
IMPROVED CLUSTERING AND ROUTING APPROACH FOR HOTSPOT MITIGATION IN WIRELESS SENSOR NETWORKS USING LOAD-AWARE CLUSTER-HEAD SELECTION

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ABSTRACT

Wireless Sensor Networks (WSNs) are susceptible to hotspot formation caused by uneven traffic distribution and excessive forwarding responsibilities on selected sensor nodes. This paper presents an Improved Clustering Approach to Mitigate Hotspots (ICAMHS), developed as an enhancement of the Cluster-Based Genetic Routing Protocol (CGRP). ICAMHS integrates K-means clustering, energy- and distance-aware cluster-head selection, traffic-load consideration, an improved routing fitness function, and fault-tolerant route recovery. The proposed approach was evaluated against CGRP using two performance metrics: decoding probability for a 1000-node network and end-to-end latency. At a decoding rate of 1.5, ICAMHS achieved a decoding probability of 0.35, compared with 0.10 for CGRP, representing a 250% relative improvement. At a decoding rate of 3.0, ICAMHS achieved 1.00 compared with 0.98 for CGRP, representing a 2.04% relative improvement. For latency, ICAMHS achieved 998 ms at 1000 nodes compared with 1000 ms for CGRP, representing a 0.20% reduction. The results indicate that ICAMHS improves decoding performance while maintaining comparable latency under the evaluated simulation conditions. The evaluation is limited to decoding probability and latency; energy consumption, network lifetime, scalability, computational overhead, and repeated-run statistical analysis are left for future work.

Keywords: Wireless Sensor Networks; hotspot mitigation; ICAMHS; clustering; CH selection

1. INTRODUCTION

Wireless Sensor Networks (WSNs) consist of distributed sensor nodes that collect environmental information and transmit data to a base station (BS). They are widely used in monitoring and automation applications. However, limited energy and communication resources make efficient clustering and routing essential for reliable operation (Patil & Kohle, 2024).

A major challenge in clustered WSNs is hotspot formation, where some nodes experience disproportionately high communication and forwarding loads. CHs close to the BS may aggregate their own data while relaying traffic from other clusters, resulting in increased communication burden and faster resource depletion (Lonkar et al., 2026). Clustering reduces communication overhead by grouping nodes under CHs, which collect, aggregate, and forward data to the BS. Genetic Algorithms (GAs) have also been applied to WSN routing to optimise routing configurations based on predefined fitness criteria (Khalaf et al., 2022).

CGRP combines clustering with GA-based route optimisation to improve routing performance (Patil & Kohle, 2024). However, its CH selection may not sufficiently consider existing traffic loads, potentially increasing hotspot formation. To address this limitation, this study proposes ICAMHS,

which extends CGRP through traffic-aware CH selection, improved routing fitness, and fault-tolerant route recovery. The evaluation is limited to decoding probability for $N=1000$ and latency under identical simulation conditions. The proposed approach is also relevant to the conference theme of Nigeria's Growth for Sustainable Development because reliable WSNs can support distributed sensing applications such as rural environmental monitoring, agricultural monitoring, and infrastructure condition monitoring. Reducing hotspot formation can improve the reliability and operational efficiency of such sensing systems, aligning the work with the Intelligent Systems, Automation and Control Engineering sub-theme.

2. RELATED WORK

Recent studies have addressed hotspot formation and energy imbalance in WSNs through intelligent clustering, load balancing, and adaptive routing. These approaches have reported improvements in energy efficiency, network lifetime, routing performance, and CH selection. However, computational complexity, scalability, dynamic adaptation, and balanced traffic distribution remain areas requiring further investigation.

Table 1: Summary of Recent Clustering and Routing Approaches in WSNs

Study	Approach	Main Contribution	Limitation / Gap
Somula et al. (2024)	Osprey optimization-based CH selection	Improves packet delivery and network lifetime through optimized CH selection	Limited adaptaton to dense and heterogeneous networks
Mabunga and Dela Cruz (2024)	Wild Geese Optimization-based clustering and routing	Optimizes CH selection and routing using multiple network parameters	Computational cost and scalability require further consideration
Patil and Kohle (2024)	Cluster-Based Genetic Routing Protocol (CGRP)	Combines clustering, energy/distance-based CH selection, and GA-based routing optimization	Limited consideration of traffic-load concentration and hotspot-aware CH selection
Soltani et al. (2025)	Multi-agent reinforcement-learning routing	Adapts routing using energy, hop count, hotspot proximity, and neighbourhood information	Re-clustering overhead and CH depletion remain challenges
Prince et al. (2025)	Multilevel clustering and prediction-based routing	Uses clustering and prediction to reduce hotspot effects	Centralized clustering and CH-management overhead remain concerns
Peter et al. (2026)	Density-aware clustering with Voronoi partitioning	Addresses dense WSNs using density, link quality, and dynamic reclustering	Computational complexity, delay, and implementation cost remain concerns
Ramesh et al. (2026)	Hybrid ML-based CH selection and routing	Integrates machine learning and optimization to improve network lifetime	Integrated adaptive clustering and routing may increase computational complexity
Baslem et al. (2026)	Hotspot-aware load-balanced clustering and routing	Combines energy-aware clustering, load balancing, and fault-tolerant routing	Computational cost and real-world deployment require further evaluation
Proposed ICAMHS	K-means and load-aware CH selection with improved routing fitness	Combines energy, distance, traffic load, energy-balanced routing, and fault-tolerant recovery	Further evaluation of energy consumption, network lifetime, scalability, and computational overhead is required

The reviewed studies demonstrate that energy-aware clustering, intelligent CH selection, load balancing, and adaptive routing can improve WSN performance. However, the integration of traffic-aware CH selection, energy-balanced routing, and fault-tolerant recovery remains insufficiently addressed. In particular, CGRP primarily considers residual energy and distance in CH selection, leaving traffic-load concentration insufficiently addressed (Patil & Kohle, 2024). Therefore, ICAMHS extends CGRP by incorporating traffic load into CH selection, an energy-imbalance factor into routing fitness, and fault-tolerant route recovery. The comparison in Table 1 also highlights differences in the mechanisms used to address hotspot formation. Somula et al. (2024) focus on optimisation-based CH selection and report gains in packet delivery and network lifetime, but their approach has limited adaptation to dense and heterogeneous networks. Mabunga and Dela Cruz (2024) jointly optimise clustering and routing using multiple network parameters, although computational cost and scalability remain concerns. Soltani et al. (2025) introduce multi-agent reinforcement learning for routing using energy, hop count, hotspot proximity, and neighbourhood information, but re-clustering overhead and CH depletion remain challenges. Peter et al. (2026) address dense WSNs through density, link quality, and dynamic reclustering, while Ramesh et al. (2026) combine machine learning with optimisation for CH selection and routing; both approaches may increase computational complexity. These studies indicate that hotspot mitigation can benefit from adaptive decision-making, but they do not directly combine the specific traffic-aware CH selection, energy-balanced routing fitness, and fault-tolerant recovery used in ICAMHS. ICAMHS therefore targets this combination while retaining a relatively simple K-means-based clustering structure.

3. PROPOSED ICAMHS PROTOCOL

3.1 Network Model

The proposed model assumes a homogeneous sensor network in which sensor nodes are randomly distributed within the network area, the BS remains fixed, and all nodes have equal initial energy. The nodes communicate through cluster heads. K-means clustering is used to partition the network into clusters, after which suitable CHs are selected using energy, distance, and traffic-load information. This homogeneous assumption is consistent with the simulation configuration used in the present study. Although ICAMHS is motivated by hotspot problems also reported in heterogeneous WSNs, its current evaluation does not model heterogeneous initial energies or heterogeneous node capabilities. Consequently, applicability to heterogeneous WSNs should be regarded as a limitation requiring further validation. The simulation configuration adopted from the source study uses a 1000 m² network area, 50 J initial node energy, 30 m transmission range, 10 m sensing range, 60 kbps bandwidth, 50 packets/s transmission rate, 1000-bit data packets, and a 200-time-unit operating period (Patil & Kohle, 2024).

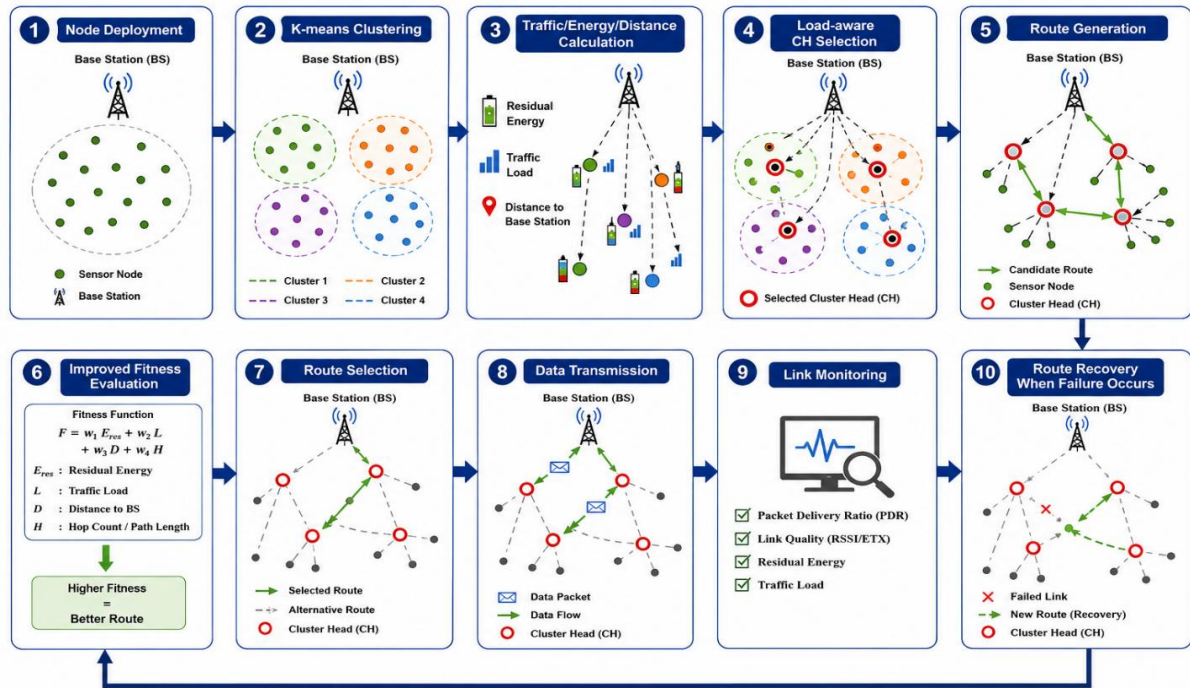


Figure 1: Conceptual Architecture of the Proposed ICAMHS Protocol

Figure 1 summarises the ten operational steps of ICAMHS. First, sensor nodes are deployed around a fixed base station (BS). Second, K-means clustering partitions the nodes according to their spatial positions. Third, residual energy, traffic load, and distance information are calculated for candidate CHs. Fourth, the load-aware CH-selection metric combines these factors to select a CH for each cluster. Fifth, candidate routes are generated between CHs and the BS. Sixth, the improved fitness function evaluates candidate routes using energy balance and routing-related criteria. Seventh, the route with the highest fitness is selected. Eighth, sensed data are transmitted along the selected route. Ninth, links are monitored using packet delivery ratio (PDR), link quality represented by RSSI/ETX, residual energy, and traffic load. Tenth, when a link becomes unacceptable, the failed link is detected and an alternative route is established through the fault-tolerant recovery mechanism.

3.2 Enhanced Cluster Formation

ICAMHS employs the K-means algorithm to group sensor nodes according to their spatial positions. For each cluster, the cluster centre is calculated as the arithmetic mean of the coordinates of all nodes assigned to that cluster. The cluster centre is given by (Guo et al., 2025).

$$C_j = \left(\frac{1}{n_j} \sum_{i=1}^{n_j} x_i, \frac{1}{n_j} \sum_{i=1}^{n_j} y_i \right) \quad (1)$$

Where (C_j) represent the centre of cluster (j) , (n_j) is the number of sensor nodes belonging to cluster (j) , and (x_i) and (y_i) are the x- and y-coordinates of node (i) .

The K-means clustering objective can additionally be expressed as

$$J = \sum_{j=1}^k \sum_{i \in C_j} \| X_i - C_j \|^2 \quad (2)$$

where K is the number of clusters, $X_i = (x_i, y_i)$ is the position vector of node i , and (C_j) is the centre of cluster j .

The objective of K-means is to minimise the total squared Euclidean distance between sensor nodes and their corresponding cluster centres. This arrangement reduces unnecessary communication distances and provides a spatial basis for subsequent CH selection.

3.3 Load-Aware Cluster-Head Selection

The principal modification introduced by ICAMHS is the incorporation of traffic load into CH selection. Conventional CH selection based primarily on residual energy and distance may repeatedly assign CH responsibilities to nodes that already carry substantial communication traffic. To address this limitation, ICAMHS introduces a load-balancing factor defined as (Baslem et al., 2026)

$$L_b = \frac{1}{1 + \alpha T_i} \quad (3)$$

Where (T_i) represents the traffic load handled by node (i) , and (α) is a positive tuning parameter that controls the influence of traffic load on CH selection.

The inverse formulation ensures that the load factor decreases as the traffic handled by a node increases. Thus, a node carrying a high traffic load receives a lower preference for additional CH responsibilities.

A normalized distance factor can be defined as (Mabunga & Dela Cruz, 2024)

$$D_i = 1 - \frac{d_{iC_j}}{d_{max}} \quad (4)$$

where d_{iC_j} is the Euclidean distance between node i and the centre of cluster j , while d_{max} is the maximum reference distance used for normalization.

The residual-energy factor is expressed as

$$E_i = \frac{E_i^{res}}{E_{max}} \quad (5)$$

where E_i^{res} is the residual energy of node i , and E_{max} is the maximum or initial node energy.

The three factors can then be combined into the proposed CH-selection metric:

$$CH_i = w_E E_i + w_D D_i + w_L L_i \quad (6)$$

$$\text{Subject to } w_E + w_D + w_L = 1 \quad (7)$$

where w_E , w_D and w_L are the weighting coefficients assigned to residual energy, distance, and traffic load, respectively.

The cluster-head node is selected according to

$$CH_i^* = \arg \max_{i \in C_j} CH_i \quad (8)$$

where CH_i^* represents the selected CH for cluster j .

This formulation gives preference to nodes with higher residual energy, shorter distance to the cluster centre, and lower traffic load. Consequently, CH responsibilities can be distributed more evenly across the network, thereby reducing the likelihood of hotspot formation.

3.4 Improved Fitness Function

The improved fitness function introduces an energy-imbalance penalty based on the maximum energy consumed by nodes participating in a candidate route. A suitable formulation is to first calculate the energy consumed by node i during a routing operation as (Guo et al., 2025)

$$E_i^{cons} = E_i^{init} - E_i^{res} \quad (9)$$

where E_i^{init} and E_i^{res} denote the initial and residual energy of node i , respectively.

The maximum energy consumption among nodes participating in a candidate route is then

$$E_{max}^{cons} = \max_{i \in R} E_i^{cons} \quad (10)$$

where R represents the set of nodes participating in the candidate routing solution.

A normalized energy-imbalance penalty can be expressed as

$$P_E = \frac{E_{max}^{cons}}{\sum_{i \in R} E_i^{cons} + \varepsilon} \quad (11)$$

where ε is a small positive constant introduced to avoid division by zero.

The improved ICAMHS fitness function can then be represented generally as (Patil & Kohle, 2024)

$$F_{ICAMHS} = F_{CGRP} - \lambda_E P_E \quad (12)$$

where F_{CGRP} is the original CGRP fitness value, PE is the maximum-energy-consumption penalty, and λ_E controls the influence of the energy-imbalance penalty.

ICAMHS modifies the original CGRP fitness function by incorporating an energy-imbalance penalty based on the maximum energy consumed by participating nodes. The purpose of this penalty is to discourage routing solutions that concentrate excessive communication responsibilities on a small number of nodes. Therefore, the GA is encouraged to select routing configurations that provide a more balanced distribution of energy consumption and reduce the likelihood of hotspot formation.

3.5 Fault-Tolerant Routing

Q_{IJ} Link quality Q_{ij} is used as a general link-quality measure in the fault-detection condition; RSSI is therefore treated as one possible measurement contributing to Q_{ij} rather than as a separate variable in the link-failure equation. A link-failure indicator between node i and neighbouring node j is defined as

$$F_{ij} = \begin{cases} 1, & Q_{IJ} < Q_{th} \\ 0, & Q_{IJ} \geq Q_{th} \end{cases} \quad (13)$$

where $F_{ij} = 1$ indicates a failed or unacceptable link, $F_{ij} = 0$ indicates an acceptable link, Q_{IJ} represents the link quality between nodes i and j , and Q_{th} is the minimum acceptable link-quality threshold.

When a link failure is detected, node i broadcasts an LREQ message to its neighbouring nodes. Each responding neighbour provides information regarding its residual energy, distance to the destination, and link quality.

The alternative-next-hop score can be defined as

$$S_i = w_E \frac{E_j}{E_{mx}} + w_D (1 - \frac{d_i D}{d_{max}}) + w_Q \frac{Q_{ij}}{Q_{max}} \quad (14)$$

where E_{ires} is the residual energy of neighbouring node j , E_{mx} is the maximum or initial node energy, $d_i D$ is the distance between node j and the destination D , d_{max} is the maximum reference distance, Q_{ij} is the link quality between nodes i and j , Q_{max} is the maximum reference link-quality value, and w_E , w_D , and w_Q are weighting coefficients.

The alternative next hop is then selected as

$$J^* = \arg \max_{i \in N_i} S_{ij} \quad (15)$$

where N_i represents the set of eligible neighbouring nodes of node i , and j^* is the neighbour with the highest link score.

This mechanism allows ICAMHS to dynamically establish an alternative communication path when the primary route becomes unavailable.

4. SIMULATION SETUP

4.1 Simulation Parameters

The simulation parameters for developing the Improved Clustering Approach to Mitigate Hotspots (ICAMHS) in WSNs are presented in Table 3.1. These values are used to evaluate the performance of the developed model.

Table 2: Simulation parameters and its values

S/N	Parameter	Default Value
1	Transmission range	30 m
2	Sensing Range	10 m
3	Initial Energy	50 J
4	Node deployment	Random
5	Nodes Bandwidth	60kbps
6	Network area	1000 Sq.m
7	Transmission Rate	50 p/s
8	Packet size	1000 bits
9	Simulation duration	200-time units

4.2 Simulation Environment

The ICAMHS model was implemented using MATLAB. The principal simulation parameters were adopted from Patil and Kohle (2024), including a 30 m transmission range, 10 m sensing range, 50 J initial energy, 60 kbps bandwidth, 1000 m² network area, 50 packets/s transmission rate, 1000-bit packet size, and a 200-time-unit operating period. The CGRP baseline was independently re-simulated in MATLAB under the same network assumptions and parameter settings to provide a direct comparison. The node positions, traffic conditions, and simulation parameters were kept identical for ICAMHS and CGRP.

5. RESULTS AND DISCUSSION

5.1 Decoding Probability

Figure 2 shows the decoding probability of CGRP and ICAMHS for a network of 1,000 sensor nodes. ICAMHS consistently achieves a higher decoding probability than CGRP across the evaluated decoding rates. The improvement is more pronounced at lower decoding rates and decreases as both protocols approach a decoding probability of 1.00.

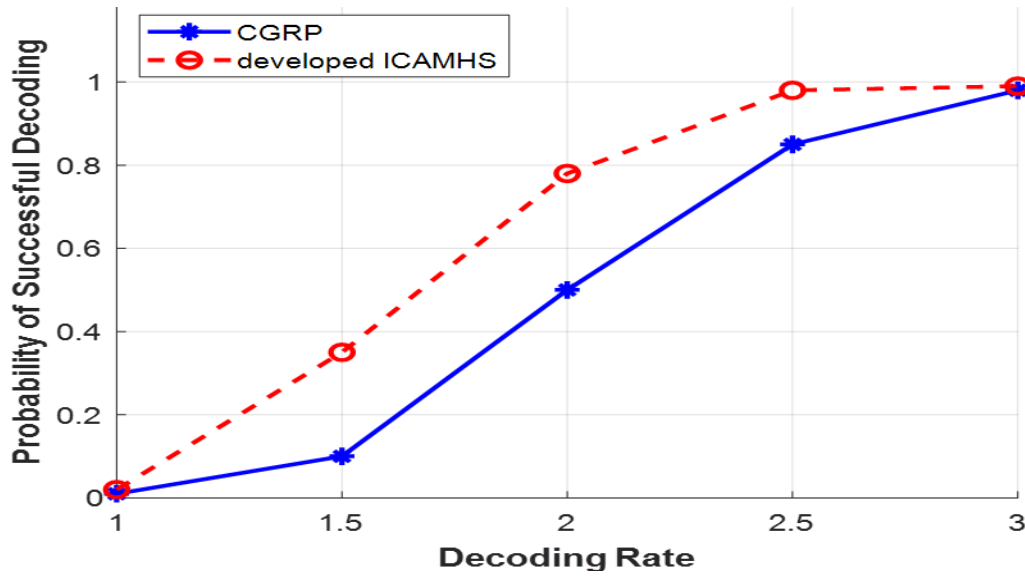


Figure 2: Decoding Probability versus Decoding Rate

At a decoding rate of 1.5, the decoding probability increases from 0.10 for CGRP to 0.35 for ICAMHS, representing a 250% relative improvement. At a decoding rate of 3.0, the improvement is 2.04%. These results indicate that the traffic-aware cluster-head selection and modified routing fitness function improve communication reliability, particularly at lower decoding rates. The numerical results are summarized in Table 3.

Table 3: Decoding Probability Comparison for N=1000

Decoding Rate	CGRP	ICAMHS	Improvement (%)
1.0	0.00	0.00	0.00
1.5	0.10	0.35	250.00
2.0	0.50	0.78	56.00
2.5	0.85	0.98	15.29
3.0	0.98	1.00	2.04

The improved performance can be attributed to the traffic-aware CH-selection mechanism and the modified routing fitness function. By reducing the probability of assigning additional forwarding responsibility to heavily loaded nodes, ICAMHS provides a more balanced communication structure and improves the likelihood of successful data delivery.

5.2 Latency Performance

Figure 3 presents the latency performance as the number of sensor nodes increases. ICAMHS maintains slightly lower latency than CGRP across the evaluated network sizes. The small difference indicates that the additional traffic-aware mechanisms do not introduce a substantial latency penalty under the simulated conditions.

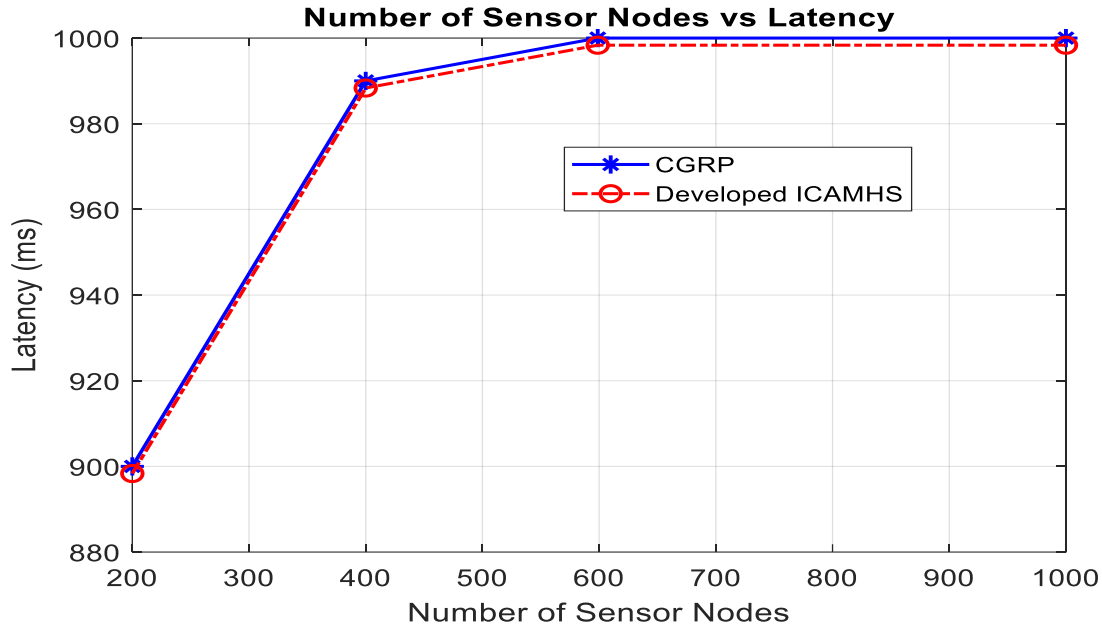


Figure 3: Latency Comparison of CGRP and ICAMHS

At 200 nodes, latency decreases from 900 ms for CGRP to 899 ms for ICAMHS, corresponding to a 0.11% reduction. At 400 nodes, the reduction is 0.20%. For 600–1000 nodes, ICAMHS maintains a latency of 998 ms compared with 1000 ms for CGRP, giving a 0.20% reduction. The detailed results are presented in Table 4.

Table 4: Latency Comparison between CGRP and ICAMHS

Number of Nodes	CGRP (ms)	ICAMHS (ms)	Reduction (%)
200	900	899	0.11
400	990	988	0.20
60	1000	998	0.20
800	1000	998	0.20
1000	1000	998	0.20

The results indicate that the additional processing associated with traffic-aware CH selection and routing optimisation does not produce a substantial latency penalty under the simulated conditions. The main performance advantage of ICAMHS is therefore the improvement in decoding probability rather than a major reduction in latency.

5.3 Comparative Discussion

The two performance metrics provide complementary evidence of ICAMHS performance. ICAMHS achieves higher decoding probability than CGRP across the evaluated decoding rates, with the highest relative improvement of 250.00% at a decoding rate of 1.5. For latency, the improvement is small. At 1000 nodes, ICAMHS reduces latency from 1000 ms to 998 ms, representing a 0.20% reduction. Thus, the main advantage of ICAMHS is improved decoding performance while maintaining comparable latency.

The improved decoding performance is consistent with the load-aware CH-selection strategy, which considers traffic load alongside residual energy and distance. This reduces the likelihood of assigning additional communication responsibilities to heavily loaded nodes. The improved routing fitness further promotes more balanced routing decisions. Overall, ICAMHS improves decoding performance without significantly affecting latency under the evaluated simulation conditions.

6. CONCLUSION

This paper presented ICAMHS, an improved clustering and routing approach for hotspot mitigation in large-scale Wireless Sensor Networks. The approach extends CGRP by incorporating traffic-aware cluster-head selection, an energy-imbalance factor in the routing fitness function, and fault-tolerant route recovery. The evaluation showed that ICAMHS achieved a decoding probability of 0.35 at a decoding rate of 1.5, compared with 0.10 for CGRP, representing a 250.00% relative improvement. At a decoding rate of 3.0, ICAMHS achieved 1.00 compared with 0.98 for CGRP, representing a 2.04% relative improvement. For latency, ICAMHS achieved 998 ms at 1000 nodes compared with 1000 ms for CGRP, representing a 0.20% reduction.

These results indicate that ICAMHS improves decoding performance while maintaining latency comparable to CGRP under the evaluated simulation conditions. The study has several limitations. The evaluation uses a homogeneous network model, considers only decoding probability and latency, and is based on a single simulation run without confidence intervals or statistical significance testing. Energy consumption, network lifetime, scalability beyond the evaluated network sizes, and computational overhead were not quantitatively evaluated. Future work will therefore include repeated simulation trials with statistical analysis, direct evaluation of energy consumption and network lifetime, scalability tests for larger networks, evaluation under heterogeneous node conditions, computational-overhead analysis, and validation using real sensor-network hardware.

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