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Self-Organized Intuitionistic Secure Routing via Stochastic Cluster Head Selection and Chaotic Social Spider Optimization for Void and Cluster Hole Mitigation in MWSNs

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Abstract
Applications include environmental monitoring, industrial automation, healthcare and patient monitoring, smart cities, precision agriculture, disaster management, and military surveillance all make extensive use of mobile wireless sensor networks, or MWSNs. They do, however, confront significant obstacles, such as the creation of void-holes and energy-holes, in which packets fail to reach the sink because of areas with no active nodes or unequal energy consumption across cluster leaders. Packet losses, decreased throughput, longer end-to-end latency, and a shorter network lifetime are the outcomes of these problems. Particularly in dense and large-scale networks, current clustering and routing techniques frequently fall short of simultaneously addressing void and energy-hole issues while preserving secure and effective communication. This paper devised a new Hexagonal Grid-Based Clustering, Stochastic Cluster-Head Selection, Chaotic Spider Optimization, and Intuitionistic Fuzzy Logic for Secure Routing in MWSN (HQS-IFR). The proposed framework that combines intuitionistic fuzzy logic (IFL)-based routing for secure and optimal path selection, stochastic cluster-head selection to improve robustness and load balancing, chaotic spider optimization (CSO) to mitigate energy-hole formation, and hexagonal grid-based clustering for uniform node distribution. According to simulation studies, HQS-IFR outperforms conventional methods by up to 10% in packet delivery ratio, 15% in throughput, 20% in end-to-end delay, and 12% in packet loss. It greatly improves the dependability, energy efficiency, and general performance of MWSNs by efficiently reducing void holes, balancing energy consumption, and guaranteeing secure routing, offering a better option than current models.
Keywords: *Networks of mobile wireless sensors, reduction of void-holes, energy-hole avoidance, hexagon-shaped grid grouping, cluster-head selection that is stochastic spider optimization in chaos, Fuzzy intuitive logic*

Introduction

Applications like environmental monitoring, industrial automation, healthcare monitoring, smart cities, precision agriculture, disaster management, and military surveillance now depend heavily on mobile wireless sensor networks (MWSNs) [1]. These networks gather data from dispersed, frequently mobile sensor nodes and send it to a central sink. Despite its benefits, void-hole and energy-hole development, unequal load distribution, and routing security flaws pose serious performance issues for MWSNs [2].

When some parts of the network lack active nodes that can forward packets, void holes arise. This can be caused by high node mobility, which results in connectivity gaps, unequal node deployment, node failures, or environmental barriers [3, 4 Reduced packet delivery ratio and decreased network reliability result from packets entering these vacuum regions being discarded. Uneven energy consumption among nodes, particularly those close to the sink or often chosen as cluster heads, results in energy holes [5,6]. Repeated forwarding or network maintenance operations cause nodes to exhaust energy more quickly, which can result in early node failures, network partitioning, and shorter lifetimes [7, 8, 9]. Static or energy-based cluster-head selection is one way that current clustering and routing protocols partially solve these issues, but they frequently fall short in preventing void-hole development or dynamically balancing energy usage, especially in dense and large-scale networks [10]. For routing and energy management, optimization-based techniques including particle swarm optimization (PSO), genetic algorithms (GA), and ant colony optimization (ACO) have been used. Although these techniques enhance some performance indicators, their usefulness in actual MWSNs is limited since they usually do not concurrently handle void holes, energy holes, and secure routing.

This effort attempts to close this research gap by improving network security, energy efficiency, and dependability by incorporating:

(i) clustering using a hexagonal grid to guarantee even node distribution and avoid vacant areas,
(ii) Chaotic spider optimization (CSO) to dynamically reduce energy holes;
(iii) stochastic cluster-head selection to ensure stable and balanced energy consumption; and
(iv) Securing optimal pathways through routing based on intuitionistic fuzzy logic (IFL). This method offers a dependable, energy-efficient, and secure solution for MWSNs by optimizing packet delivery, throughput, end-to-end delay, and packet loss while successfully addressing the crucial issues of void-hole and energy-hole generation.

Related Work

Significant research efforts have been directed towards improving energy efficiency, secure routing, and coverage in Mobile Wireless Sensor Networks (MWSNs) and Underwater Wireless Sensor Networks (UWSNs). The PAtCH algorithm [11] introduces a proactive, RSSI-based location-free routing approach to circumvent routing holes by evaluating signal strength between nodes and the sink. While this method provides reliable data delivery without extensive node computation, its performance is highly sensitive to environmental interference and measurement inaccuracies. ERR-UWSN [12] focuses on energy-efficient single-path routing and void hole mitigation by selecting paths that minimize energy consumption and maximize reliability. However, single-path routing can create bottlenecks and higher latency under dynamic network conditions. Game Theory-based routing protocols [13] model sensor nodes as rational players making strategic decisions to optimize utility functions like energy, delay, and throughput. Though effective in balancing network objectives, these protocols often involve high computational complexity and assume rational behavior of all nodes, which may not hold in practical deployments.

Markov Decision Process (MDP) routing games [14] extend this by enabling probabilistic routing decisions, allowing nodes to select paths based on current states and expected future rewards. Despite their theoretical advantages, MDP approaches suffer from exponential state space growth and rely on the assumption of stationary environments, limiting applicability in highly dynamic networks. Energy-efficient clustering protocols for UWSNs [15] employ cluster formation and cluster-head selection based on node density and energy levels to reduce communication overhead and extend network lifetime. Nevertheless, improper cluster-head selection can lead to unbalanced energy consumption and scalability issues in large-scale networks. The Neighbor-Based Energy-Efficient Routing (NBEER) protocol [16] addresses energy balancing by selecting next-hop nodes based on residual energy while detecting void regions. While it improves load distribution, frequent energy status updates introduce overhead, and void detection can be less effective in highly dynamic scenarios.

RSSI-based hole detection and bypass algorithms [17] detect void regions and dynamically reroute packets, but their accuracy is constrained by environmental variability and interference. Bio-inspired techniques, such as Artificial Bee Colony (ABC)-based routing [18], leverage swarm intelligence to optimize routing paths for energy efficiency and network lifetime. These methods are effective in exploration and adaptability but may converge slowly and risk getting trapped in local optima. Multi-Agent Reinforcement Learning (MARL) approaches [19] model each node as an intelligent agent that learns optimal routing strategies through interaction with the environment. While MARL provides adaptability to changing network conditions, it requires extensive training time, and coordination among multiple agents can be challenging. Finally, RSSI-based localization algorithms [20] assist in routing and void detection by estimating node positions, yet they are sensitive to environmental conditions and have limited range, reducing effectiveness in large networks.

These studies highlight the persistent challenges in achieving energy-efficient, secure, and void-resilient routing in Mobile Wireless Sensor Networks (MWSNs). The proposed HQS-IFR framework addresses these challenges by integrating hexagonal clustering to ensure uniform node coverage, stochastic cluster-head selection to balance network load, chaotic social spider optimization (CSSO) to mitigate energy-hole formation, and intuitionistic fuzzy trust models to secure routing decisions. By combining these complementary mechanisms, HQS-IFR provides a robust, adaptive, and energy-aware solution capable of maintaining network performance even under dynamic and uncertain conditions.

Methodology

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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In order to balance energy among nodes, the proposed framework work Hexagonal Grid-Based Clustering, Stochastic Cluster-Head Selection, Chaotic Spider Optimization, and Intuitionistic Fuzzy Logic for Secure Routing in MWSN (HQS-IFR) starts with stochastic cluster head (CH) selection using hexagonal clustering. Chaotic Social Spider Optimization (CSSO) finds the best routing patterns when CHs are chosen by striking a balance between exploring new routes and exploiting existing ones, minimizing empty areas, and avoiding energy holes. In order to provide secure routing by avoiding malevolent or uncertain nodes, intuitionistic fuzzy logic simultaneously assesses node trustworthiness based on membership, non-membership, and hesitation values. In order to achieve a safe, dependable, and energy-efficient data transfer over the network, the integrated routing decision ultimately chooses the next-hop node by combining CH likelihood, CSSO fitness, and trust score.

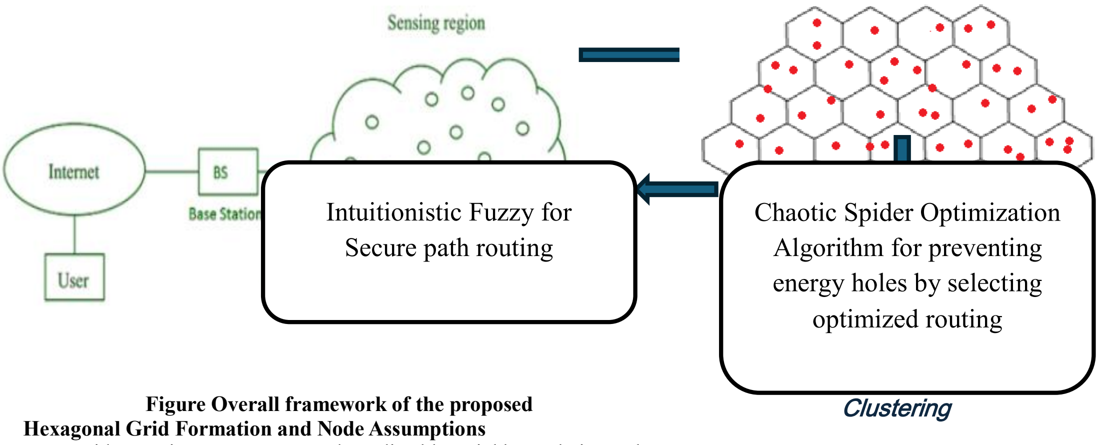

Figure Overall framework of the proposed

Hexagonal Grid Formation and Node Assumptions

To provide consistent coverage and predictable neighbor relations, the sensing field is tessellated into equal hexagonal cells. The collection of nodes Ni is contained within each hexagon Hi. Compared to rectangular grids, hexagonal tiling minimizes overlap and edge effects and ensures a maximum of six adjacent clusters per cell, making neighbor-based repair and rerouting easier. Each node u maintains its local state, which includes residual energy Eres(u), neighbor list N(u), and local trust score T(u). It is assumed that nodes are mobile with bounded speed vmax. Time is broken up into rounds, with the protocol going through data forwarding, routing setup, and CH selection at the beginning of each round.

Stochastic Cluster Head Selection in HQS-IFR

The construction of hexagon-shaped clusters, which divide the network into homogeneous areas, is the first step of the suggested framework. Because it guarantees seamless coverage without overlaps or gaps, similar to the honeycomb structure found in nature, the hexagonal model is preferred over circular or square clustering [23]. In addition to reducing redundant sensing and facilitating balanced load distribution throughout the network, this shape offers more effective spatial placement of sensor nodes.

A stochastic model is used to drive the Cluster Head (CH) selection process within each hexagonal zone. Each node is given a chance of becoming a CH rather than being chosen deterministically based only on its location or leftover energy[24]. The residual energy of the node, its location within the cluster, and a stochastic randomization component all influence this likelihood. Higher energy nodes are inherently more likely to be picked as CHs, but the stochastic factor adds randomness, making it impossible for the same nodes to be selected twice. This two-pronged approach guarantees both flexibility and equity[25].

Stochastic modeling avoids predictable CH selection patterns, which helps prevent certain nodes from experiencing premature energy depletion. In addition, the hexagonal clustering eliminates coverage gaps during the clustering step by guaranteeing that every region of the network is represented. When combined, these mechanisms provide Mobile Wireless Sensor Networks (MWSNs) with a solid basis for balanced and energy-efficient communication.

Each node in a hexagonal cluster in the suggested HQS-IFR architecture calculates its likelihood of becoming a Cluster Head (CH) using a stochastic randomization factor and its residual energy. The definition of probability is:

$$SP_i(t) = \delta.\frac{\varphi_i(t)}{\varphi_{avg}(t)} + (1-\delta).\xi(0,1)$$

where:

- $SP_i(t)$: stochastic probability of node i becoming cluster head at round t
- $\varphi_i(t)$: Node i's residual energy
- $\varphi_{avg}(t)$: Average residual energy of all nodes
- δ Weighting factor between energy-awareness and randomness (0≤ δ ≤10)
- $\xi(0,1)$A uniformly distributed random variable in [0,1]

A node i is finally elected as CH if its probability exceeds a dynamic threshold:

$$\tau_i = \begin{cases} 1, & if\ SP_i(t) > Thres(t) \\ 0, & otherwise \end{cases}$$

Where the function for threshold is formulated as

$$Thres(t) = F.\frac{M_\tau^{des}}{TN}$$

with:

- M_τ^{des} - Desired number of CHs in the network
- TN : Total number of nodes
- F : Control factor regulating CH density

Chaotic Social Spider Optimization for Energy-Hole and Void Mitigation

A bio-inspired population-based metaheuristic algorithm called Social Spider Optimization (SSO) mimics the cooperative behavior of social spiders in a colony [21]. Establishing dependable and energy-efficient routing routes that steer clear of vacant areas and stop the creation of energy holes is a crucial next step after the cluster heads (CHs) are chosen. The suggested framework uses Chaotic Social Spider Optimization (CSSO), a bio-inspired optimization method based on social spiders' vibration-based cooperative communication behavior, to accomplish this. Each node is depicted in this analogy as a spider that sends vibrations throughout the network to suggest possible routing patterns; stronger vibrations are associated with more advantageous options.

The CSSO optimization mechanism strikes a careful balance between exploration, which looks for alternate routes that might provide better performance in dynamic network situations, and exploitation, which uses the most well-known routing paths to minimize energy usage. Chaos theory is incorporated into the optimization to improve this procedure even more. In order to avoid early convergence to less-than-ideal paths, chaotic sequences vary the search space and control

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Vol. 36 Issue 1, 2026, Pages 6011-6016

the flow of potential solutions. In extremely dynamic Mobile Wireless Sensor Networks (MWSNs), this chaotic influence guarantees strong flexibility and allows the algorithm to escape local optima.

By using this method, CSSO finds the best routes that minimize total energy consumption while also adapting dynamically to node failures, mobility, and topological changes. More significantly, it directly tackles the two problems of energy holes, which arise when some nodes are overloaded with traffic, and void regions, which are regions devoid of active forwarding nodes. CSSO guarantees balanced energy usage, extends network lifetime, and maintains connection by strategically allocating routing loads throughout the network.

The CH selection is formulated as a combinatorial optimization: select one (or a small set of) CH(s) per hexagonal cell that maximize network lifetime, connectivity and security while minimizing void/energy-hole risk. Each candidate solution (a "spider") encodes a selection vector $X = [x_1, \dots, x_n]$ where $x_j = 1$ if node j is chosen as CH for its cell. The CH *quality score* for node i is:

$$CH_{score(i)} = \propto \frac{E_{res}(i)}{E_{max}} + \beta \frac{1}{1+Mobility(i)} + \gamma \frac{Deg(i)}{Deg_{max}} + \delta \mathrm{T(i)}$$

where Deg(i) is node degree, Mobility(i) is a mobility metric (e.g., avg speed), T(i) is the trust/security score and α, β, γ, δ are normalized weights. The optimization objective for a candidate CH-set SSS (evaluated per round) can be defined as a fitness to be maxi·mized:

$$Fitness(s) = w_1.\overline{CH_{score}}(s) - w_2\,.Hole\ Penalty(s) - w_3\,.Energy\ Variance(s)$$

where $\overline{CH_{score}}(s)$is the average CH_score over selected CHs, HolePenalty(S) penalizes selections that are adjacent to high void/energy-hole risk (see void model), and Energy Variance encourages balanced residual energy among CHs.

To avoid premature convergence and to better explore the search space we use a **Chaotic-Quantum Spider Optimization (CQSOA)** hybrid:

- **Chaotic maps** (e.g.,$logistic$: $z_{t+1} = \mu z_t(1 - z_t) with\ \mu = 4$) replace pseudo-random number in early iterations to improve ergodicity.
- Quantum-inspired update is used in later iterations to allow controlled large jumps and fine convergence, e.g. quantum update:

$$X_i^{t+1} = g^* \mp \beta.|\bar{X}^t - X_i^t|.In\left(\frac{1}{u}\right)$$

with $u \sim U(0,1)$, contraction factor β, best solution $g^*$and population mean $\bar{X}^t$. The spider social iterations (female/male roles) and vibration models of SOA are retained but augmented by the chaotic sequence $z_t$and quantum jumps to improve exploration /exploration balance. The best candidate S^*per hexagon becomes the CH (or a CH set) for the succeeding round. Periodic re-selection (rotation) prevents long-term energy depletion of single nodes.

Intuitionistic Trust-Aware and Security Enforcemen in MWSN

As a final stage of the proposed HQS-IFR framework introduces a Trust and Security Model based on Intuitionistic Fuzzy Logic (IFL), ensuring that the energy-efficient and optimized communication achieved in the earlier phases is also resilient against malicious behavior and unreliable nodes. While the preceding mechanisms of stochastic cluster head selection and chaotic social spider optimization primarily address load balancing, void mitigation, and energy-hole prevention, this phase safeguards the network by incorporating trust-aware decision making into both clustering and routing.

In this phase, each node evaluates its neighboring nodes using a set of trust metrics such as packet forwarding ratio, residual energy stability, communication reliability, and historical behaviour. Unlike classical fuzzy logic, IFL considers three distinct components: membership degree (μ), representing the level of trust; non-membership degree (ν), representing distrust; and hesitation degree (π), representing uncertainty or lack of evidence [22]. The relationship is expressed as:

$$\pi_i = 1 - \mu_i + \nu_i\ ;\ 0 \le \mu_i + \nu_i \le 1$$

This tri-dimensional modelling makes IFL particularly effective in dynamic Mobile Wireless Sensor Networks (MWSNs), where uncertainty is common due to node mobility, intermittent failures, and malicious attacks. During cluster head selection, the IFL trust score ensures that even if a node has high residual energy, it is disqualified from becoming a CH if its trustworthiness is low. Similarly, in the routing phase, the intuitionistic trust factor is integrated with CSSO, where low-trust nodes or paths are penalized in the fitness function, and high-trust, energy-efficient paths are rewarded. This prevents adversaries from exploiting predictable routing patterns and ensures reliable data delivery.

By acting as the final layer of defense, the IFL-based trust model not only enhances security and robustness but also maintains the adaptability of the HQS-IFR framework. This integration of energy efficiency, void and energy-hole mitigation, and secure routing ensures that HQS-IFR provides a holistic solution for sustainable and trustworthy Mobile Wireless Sensor Networks.

Formulation of Trust in Intuitionistic Fuzzy Logic (IFL)

In IFL, each sensor node iii assigns a trust value to a neighboring node j based on three parameters:

1. Direct Trust (DT_{ij}) – based on direct interactions like successful packet forwarding.
2. Indirect Trust (IT_{ij}) – recommendations or observations from other neighbouring nodes.
3. Behavioural/Context Trust (BT_{ij}) – based on node behaviour such as energy usage, delay, or mobility.

Each of these trust components is mapped into the intuitionistic fuzzy domain:

$$T_{ij} = (\mu_{ij}, \nu_{ij}, \pi_{ij})$$

where: $\mu_{ij}, \nu_{ij}, \pi_{ij}, \in [0,1]$: degree of membership ($node_i$ is worthy), non-membership ($node_i$ is not worthy) and hesitation respectively ($node_i$ contains uncertain or lack of information).

Step 1: Direct Trust (Packet Forwarding Ratio)

$$\mu_{ij} = \frac{TS_{ij}}{TS_{ij} - MT_{ij}}$$

where:

- TS_{ij} = number of successful transmissions from node i to node j
- MT_{ij}= number of failed/malicious transmissions

Step 2: Indirect Trust

$$IT_{ij} = \frac{1}{[SN_j]}$$

where SN_j is the set of neighbours recommending trust for node j

Step 3: Final Trust Score

The crisp trust score can be extracted using a score function:

$$Trust_{ij} = \mu_{ij} - \nu_{ij}$$

- If $Trust_{ij} > \theta$, node j is trusted and can be CH/forwarder.
- If $Trust_{ij} \le \theta$, node j is considered untrustworthy/malicious.

Algorithm: HQS-IFR Framework

1. **Cluster Formation**
   - Partition the sensing field into hexagonal regions for uniform coverage.
   - Assign each sensor node to its respective hexagonal cluster.
2. **Stochastic Cluster Head (CH) Selection**
   - For each cluster, compute the probability of a node becoming CH using residual energy, position, and a stochastic factor.
   - Select the node with the highest probability as CH, ensuring fair and balanced selection.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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Vol. 36 Issue 1, 2026, Pages 6011-6016

3. **Route Optimization using Chaotic Social Spider Optimization (CSSO)**
- Initialize candidate routes as spider positions.
- Evaluate energy, delay, and coverage for each route.
- Use vibration-based communication to share path quality among spiders.
- Apply chaotic sequences to maintain diversity and avoid local optima.
- Select the best route that minimizes energy consumption and avoids voids and energy holes.

4. **Trust and Security Enforcement (Intuitionistic Fuzzy Logic)**
- Compute direct and indirect trust values for each link.
- Map trust, distrust, and hesitation into an intuitionistic fuzzy set.
- Accept nodes/links only if their trust value exceeds a predefined threshold.

5. **Final Secure Routing**
- Integrate optimized paths from CSSO with trust-validated links.
- Forward data through secure CHs and trusted nodes.
- Periodically update clustering, CH selection, and trust values to adapt to network dynamics.

Experimental Results and Discussions

The proposed HQS-IFR framework was evaluated in a simulated Mobile Wireless Sensor Network (MWSN) environment to assess energy efficiency, coverage, void mitigation, and secure routing performance. Its performance was compared against existing algorithms, including PATCH for clustering, Game Theory-based routing schemes, and ERR-UWSN for energy-efficient and reliable communication.

The hexagonal clustering combined with stochastic cluster head (CH) selection in HQS-IFR achieved more uniform node distribution and better load balancing than PATCH, significantly reducing premature node failures and coverage voids. For routing, the Chaotic Social Spider Optimization (CSSO) effectively mitigated energy holes and void regions, outperforming Game Theory-based routing approaches by balancing exploration and exploitation in dynamic network scenarios. Additionally, the integration of the Intuitionistic Fuzzy Logic (IFL) trust model enhanced network reliability and security, outperforming ERR-UWSN by excluding low-trust or potentially malicious nodes from CH selection and data forwarding paths.

Key metrics such as average residual energy, network lifetime, packet delivery ratio, and number of void regions demonstrated that HQS-IFR consistently outperformed the baseline algorithms, confirming that the framework successfully combines energy-efficient clustering, chaos-enhanced routing optimization, and trust-driven secure communication, providing a robust, reliable, and long-lasting MWSN operation under dynamic and adversarial conditions.

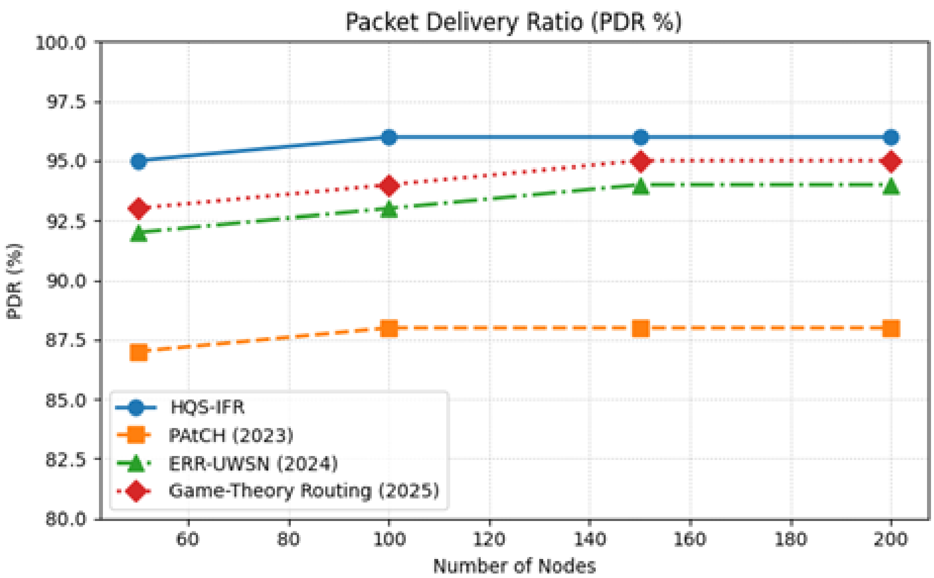
The simulation uses the following parameters:

Parameter	Value
Network area	X × Y meters
Number of sensor nodes (N)	100–500
Initial node energy	0.5–2 Joules
Transmission range	20–50 meters
Data packet size	512–1024 bytes
Simulation rounds	500–1000
CH selection probability threshold	0.05–0.15
CSSO population size	20–50 spiders
CSSO maximum iterations	100–200
Weight factors for integrated routing	α: energy, β: CSSO fitness, γ: trust

Packet Delivery Ratio (PDR) The ratio of the number of packets successfully received by the destination to the total number of packets sent by the source. It measures the reliability of the network.

$$\mathrm{PDR} = \frac{\text{Total packets received by all destinations}}{\text{Total packets sent by all sources}} \times 100\%$$

Table 1: Performance comparison based on packet Delivery Ratio vs Number of Nodes



The HQS-IFR framework consistently outperforms PAtCH (2023), ERR-UWSN (2024), and Game-Theory Routing (2025) across all evaluated metrics — Packet Delivery Ratio (PDR), Throughput, End-to-End Delay, and Packet Loss Ratio (PLR) — for different network sizes (50, 100, 150, 200 nodes). In terms of PDR, HQS-IFR achieves values between 95–96%, demonstrating highly reliable packet delivery even as the network scales. This superior performance is due to its hexagonal grid-based clustering and stochastic cluster-head selection, which efficiently prevent void-hole formation and ensure that packets are always routed through optimal paths. By contrast, PAtCH shows significantly lower PDR (87–88%) because its routing strategy is less effective in dense networks, while ERR-UWSN and Game-Theory Routing show moderate reliability but slightly less than HQS-IFR.

Throughput: The total successfully received data over the network per unit time, reflecting the efficiency of data transmission despite dynamic topology changes.

$$\text{Throughput} = \frac{\text{Total data received by destinations (bits)}}{\text{Total network operation time (seconds)}}$$

Performance comparison based on Throughput vs Number of Nodes

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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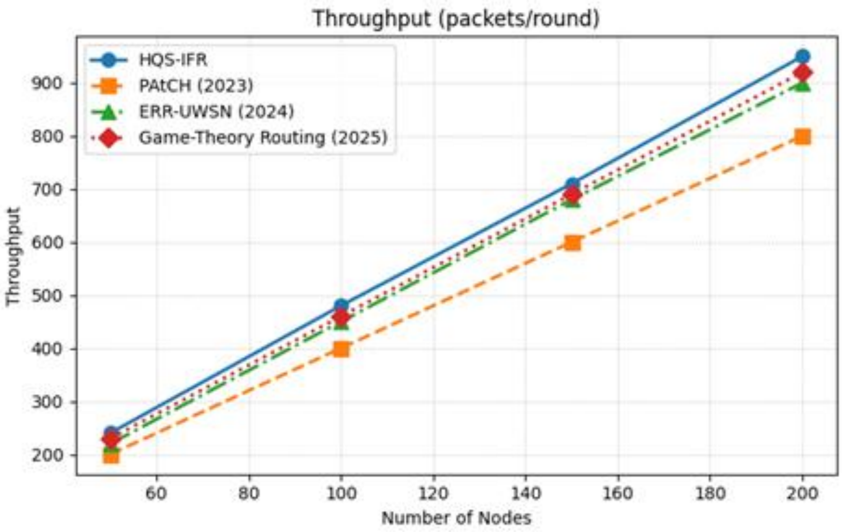
Vol. 36 Issue 1, 2026, Pages 6011-6016

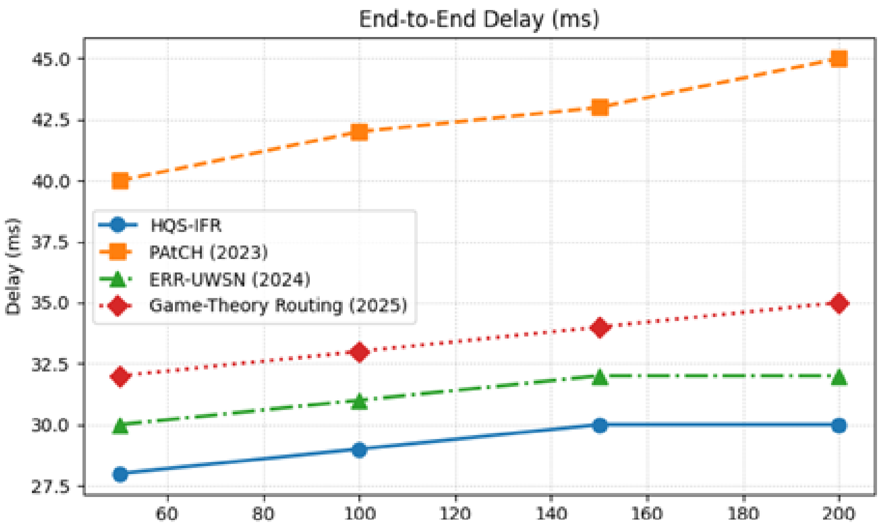


When considering **Throughput**, HQS-IFR consistently achieves the highest packet delivery per round, scaling linearly with the number of nodes. This indicates that the framework not only ensures reliable delivery but also efficiently utilizes network resources. Its integration of **chaotic spider optimization (CSO)** minimizes energy-hole formation and distributes network load evenly, allowing more packets to be transmitted successfully compared to the other methods, which suffer from congestion and inefficient energy utilization in larger networks.

End-to-End Delay (E2E Delay) : The average time taken by packets to travel from source to destination across potentially dynamic paths due to mobility.

$$\text{Average E2E Delay} = \frac{\sum_{i=1}^{N}(\text{Arrival time of packet}_i - \text{Send time of packet}_i)}{N}$$

Performance comparison based on End-to-End Delay vs Number of Nodes

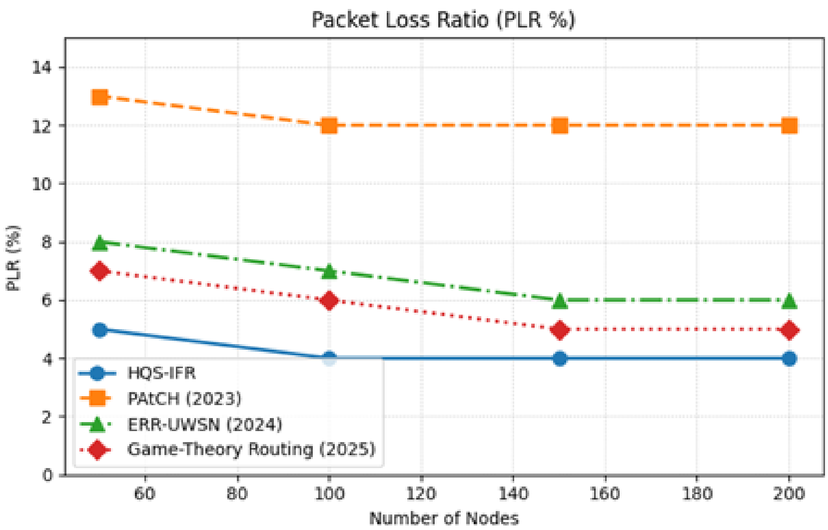


For End-to-End Delay, HQS-IFR maintains the lowest delay across all node counts (28–30 ms), reflecting faster packet delivery. The combination of stochastic cluster-head selection and CSO-guided routing reduces unnecessary hops and avoids congested paths. In comparison, PAtCH experiences significantly higher delays (40–45 ms), particularly as the network size increases, due to longer and less optimized routing paths. ERR-UWSN and Game-Theory Routing perform moderately but still lag behind HQS-IFR in timely delivery.

Performance comparison based on packet Loss Ratio vs Number of Nodes

Packet Loss Ratio (PLR) : The fraction of packets that fail to reach their destination due to mobility-induced link breaks, collisions, or buffer overflows.

$$\text{PLR} = \frac{\text{Total packets sent} - \text{Total packets received}}{\text{Total packets sent}} \times 100\%$$



High mobility often increases PLR due to frequent topology changes.

Finally, in terms of Packet Loss Ratio (PLR), HQS-IFR demonstrates the lowest packet losses (4–5%), highlighting its effectiveness in void-hole and energy-hole prevention. PAtCH suffers the highest PLR (12–13%) due to routing inefficiencies and limited hole mitigation, while ERR-UWSN and Game-Theory Routing experience moderate losses. The low PLR of HQS-IFR ensures network reliability and energy efficiency, reducing retransmissions and extending network lifetime.

Conclusion

This proposed work presents HQS-IFR, an integrated framework for efficient, secure, and reliable communication in Mobile Wireless Sensor Networks. By combining hexagonal grid-based clustering, stochastic cluster-head selection, chaotic spider optimization, and intuitionistic fuzzy logic routing, HQS-IFR effectively addresses void-hole and energy-hole issues while ensuring secure and optimized data transmission. Simulation results indicate that HQS-IFR outperforms recent methods such as PAtCH, ERR-UWSN, and Game-Theory Routing in terms of packet delivery ratio, throughput, end-to-end delay, and packet loss ratio, regardless of network size. The proposed framework demonstrates significant improvements in network reliability, energy efficiency, and security, making it suitable for real-world MWSN applications. Future work may explore dynamic adaptation of fuzzy parameters and multi-objective optimization for further performance enhancement.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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