination communication requirements and packet-generation events.*
10	**Optimise routing: Apply the SO** *to search for energy-aware multi-hop routes considering path distance, energy cost, link quality, and interference.*
11	**Transmit packets**: *Forward packets through the selected routes and evaluate link feasibility and SINR/interference conditions.*
12	**Update network state**: *Calculate transmission delay, queue effects, packet delivery/loss, and node energy consumption; update residual energy accordingly.*
13	**Dynamic adaptation**: *Update node positions and network connectivity. If required, repeat clustering and routing optimisation for the changed network state.*
14	**Evaluate performance**: *Calculate throughput, delay, energy consumption, packet delivery, packet loss, residual energy, alive/dead nodes, and network lifetime.*
15	**Comparison**: *Execute the corresponding baseline and proposed simulations under synchronised network, traffic, mobility, and communication conditions.*

Algorithm 1. HF-Snake-WERF: Hybrid HHO–FF and Snake-Based Wireless Energy-Efficient Routing	
16	**Return results**: *Store and compare the performance results of the baseline and HF-Snake-WERF methods.*

4 Results and Discussion

We tested the proposed Hybrid HHO–FF and Snake-based Wireless Energy-efficient Routing Framework (HF-Snake-WERF) against the conventional minimum-hop routing approach under the same network settings. We simulated the network with 1000 randomly distributed heterogeneous sensor nodes over a $300x300$ m² area for 500 frames. Each node is assigned a heterogeneous residual energy, transmission range, queue capacity, processing delay and mobility speed. The initial energy of the nodes varies between 1 and 5 J, and the network is populated with a 960-bit packet with a 20-frame reclustering interval. The wireless environment also includes path loss, shadow fading, Rayleigh fading, additive noise, and SINR-based packet reception. Our framework combines HHO–FF cluster-head optimisation with SO multi-hop routing. HHO explores cluster-head configurations globally, and FF localises the cluster by jointly considering residual energy, compactness within the cluster, separation between clusters, and cluster-size balance. After cluster formation, SO finds energy-efficient routes based on transmission distance, energy consumption, hop count and avoiding low-energy nodes. The evaluation considers five main performance indicators: PDR, throughput, average end-to-end delay, residual energy, and network lifetime, as well as Normalized Average Energy Consumption (NAEC). These metrics offer complementary views on communication reliability, data-transfer capacity, latency, energy efficiency and network sustainability.

4.1 NAEC

The first is the energy efficiency of the proposed routing framework. The average NAEC decreases from 1.452 J/packet to 0.929 J/packet for HF-Snake-WERF, as shown in Fig. 2. This is a 36% reduction, as indicated in Table 9. The reduction in NAEC shows that our framework can produce packets with much lower energy expenditure. This improvement likely stems from the joint operation of both optimisation levels. At the clustering level, HHO-FF selects clusters by considering the residual energy and cluster structure rather than just the proximity of the two nodes. At the routing level, the SO avoids overreliance on low-energy nodes while considering transmission distance and route characteristics.

One important observation is that conventional routing strategies increase energy consumption as nodes become overloaded. The optimised approach spreads communication traffic between energy-rich nodes, leading to more energy-efficient results in the simulation. Thus, the NAEC results provide direct evidence that the proposed optimisation not only improves routing but also lowers the energy cost of successful packet delivery. This is especially important in sensor networks, where node energy directly affects network operation time.

Table 9
Energy-consumption comparison

Routing approach	Average NAEC (J/packet)	Interpretation
Conventional minimum-hop routing	1.452	Higher energy expenditure
HF-Snake-WERF	0.929	Lower energy expenditure
Improvement	≈ 36% reduction	Improved energy efficiency

4.2 Throughput Performance

The throughput results in Fig. 3 also show HF-Snake-WERF's effectiveness. The average throughput increases from 709.43 kbps for the minimum-hop approach to 986.54 kbps for the optimised framework. This is a 39% improvement, as indicated in Table 10. The higher throughput indicates that HF-Snake-WERF can sustain more successfully transmitted data during network operation. This is confirmed in the PPTX because of the route selection in SO and the CH selection in HHO–FF. So, SO selects routes that balance the use of energy and the short transmission distance between clusters, while HHO–FF picks clusters that are stable and properly distributed.

This combination matters because throughput depends not only on the chosen path but also on the stability and effectiveness of the cluster structure. Stable CHs minimise unnecessary communication disruptions, while energy-aware routing enables forwarding. The resulting reduction in retransmissions and better channel utilisation contribute to the higher throughput of the proposed framework.

Table 10
Throughput comparison

Routing approach	Average throughput (kbps)	Improvement
Conventional minimum-hop routing	709.43	—
HF-Snake-WERF	986.54	≈ 39% higher

This throughput result supports the framework's effectiveness from a data-delivery perspective. HF-Snake-WERF transfers more information while achieving lower normalized energy consumption.

4.3 End-to-End Delay

Figure 4 reveals a major trade-off between energy-aware routing and latency. The average end-to-end delay of HF-Snake-WERF is 0.360 s, compared with 0.356 s for conventional minimum-hop routing. The difference is thus very small, as indicated in Table 11. The delay increase is marginal and reflects the SO's routing goal. Unlike the conventional minimum-hop strategy (which mainly rewards paths with fewer hops), our approach prioritises energy balance and communication reliability. So, the optimised method can sometimes pick a route with additional hops when it finds better energy savings or reliability.

In particular, the increase from 0.356 s to 0.360 s is only 0.004 s; thus, the additional routing does not result in a significant latency penalty. This result shows that HF-Snake-WERF achieves its energy and reliability gains without significantly impacting the end-to-end communication delay.

Table 11
Average end-to-end delay comparison

Routing approach	Average delay (s)	Observation
Conventional minimum-hop routing	0.356	Slightly lower
HF-Snake-WERF	0.360	Marginally higher
Difference	0.004	Negligible increase

Thus, the delay result should not be viewed as a weakness of the proposed framework in isolation. Rather, it shows that a very small latency increase yields large improvements in energy efficiency, throughput, and packet delivery.

4.4 PDR

The PDR provides the strongest evidence of HF-Snake-WERF's reliability improvement. The proposed framework achieves an average PDR of 0.869, compared with 0.603 for conventional minimum-hop routing, as indicated in Table 12. This difference shows that the proposed framework achieves a much higher proportion of transmitted packets. In addition, the temporal behaviour of PDR demonstrates that the HF-Snake-WERF is always better in the simulation. The optimised approach remains above 0.81 in the simulation, as shown in Fig. 5, whereas the conventional approach quickly falls below 0.45. This degradation in the traditional approach leads to energy depletion and unstable routing. As highly utilised nodes lose energy, their forwarding capability decreases, affecting packet delivery. In contrast, HHO-FF better manages cluster-head responsibilities, and SO avoids routes based on weak, low-energy nodes.

The PDR results show that the proposed framework is optimised not only for energy consumption. It also improves communication reliability through energy-aware cluster-head selection and route discovery.

Table 12
PDR comparison

Routing approach	Average PDR	Observed behaviour
Conventional minimum-hop routing	0.603	Degrades below 0.45 during simulation
HF-Snake-WERF	0.869	Maintains PDR above 0.81
Difference	0.266	Substantial reliability improvement

The higher PDR is especially important when considered alongside the throughput result. The proposed framework also provides a larger fraction of packets and a faster data-transfer rate, so its optimisation

strategy achieves both reliability and effective network utilisation.

4.5 Network Lifetime and Alive-Node Ratio

Figure 6 evaluates network lifetime by the fraction of nodes alive during the simulation. HF-Snake-WERF achieves an average alive-node ratio of 0.363 compared to 0.341 for conventional minimum-hop routing. Although the numerical difference from Table 13 is small, the temporal behaviour matters. The number of alive nodes in the efficient framework decreases more slowly than the number of dead nodes in the less optimised setup because HHO-FF distributes cluster-head responsibilities more evenly and avoids using nodes critical to Snake routing.

The resulting NAEC is also consistent with the lower NAEC for HF-Snake-WERF. When the energy required for packet delivery is lower, and forwarding work is spread more evenly, nodes are less likely to become energy bottlenecks. This promotes continued network operation and thus the alive-node profile.

Table 13
Network-lifetime comparison

Routing approach	Average alive-node ratio	Observation
Conventional minimum-hop routing	0.341	Faster decline in active nodes
HF-Snake-WERF	0.363	Slower decline in active nodes
Difference	0.022	Improved node survival

The network lifetime results complement the energy consumption analysis. The lower NAEC for HF-Snake-WERF indicates more balanced energy depletion and a higher percentage of operational nodes in the simulation.

4.6 Overall Comparative Discussion

Overall, Table 14 indicates that HF-Snake-WERF is a more balanced solution than current minimum-hop routing. The main improvement is in packet delivery, where the average PDR increases from 0.603 to 0.869. This improvement is accompanied by a significant increase in throughput from 709.43 kbps to 986.54 kbps. At the same time, the average NAEC decreases from 1.452 J/packet to 0.929 J/packet, indicating that the delivered data are transmitted at a lower normalised energy expenditure. Communication reliability and energy efficiency increase with only a slight rise in average end-to-end delay, from 0.356 s to 0.360 s. This is only 0.004 s, showing that the energy-aware route-selection strategy does not impose a substantial latency burden. The alive-node results also support the proposed framework's energy-balancing capability. HF-Snake-WERF has an average alive-node ratio of 0.363, compared to 0.341 for minimum-hop routing, and the percentage of active nodes decreases slowly throughout the simulation.

Table 14
Overall performance comparison of HF-Snake-WERF with baseline

Metric	Conventional minimum-hop	HF-Snake-WERF	Overall effect
Average NAEC	1.452 J/packet	0.929 J/packet	≈ 36% reduction
Average throughput	709.43 kbps	986.54 kbps	≈ 39% improvement
Average delay	0.356 s	0.360 s	0.004 s increase
Average PDR	0.603	0.869	Substantial improvement
Average alive-node ratio	0.341	0.363	Improved node survival

Overall, the proposed framework achieves its multi-objective behaviour. Instead of optimising only one routing behaviour, HF-Snake-WERF also considers the energy consumption, communication reliability, throughput, and node survival. The main trade-off in the reported results is a small increase in delay.

4.7 Role of HHO–FF Clustering and Snake Routing & Effect of Dynamic Reclustering

The performance improvement stems from the complementary roles of the optimisation components. HHO provides global exploration for cluster-head selection while FF exploits promising cluster-head sites locally. The optimisation weighs the residual energy, intra-cluster compactness, inter-cluster separation, and cluster size. This yields a cluster structure that avoids over-sharing communication responsibilities (and thus clustering) within a cluster. The SO then operates at the routing level. Its goal is to minimise the transmission distance, energy consumption, and hop count while avoiding low-energy nodes. Thus, routing decisions are based not only on the shortest available path. The chosen path also reflects network efficiency and sustainability. Together, these mechanisms explain the consistent pattern across the reported metrics. Better cluster-head distribution helps balance energy, and energy-aware routing reduces the likelihood of repeatedly using vulnerable nodes. Together, these mechanisms reduce NAEC, improve throughput and PDR, and slow the decline in alive nodes.

The proposed framework also includes dynamic reclustering because node mobility changes the network topology. The simulation uses random node mobility, but nodes remain within the network boundaries, and cluster reconstruction occurs every 20 frames. Dynamic reclustering allows the cluster structure to adapt to changing node positions and communication conditions. This is especially relevant to the observed reliability and energy results, as a cluster configuration that is suitable at one point in the simulation may become less effective after node movement. Periodic reconstruction thus helps maintain efficient communication relationships and balanced energy utilisation. The PDR and alive-node trends are consistent with this adaptive behaviour. HF-Snake-WERF keeps PDR above 0.81 as the simulation proceeds and reduces alive nodes more slowly than conventional routing.

In conclusion, HF-Snake-WERF significantly outperforms conventional minimum-hop routing on the most important performance parameters. The key advantages are in packet delivery, throughput, and normalised energy consumption. The framework achieves better PDR and throughput while requiring less energy for successful packet delivery. The higher alive node ratio also suggests that these advantages stem from more balanced use of network resources. The main trade-off is the small increase in end-to-end delay from 0.356 s to 0.360 s. However, this increase is negligible compared with the gains in PDR, throughput, and energy efficiency. The results show that the SO can sometimes select routes that are not strictly minimum-hop paths when it is more energy-balanced and communication-reliable. Therefore, our results support the main design principle of HF-Snake-WERF: joint optimisation of clustering and routing is more effective than minimum-hop path selection in a heterogeneous mobile wireless sensor network. The HHO-FF mechanism improves cluster-head selection by considering node energy and cluster quality, while the SO improves route selection by jointly considering distance, residual energy and hop count. Our framework provides a more reliable, energy-efficient and sustainable network operation, as reflected in our experimental metrics.

5 Conclusion

We presented HF-Snake-WERF, a hybrid optimisation framework for energy-efficient clustering and multi-hop routing in dynamic wireless sensor networks. We recommend HHO-based global exploration and FF-based local refinement for cluster-head selection, combined with SO-based routing, to address the interdependent requirements of cluster quality, residual energy, transmission distance, and hop efficiency. Unlike the traditional minimum-hop method, which focuses on short communication paths, our proposed framework uses energy-aware cluster formation and routing and accounts for node configurations, mobility, queueing, processing and propagation delays, wireless channel impairments, interference, and SINR-based communication reliability. We show that our coordinated strategy improves the PDR from 0.603 to 0.869, significantly increasing reliability, and the average throughput from 709.43 to 986.54 kbps. We also show that periodic reclustering adapts to changes in node position and energy availability. Similarly, NAEC decreases from 1.452 to 0.929 J/packet, corresponding to about 36% less energy cost per successful packet. The average end-to-end delay remains similar to the current approach, increasing only from 0.356 to 0.360 s, while the average alive-node ratio improves from 0.341 to 0.363. In sum, the results show that clustering and routing can work better together to balance energy efficiency, reliability, throughput, and network life than the shortest-path approach.

Despite the exciting results, the optimisation work has several limitations. First, we simulated the network with a fixed set of desired network size, node number, mobility mode, resource range, and channel parameters, so the results may not represent all WSN deployments. Furthermore, our optimisation approach uses HHO and FF optimisation for cluster-head selection and SO for routing. This computational cost might be relevant for resource-constrained sensor hardware today if we optimise the routing at each node. Third, the routing fitness considers only transmission distance, residual energy penalty and hop count, not all network quality-of-service parameters. We also note that the communication model (which employs path loss, shadowing, Rayleigh fading, noise, interference, and

SINR) simulates real wireless environments. Finally, we compare primarily with a standard minimum-hop routing strategy. Comparisons with many state-of-the-art clustering and routing methods, as well as with real-world installations and testbeds, will provide stronger evidence of generalisation.

We look forward to further development of HF-Snake-WERF for more adaptive, scalable, and deployment-oriented WSN optimisation. A key area of future work is developing lightweight or distributed versions of HHO–FF and SO to reduce computational and communication costs on resource-constrained sensor nodes. The routing objective can also be expanded to a fully multi-objective formulation to optimise energy consumption, latency, packet delivery reliability, residual energy balance, congestion, and throughput in a network. Reinforcement learning or online learning could adapt optimisation parameters and routing decisions to traffic, energy, and channel conditions. Future work could include more detailed analysis to consider larger and irregular network geometries, different mobility models, traffic loads, different sink placements, and more severe interference conditions. Security-aware clustering and routing are also critical extensions for applications where malicious or compromised nodes may affect route reliability. Finally, real WSN testbeds or experimentally measured channel traces would help validate the framework's practical impact and understand its computational overhead, scalability, robustness, and energy-saving ability in real deployment environments.

Declarations

Declarations

Competing Interests

-N/A

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Author Contribution

All authors contributed to the study conception and design. Conceptualization and Writing—original draft preparation: [Pallavi Charde]; Data Collection: [Pallavi Charde], [Uma Patel]; Formal analysis and investigation: [Pallavi Charde], [Uma Patel]; Writing—review and editing: [Pallavi Charde], [Uma Patel].

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Figures

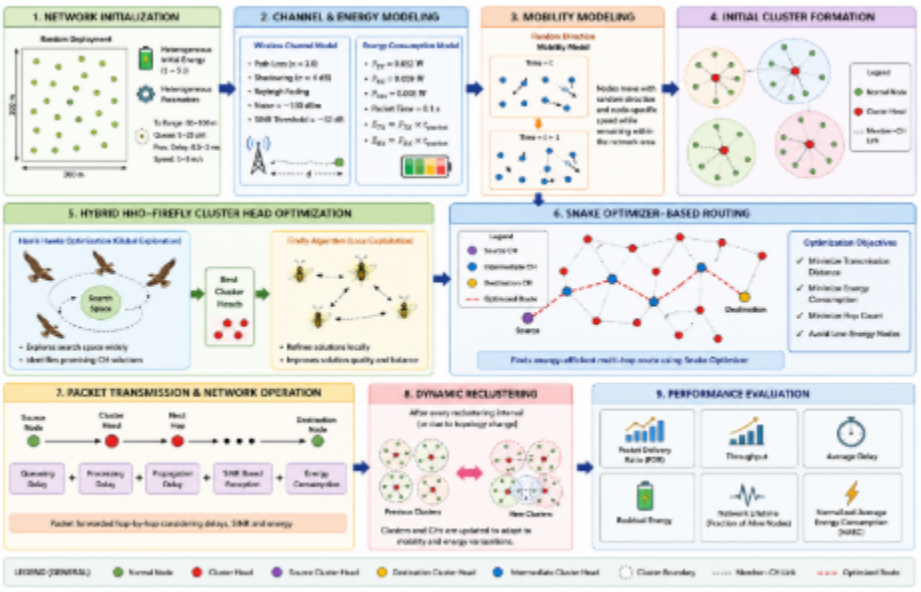


Figure 1

The proposed HF-Snake-WERF framework

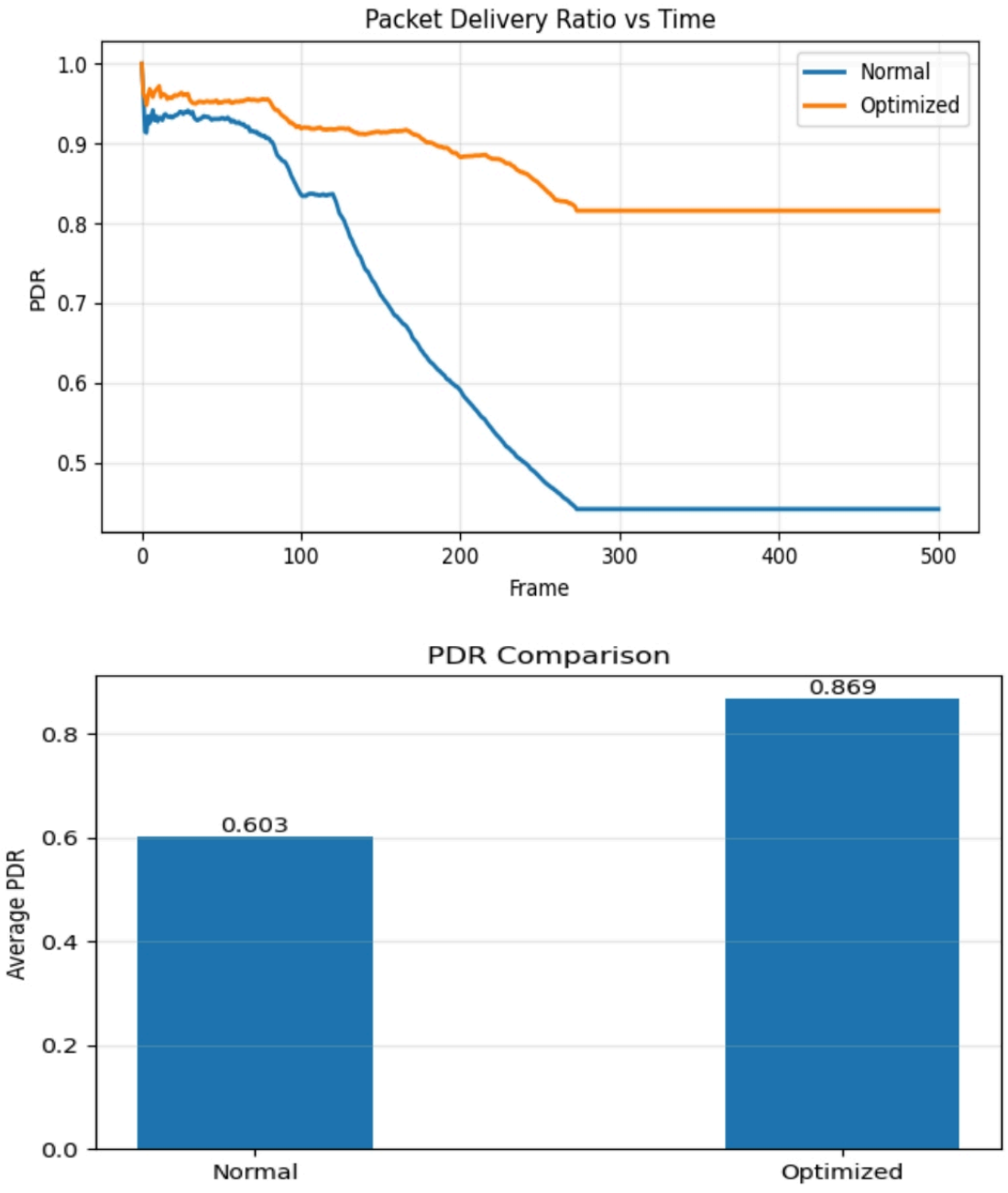


Figure 5

Comparative performance for PDR over 500 frames

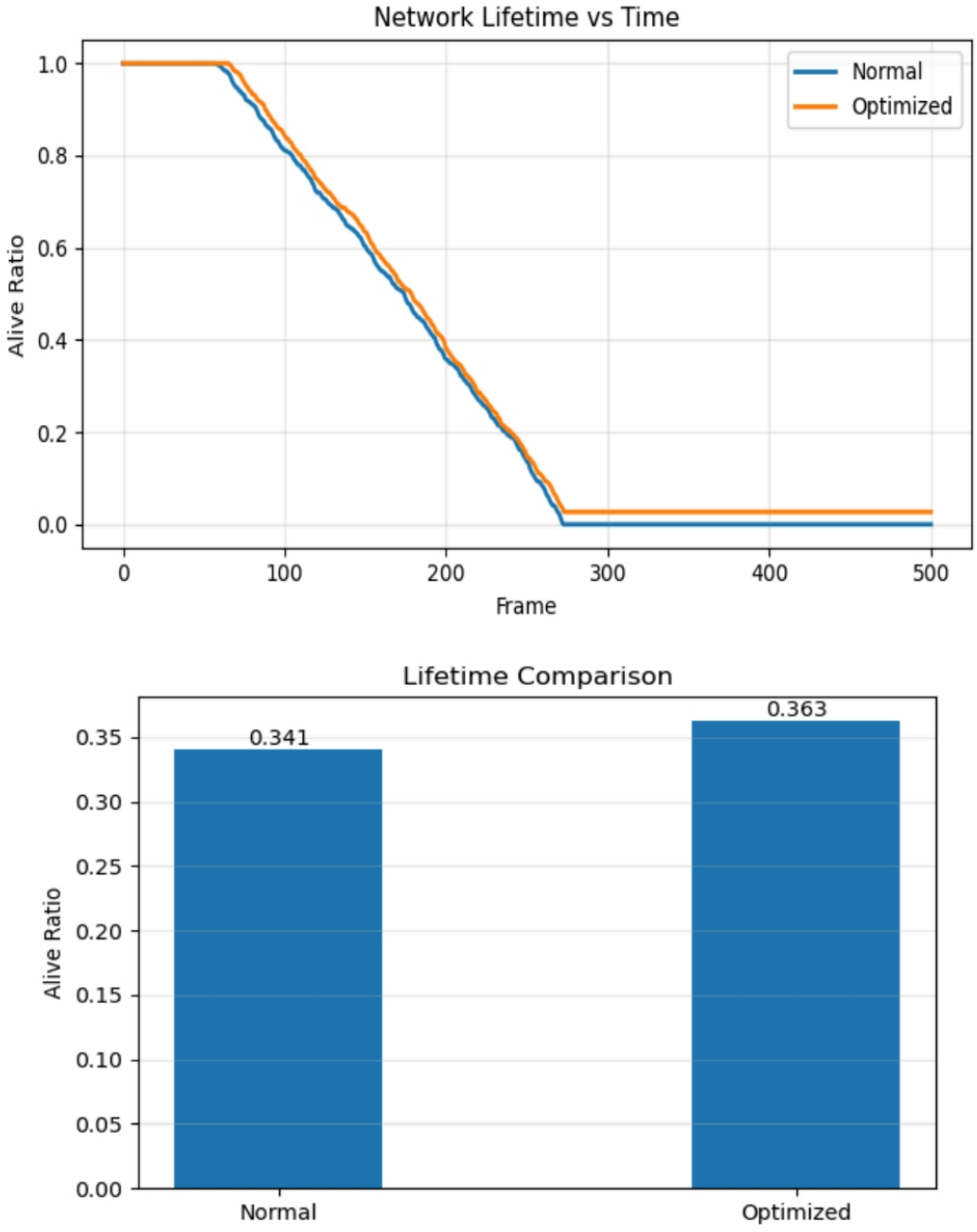


Figure 6

Comparative performance for network lifetime over 500 frames