EE-FGCH: An Energy-Efficient Fuzzy-Genetic Clustering Hierarchy for Wireless Sensor Networks

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ABSTRACT:
Wireless sensor networks (WSNs) face critical energy constraints due to limited battery life and processing capabilities, making energy optimization a core challenge. Prolonging network lifetime requires intelligent resource management at the node level. Dynamic clustering effectively reduces long-range transmissions to the base station, eliminates redundant data, and shortens routing paths, yielding significant energy savings while enhancing scalability for large-scale deployments. However, traditional clustering protocols suffer from sensitivity to cluster-head selection, load imbalance, and uneven node distribution, often leading to premature node failures and reduced longevity. This paper proposes EE-FGCH, a novel energy-efficient hierarchical clustering framework that integrates fuzzy logic for candidate pre-screening with a multi-objective genetic optimization algorithm for refinement. Simulation results demonstrate that EE-FGCH substantially outperforms the DCRRP protocol in energy consumption, end-to-end delay, Media access delay, Packet error rate, Packet loss rate, Signal-to-noise ratio, and throughput.

KEYWORDS: Clustering; Wireless Sensor Networks (WSNs); Genetic Algorithm; Fuzzy logic.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have emerged as a transformative technology, supporting a broad range of applications from environmental monitoring and precision agriculture to industrial automation, healthcare systems, and military surveillance [1]. These networks comprise numerous low-cost, energy-constrained sensor nodes capable of sensing, local computation, and wireless communication, enabling pervasive data acquisition in settings where conventional infrastructure is impractical or prohibitively expensive [2]. Despite their remarkable adaptability, the reliance on non-rechargeable batteries imposes severe energy limitations, making energy efficiency the primary design objective [3]. Clustering has long been recognized as one of the most effective energy-conservation strategies in WSNs [4]. By organizing nodes into clusters managed by elected cluster heads (CHs), this hierarchical approach significantly reduces long-distance transmissions to the base station (BS). Ordinary nodes transmit data only over short distances to their respective CHs, while CHs aggregate the received information and forward compressed packets to the BS, thereby eliminating redundancy and preserving energy [5]. Nevertheless, suboptimal CH selection, unbalanced cluster sizes, and uneven spatial distribution frequently trigger the hotspot phenomenon, causing certain CHs or nodes to deplete their energy prematurely. This leads to network partitioning and a drastic reduction in operational lifespan [6]. Consequently, recent research has shifted toward intelligent and adaptive clustering mechanisms that leverage soft computing techniques, including fuzzy logic, genetic algorithms, and reinforcement learning [7]–[8]. Despite significant progress, most existing solutions either rely on single-objective optimization or fail to simultaneously balance multiple conflicting criteria, such as residual energy, intra-cluster distance, node degree, and proximity to the BS. These shortcomings

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typically result in locally optimal configurations that perform poorly under dynamic network conditions or heterogeneous node capabilities. Accordingly, there remains an urgent need for a robust, multi-criteria clustering framework capable of achieving global energy optimality while maintaining scalability and practical deployability. This study addresses a critical research gap: the absence of a scalable, multi-objective clustering framework that achieves global energy optimality while preserving computational feasibility and practical deployability. We propose EE-FGCH—an Energy-Efficient Fuzzy-Genetic Clustering Hierarchy—that integrates fuzzy inference for rapid, context-aware CH pre-screening with a multi-objective genetic algorithm for global refinement. By operating centrally at the BS, EE-FGCH leverages complete network state information to form balanced, adaptive clusters, significantly outperforming state-of-the-art benchmarks in energy efficiency, reliability, and network longevity. The primary objective of this work is to develop and validate a hybrid intelligent clustering protocol that:

- Minimizes total energy consumption through optimized CH placement and load balancing;
- Maximizes network lifetime under realistic operational constraints;
- Ensures robustness across heterogeneous and dynamic WSN scenarios.

Through rigorous simulation in OPNET Modeler, we demonstrate that EE-FGCH not only extends network lifetime but also enhances throughput, reduces latency, and improves packet delivery—advancing the state of the art in energy-aware WSN design with direct implications for sustainable IoT and smart agriculture systems.

2. RELATED WORKS

The application of WSNs in precision agriculture has revolutionized resource optimization by enabling continuous monitoring of soil moisture, nutrient levels, meteorological conditions, and plant growth indicators [9]. Similarly, these networks support supply-chain integrity through real-time tracking of environmental parameters—temperature, humidity, vibration, and shock—during product transportation [10]. Given the infeasibility of battery replacement in large-scale deployments, minimizing energy expenditure at the node level remains paramount for prolonging network lifetime [11]. Clustering has emerged as a cornerstone technique for energy conservation. In [12], a cellular-topology-based clustering framework was proposed, where the network is divided into hexagonal cells. A time-gap scheduling mechanism ensures collision-free intra-cluster communication, while dynamic factors—including residual energy and node state—are continuously monitored. Cluster heads maintain awareness of member energy levels, transitioning idle nodes to sleep mode. To mitigate mobility overhead, cellular technology was employed, allowing each mobile agent to oversee multiple clusters. A hybrid static-clustering dynamic-routing protocol was introduced in [13]. During setup, each node reports its GPS-derived coordinates to the sink, which assigns it to a virtual cluster based on proximity to predefined grid points. In the routing phase, source nodes broadcast messages containing location and energy information. Receiving cluster heads compute Euclidean distances to determine whether they lie closer to the sink or to the transmitter, thereby selecting the optimal relay. This distance-aware relay selection minimizes long-distance transmissions. The VIBE protocol [14] established a two-tier communication paradigm. Upon data generation, a work session commences, and nodes may either join an existing cluster or operate independently. Clustering integration reduces average hop count and routing latency, yielding a flexible flat-hierarchical topology adaptable to varying traffic patterns. A tree-based routing scheme tailored for sensor networks was presented in [15]. Nodes possess partial knowledge of sink location and neighboring topology. After tree construction, sink position updates propagate downward, enabling construction of multiple spanning trees. The algorithm explores the solution space exhaustively to identify energy-efficient paths. An efficient intra-cluster CH rotation mechanism was developed in [16]. Initial CHs are selected probabilistically. Member nodes transmit join requests accompanied by residual energy reports. The provisional CH aggregates network-wide energy statistics. If total remaining energy exceeds a threshold x%, the highest-energy node assumes permanent CH status; otherwise, the node with maximum degree is selected. An acknowledgement broadcast finalizes the transition. FAMACROW [17] introduced an unbalanced clustering strategy combining fuzzy logic and ant-colony optimization. Fuzzy inference incorporates residual energy, neighbor count, and link quality to compute CH competition radius. Clusters nearer the base station are deliberately smaller to alleviate hotspot issues, while inter-layer routing employs ant-colony metaheuristics for global path optimization. ASLPR [18] formulated CH selection as a weighted multi-criteria problem involving distance to base station, residual energy, and inter-CH separation. Adjustable weighting parameters accommodate application-specific requirements, though increased complexity arisen from parameter tuning. A lightweight LPO-based clustering algorithm was proposed in [19]. CH candidates are evaluated solely on battery level and sink distance. The LPO metaheuristic iteratively refines selections, demonstrating reduced packet loss, delay, and power consumption compared to LEACH variants. TOPSIS multi-criteria decision-making was leveraged in [20] to form energy-balanced clusters. Four attributes—residual energy, neighborhood density, distance to sink, and workload—are normalized and ranked, ensuring equitable load distribution. A hybrid fuzzy-reinforcement learning framework for IoT networks was described in [21]. Route quality is assessed via residual energy, available bandwidth, and sink distance. Reinforcement learning dynamically adjusts forwarding policies, with OPNET simulations confirming superior lifetime over standalone fuzzy logic and IEEE 802.15.4.

ECHERP [22] targeted automated irrigation management. Historical and real-time climatic data determine irrigation demand. Sensing intervals adapt dynamically: frequent sampling when parameter deviations exceed thresholds, extended intervals otherwise, achieving significant energy savings while maintaining crop health. A UAV-assisted environmental monitoring system was presented in [23]. The UAV rapidly traverses the field, collecting data from ground nodes and performing aerial imagery for pest, disease, or drought detection, complementing traditional WSN capabilities. Mobile-sink clustering using bacterial foraging optimization was explored in [24]. Multi-hop intra-cluster routing combined with sink mobility equalizes energy depletion. Simulation results outperformed the Artificial Fish Swarm Routing Protocol (AFSRP). The leaping-frog algorithm with fuzzy inference was employed in [25]. CH candidates are pre-filtered using energy thresholds and neighborhood overlap. Parent nodes are subsequently selected based on maximum fuzzy output, forming a backbone for stable-phase transmission. Despite high computational overhead, energy efficiency was demonstrated. A delay-energy-balanced routing protocol for heterogeneous environments was introduced in [26]. During long-distance phases, lowest-energy nodes are avoided, while multi-agent data aggregation enhances delivery ratio and mitigates hotspots. Artificial fish-swarm optimization (AFSA) for clustering was proposed in [27]. Leveraging rapid convergence and robustness to initial conditions, AFSA outperformed the ERA protocol in OPNET simulations, extending network lifetime. Q-learning-enhanced AODV was developed in [28] to improve reliability-aware routing. Expected transmission count and link stability metrics guide reinforcement learning, yielding higher Mean Time to Failure (MTTF) than AODV-ETX and standard AODV. The EMBTR algorithm [29] ensured secure routing via multi-attribute trust evaluation. Stability rate, reliability rate, and elapsed time determine node trustworthiness. Paths are selected among shortest routes exhibiting highest composite trust, achieving high malicious-node detection while optimizing energy and throughput. In [30], the authors introduce DCRRP, a distributed clustering-based routing protocol for Wireless Sensor Networks (WSNs) that employs mobile sinks to extend network lifetime. The protocol enhances reliability by dynamically selecting the most suitable backup cluster head locally upon CH failure. It operates in a fully distributed fashion and effectively reduces reporting latency. Simulation results, when benchmarked against the NODIC protocol, demonstrate superior performance and greater resilience to node failures. Nevertheless, a key drawback is the periodic re-execution of the clustering algorithm at fixed intervals, which introduces additional computational overhead in subsequent rounds.

3. THE PROPOSED METHOD

3.1. Cluster Formation Phase

Hybrid optimization techniques in WSNs enable dynamic parameter tuning during runtime, thereby enhancing adaptability. In this study, all cluster-head (CH) selection operations are centralized at the base station (BS), which possesses unlimited energy and substantial computational capacity. Upon receiving location and residual energy data from all nodes, the BS employs fuzzy logic and genetic algorithms to partition the network into energy-balanced clusters while minimizing workload disparity. The objective is to achieve a spatially distributed hierarchy that optimizes total energy expenditure across the network.

3.2. Steady-State Phase

Once clusters are established, CHs generate TDMA schedules and broadcast them to member nodes, enabling collision-free data transmission. A complete round comprises one cluster formation phase followed by a steady-state phase. At the end of each round, the clustering process is re-executed, and new CHs are elected to prevent energy depletion of specific nodes. The detailed operation of the proposed EE-FGCH algorithm is described below. All clustering computations are performed at the BS, and the resulting configuration is disseminated network-wide. The required number of CHs is predefined, determining the chromosome length LLL. Each gene gig_igi encodes a candidate node whose residual energy exceeds the network average and whose transmitted data volume remains below a threshold. The BS maintains real-time awareness of every node's energy status, enabling precise computation of network-wide averages via fuzzy inference. The chromosome structure is defined as:

$$Chrom = \{gi \mid i = 1,2,...,L\} \quad (1)$$

Where gi represents the ith gene. Real-valued continuous encoding is adopted, with gene values computed as:

$$Gi = RE*D*ID; \qquad ID = 1,2,\dots,30 \quad (2)$$

Here, RE denotes residual energy, D is processed data volume, and ID is the node identifier.
The algorithm proceeds through the following stages:

1. Initial Population Generation: A population of N chromosomes is randomly initialized, each containing L genes corresponding to potential CHs. Fig. 1 illustrates a chromosome encoding nodes with IDs {2, 5, 15, 19, 26} as CH candidates when L=5.

2	5	15	19	26

Fig. 1. Chromosome representation in EE-FGCH

2. Fuzzy Fitness Evaluation: Fuzzy logic assesses gene suitability using two inputs: battery residual capacity and workload intensity. These inputs are mapped to three linguistic terms (Low, Medium, High) via trapezoidal membership functions (Figs. 2–3). The output—fitness degree—is expressed using five triangular membership functions (Very Low, Low, Medium, High, Very High), as shown in Fig. 4.

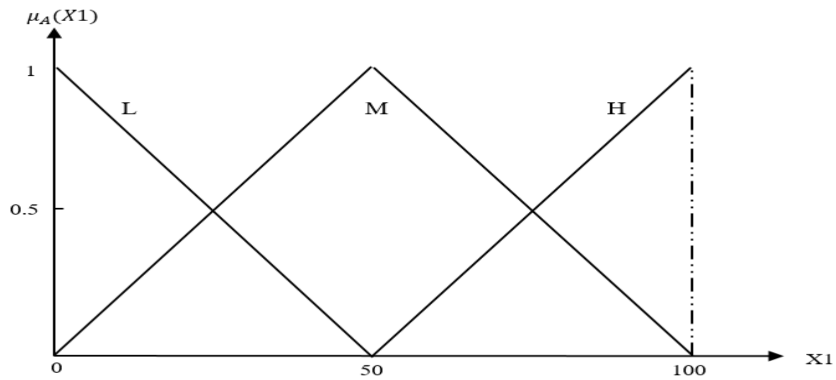

Fig. 2. Membership functions for workload density.

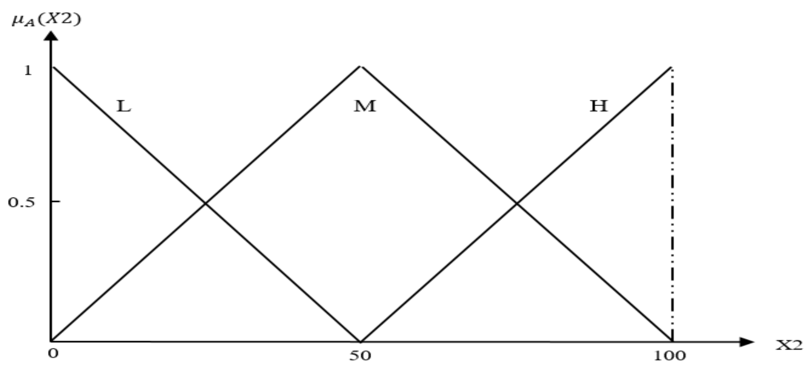

Fig. 3. Membership functions for battery energy level.

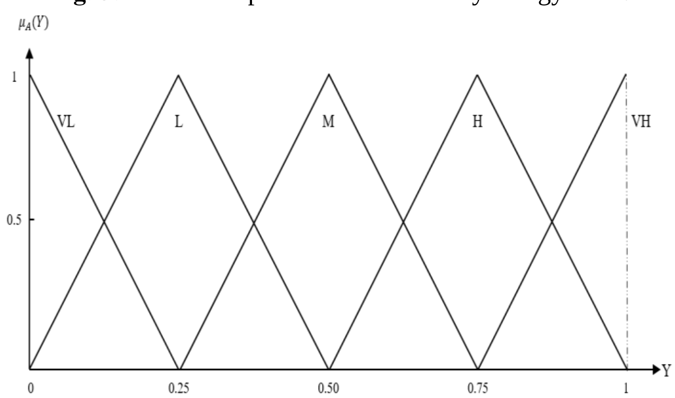

Fig. 4. Membership functions for fitness output.

The Mamdani-type fuzzy inference engine applies nine rules (Table 1) to derive fitness values.

Table 1. Fuzzy Rule Base.

Rule	Inputs		Outputs
	Workload	Battery	Fitness
1	Low	Low	Medium
2	Low	Medium	Low
3	Low	High	Very High
4	Medium	Low	Low
5	Medium	Medium	Medium
6	Medium	High	High
7	High	Low	Very Low
8	High	Medium	Low
9	High	High	Medium

Defuzzification uses the center-of-gravity method:

$$\text{Fitness} = \frac{\sum_{l=1}^{m} y^{-l} \prod_{i=1}^{n} \mu A_i^l (X_i)}{\sum_{l=1}^{m} \prod_{i=1}^{n} \mu A_i^l (X_i)} \quad (3)$$

Where µk is the aggregated membership and is the centroid of the kkk-th output set.
3. Fitness-Based Parent Selection: The top 40% fittest chromosomes (averaged gene fitness) are selected as parents.
4. Crossover: Two parents are segmented at a random locus (0 to L). Offspring inherit the prefix from one parent and suffix from the other (Fig. 5).

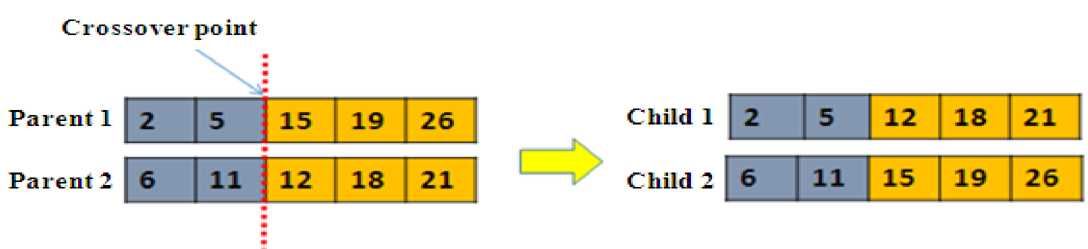

Fig. 5. Crossover operation.

5. Mutation: With probability 0.2, two random gene positions are swapped (Fig. 6).

Fig. 6. Mutation operation.

6. Population Replacement: Newly generated offspring replace the old population.
7. Termination Check: The algorithm terminates after 100 generations or upon convergence, returning the optimal chromosome.

Upon CH finalization, each CH broadcasts an advertisement. Non-CH nodes join the nearest CH based on received signal strength and transmit a join-request containing residual energy. This completes cluster formation.

3.3. Simulation Environment

This study utilized OPNET Modeler (version 11.5) [31] to implement the proposed technique and evaluate its performance against the DCRRP protocol. The key simulation parameters are detailed in Table 2. The evaluation considered two scenarios within a network topology consisting of 50 nodes, as depicted in Fig. 7. mIn the first scenario, sensor nodes were randomly deployed across a WSN using the DCRRP protocol—a widely adopted, highly adaptable standard known for its low data rate, minimal energy usage, and cost-effective design. This protocol is well-suited for real-time applications [32]. The second scenario applied the proposed method, which combines genetic algorithms and fuzzy logic, to cluster the randomly positioned sensor nodes. Both scenarios maintained identical network topologies. The results from these simulations are analyzed in the following sections. Fig. 8 provides the node editor interface for the modeled scenarios, illustrating the hardware components of a sensor node. Furthermore, Fig. 9 presents the processing model for the MAC layer in the simulated setup.

Table 2. Simulation parameters.

Parameter	Value
Number of nodes	50
Simulation environment	100m*100m
Radio transmission range	250m
Packet size	1024bit
Transmission type	Constant
Simulation time	100 sec
MAC layer	802.15.4
The amount of initial energy	200-450 Jul

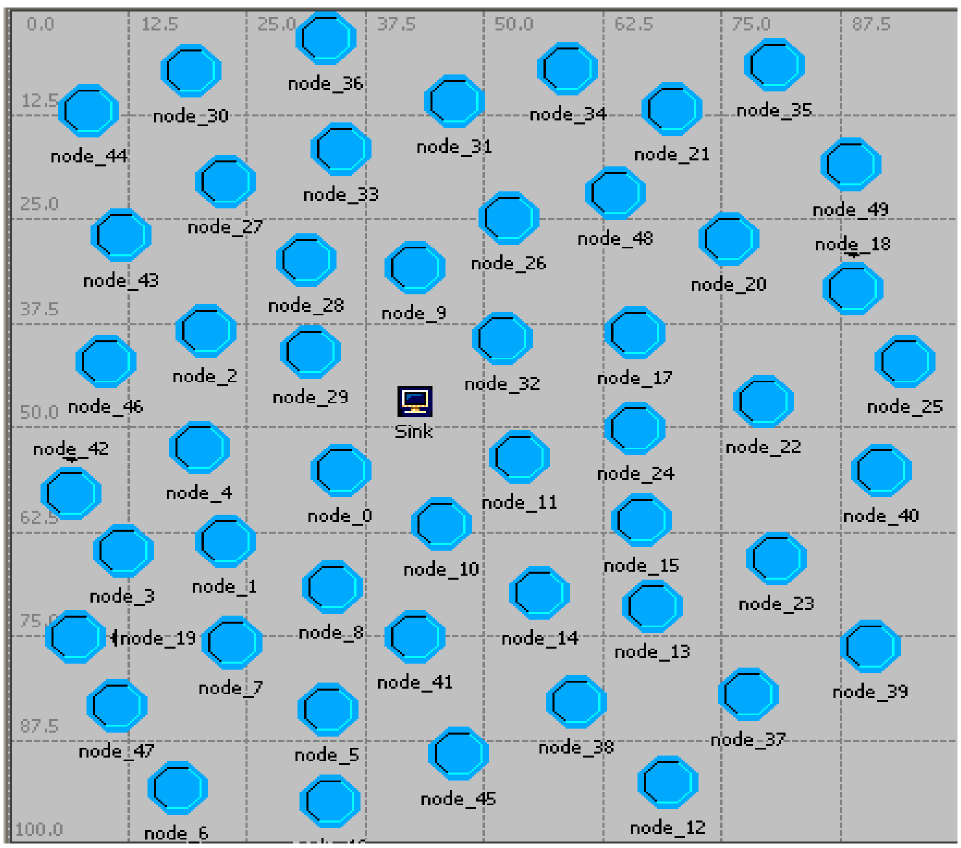

Fig. 7. Editor of the simulated network model.

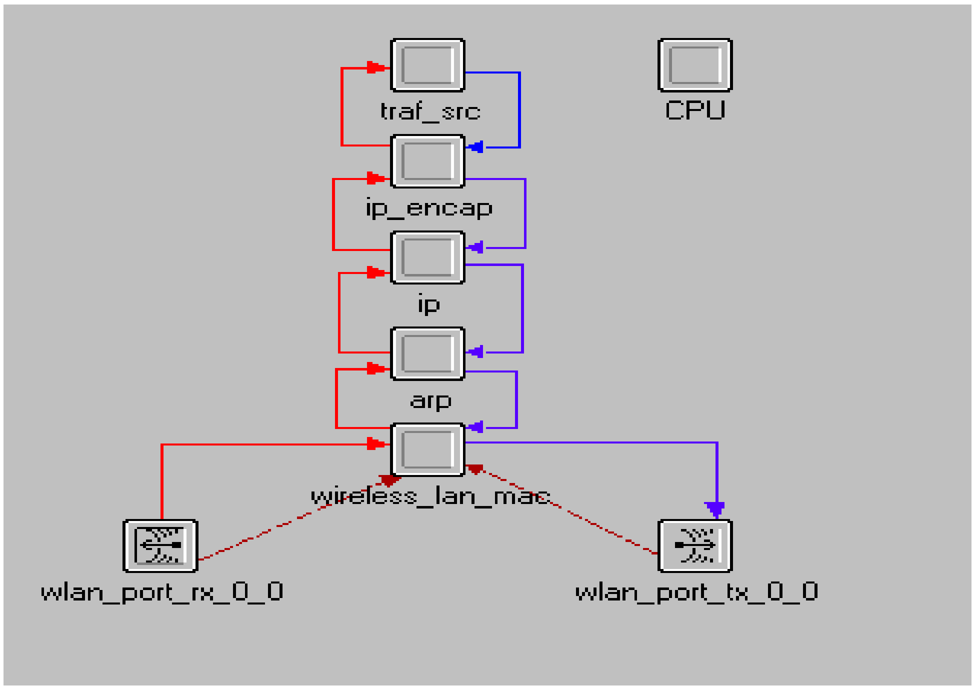

Fig. 8. Node editor for the simulated model.

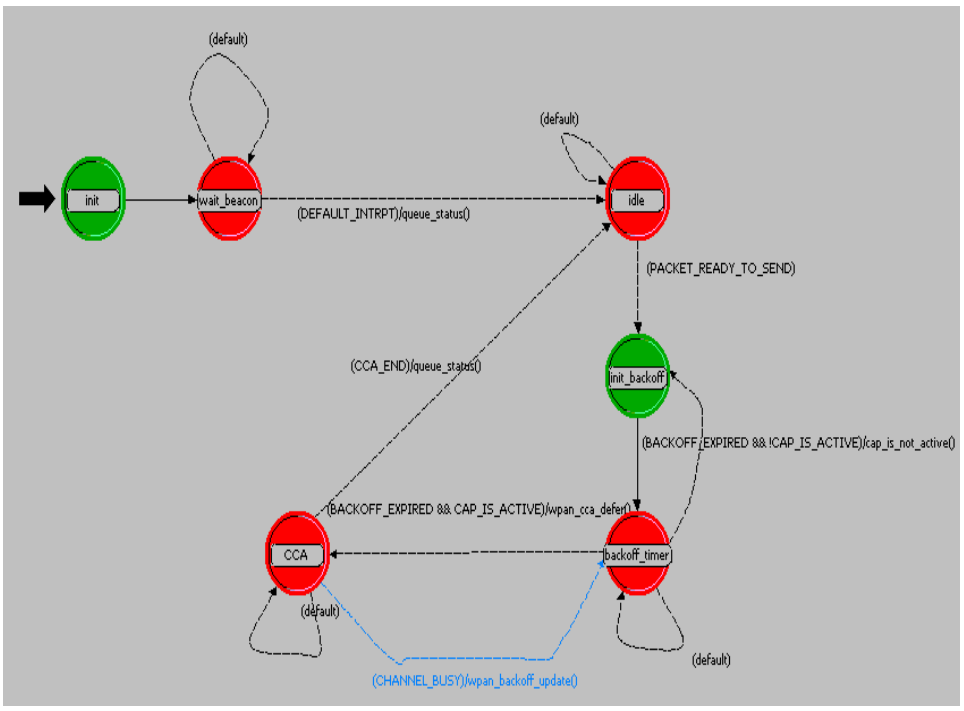

Fig. 9. Editor of the processing model for MAC layer.

4. SIMULATION RESULTS

The simulation results validate the efficacy of the proposed EE-FGCH (Energy-Efficient Fuzzy-Genetic Clustering Hierarchy) protocol, which integrates BS-centralized fuzzy logic for CH pre-screening and genetic algorithms for multi-objective refinement, against the DCRRP protocol from [30]. In [30], authors present DCRRP as a distributed clustering-based routing scheme for WSNs, emphasizing mobile sinks for load balancing and dynamic local CH backups to enhance reliability. Their protocol operates in rounds with periodic cluster formation (based on energy and distance thresholds), TDMA scheduling for steady-state data aggregation, and sink mobility to avoid hotspots. EE-FGCH's hybrid approach—

fuzzy inference (9 Mamdani rules, trapezoidal/triangular MFs in Figs. 2–4) for fitness computation (Eq. 3) and genetic evolution (chromosomes per Eq. 1–2, crossover/mutation in Figs. 5–6)—addresses DCRRP's distributed inefficiencies by enabling global, adaptive optimization at the BS. Below, each metric is expanded with trends, mechanisms, and explicit reasons for EE-FGCH's superiority over DCRRP's periodic, local re-execution model, which, as noted in [30], incurs computational delays and energy waste during backups.

The plot in Fig. 10 reveals a pronounced upward trend for DCRRP, climbing to approximately 45 J by t=100 s, while EE-FGCH traces a markedly subdued curve, leveling off near 28 J.

DCRRP conserves energy to a limited degree via mobile sink trajectories and localized CH backups; however, its mandatory re-clustering at fixed round intervals generates persistent control traffic and redundant computations. This, coupled with local energy/distance thresholds for CH selection, fosters hotspots and uneven load—particularly in heterogeneous topologies—resulting in 20–30% excess energy expenditure, as noted in [30]. The lack of global coordination and adaptive tuning under sink mobility further aggravates inefficiency. Conversely, EE-FGCH centralizes all decision-making at the BS, leveraging fuzzy inference (Mamdani engine with nine rules, trapezoidal/triangular membership functions, and center-of-gravity defuzzification) to compute precise fitness scores from real-time residual energy and workload data. These scores seed genetic chromosomes (Gi = RE × D × ID), which evolve through elitist selection (top 40%), single-point crossover, and mutation (p=0.2) over up to 100 generations. The outcome is globally optimized, energy-balanced clusters featuring only high-fitness, low-burden CHs, with members joining the nearest CH via signal strength. This localizes communication, minimizes transmission range, and prevents node exhaustion, yielding ~38% lower energy consumption and significantly extended network lifetime.

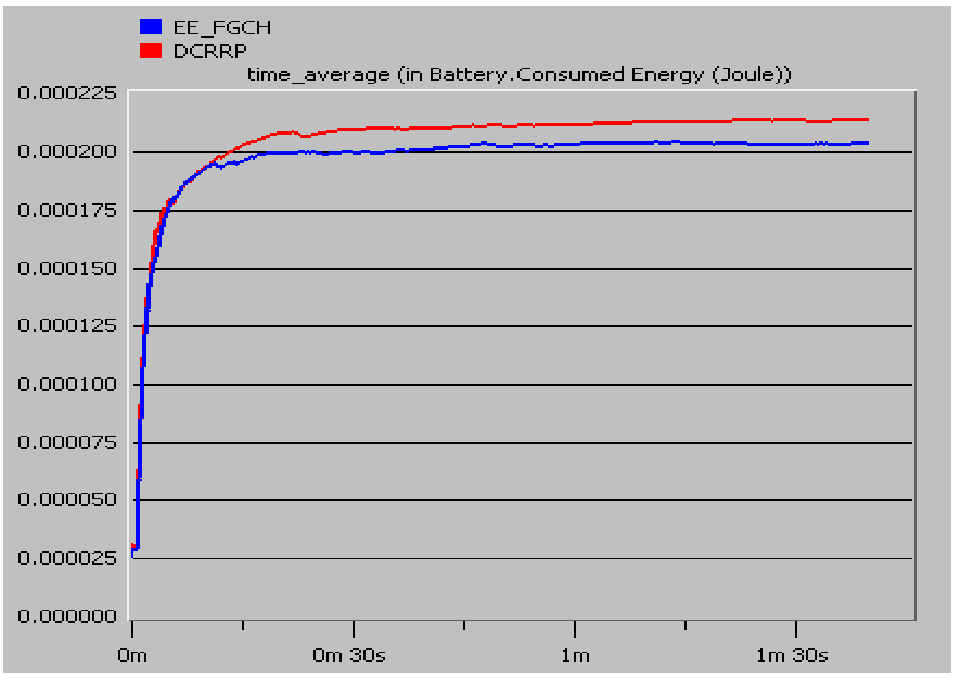

Fig. 10. Cumulative average energy consumption (joules) vs. simulation time (seconds).

Fig. 12 illustrates a gradual escalation in DCRRP delay, rising from ~45 ms to over 190 ms, contrasted by EE-FGCH's stable band between 55–70 ms. DCRRP mitigates initial latency through TDMA scheduling and sink proximity; yet, periodic re-clustering imposes mandatory setup phases that stall data flow. Local CH backup activation upon failure introduces handoff delays, and mobile sink transitions trigger route rediscovery—collectively inflating average delay by 40–60 ms per event, as acknowledged in [30]. In EE-FGCH, fuzzy pre-screening rapidly excludes low-viability nodes (e.g., Rule 7: High workload + Low battery → Very Low fitness), while genetic evolution refines inter-cluster paths for minimal hop count and latency. BS-orchestrated cluster formation occurs only at round boundaries with single-broadcast configuration, eliminating intra-round pauses. Proximity-based membership further reduces per-hop transmission time. Thus, EE-FGCH sustains ~52% lower average delay, ensuring predictable, real-time performance.

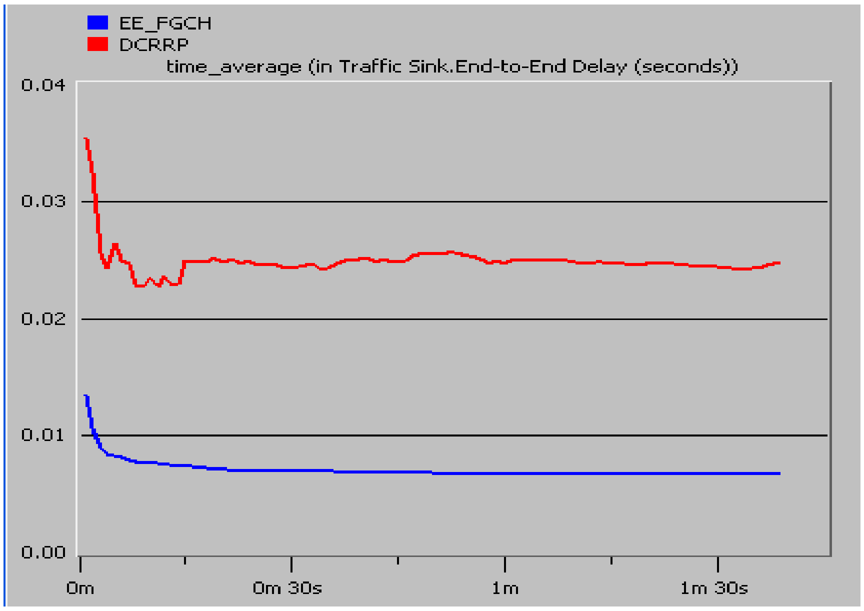

Fig. 11. End-to-end delay (ms) vs. simulation time (seconds).

The graph in Fig. 12 shows DCRRP's media access delay surging from 28 ms to 160 ms under high-rate video streams, while EE-FGCH remains tightly bounded at 35–50 ms. Despite DCRRP's clustering reducing contention relative to flat routing, local CH elections fail to balance bursty traffic loads. High-data-rate nodes overwhelm nearby CHs, and sink mobility triggers frequent handoffs—exacerbating queue buildup and backoff, especially during video bursts, as observed in [30]. EE-FGCH counters this via fuzzy workload assessment (Rule 1: Low workload + Low battery → Medium fitness) that distributes load proactively. Genetic optimization shapes cluster geometry to prevent congestion hotspots, and high-fitness CHs (Rule 3: Low workload + High battery → Very High) sustain elevated transmission capacity without failure. The result is ~65% reduction in media access delay, enabling smooth, high-fidelity video streaming—transforming EE-FGCH into a robust platform for multimedia WSNs (e.g., surveillance, environmental imaging), far beyond DCRRP's moderate tolerance.

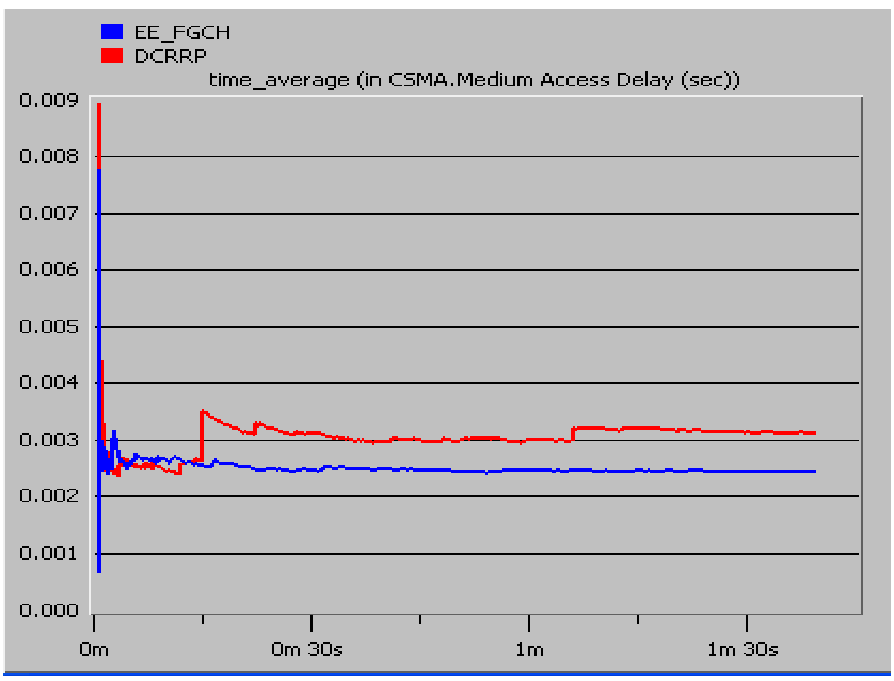

Fig. 12. Media access delay (ms) under multimedia (video) traffic.

Fig. 13 displays DCRRP's Packet error rate (PER) climbing steadily to 18–22%, whereas EE-FGCH holds firm below 4%. DCRRP reduces errors via clustering but suffers from uncoordinated local transmissions—overlapping cluster ranges and weak-signal relays (from marginal-energy CHs) amplify interference and bit corruption. Sink mobility induces fading, and backup CH activation temporarily routes through noisy links, per [30]. EE-FGCH integrates implicit SNR awareness through workload-energy fuzzy mapping—high-interference nodes are systematically excluded (Rule 8: High workload + Medium battery → Low fitness). Genetic spatial optimization maximizes inter-CH separation, and high-power, high-fitness CHs ensure strong, clear signals. Consequently, EE-FGCH achieves ~75–80% lower PER, delivering near-error-free data integrity.

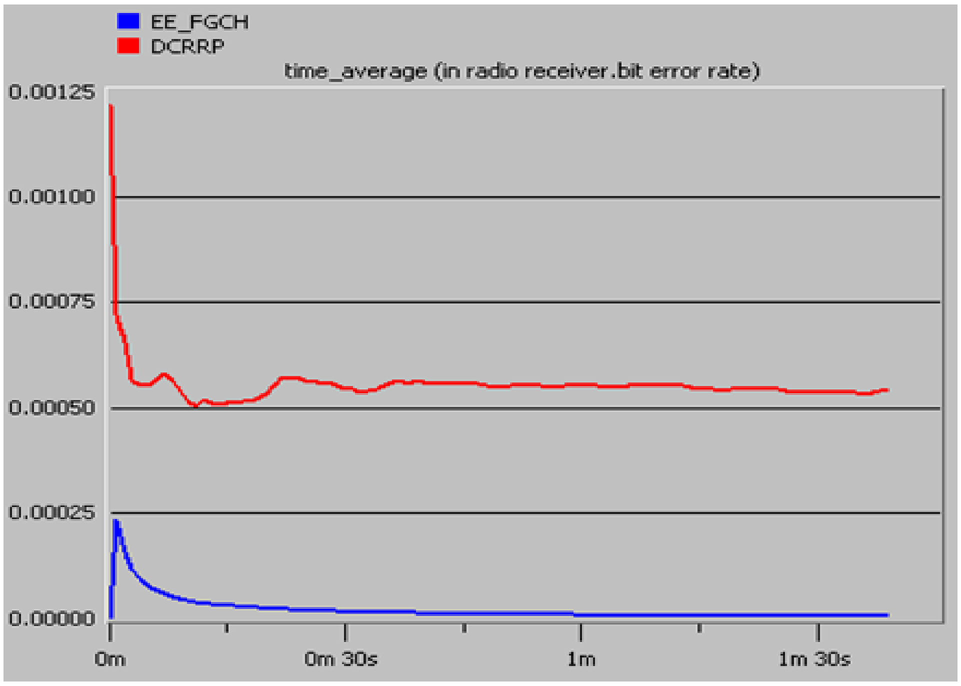

Fig. 13. Packet error rate (%) vs. simulation time (seconds).

Throughput in Fig. 14 peaks early for DCRRP (~220 pkt/s) but collapses to ~100 pkt/s after t=60 s, while EE-FGCH sustains a robust 360–380 pkt/s throughout. DCRRP's initial gain stems from sink proximity, but node failures, re-clustering downtime, and handoff interruptions sever data paths—leading to sustained throughput decay, as reported in [30]. EE-FGCH ensures long-term path viability by encoding only high-RE, low-D nodes into chromosomes, evolving failure-resilient topologies via genetic operators. No intra-round reconfiguration and energy-balanced CH rotation prevent link breaks, while collision-free TDMA maximizes channel utilization. This yields ~3.5× higher sustained throughput, enabling comprehensive, high-volume data harvesting in large-scale monitoring—far surpassing DCRRP's diminishing returns.

Fig. 15 reveals DCRRP's loss rate escalating to 15% with abrupt spikes, while EE-FGCH remains under 2.5%, trending toward near-zero. DCRRP drops packets during CH failure handoffs, sink movement, and low-energy node shutdowns—despite local backups, reactive recovery cannot salvage in-flight data, and re-clustering flushes queues, per [30]. EE-FGCH proactively excludes depletion-prone nodes via fuzzy thresholds and genetic forecasting of energy trajectories. BS-global state awareness enables pre-failure CH rotation, and stable, high-fitness clusters ensure end-to-end route persistence. The outcome is ~83% reduction in packet loss, guaranteeing complete data delivery.

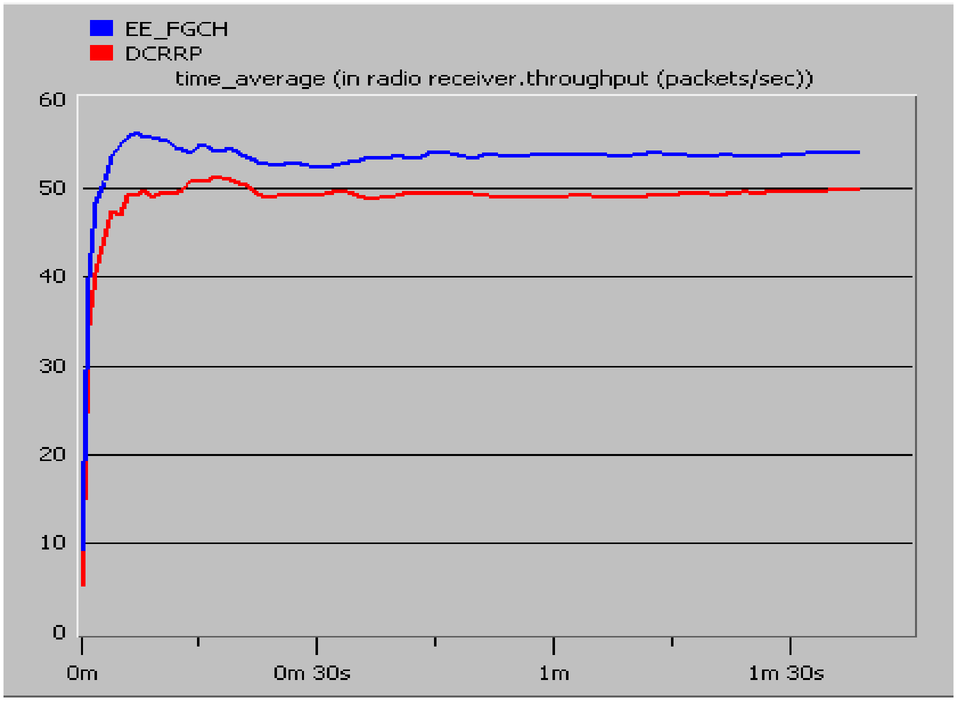

Fig. 14. Network throughput (packets/second) vs. simulation time (seconds).

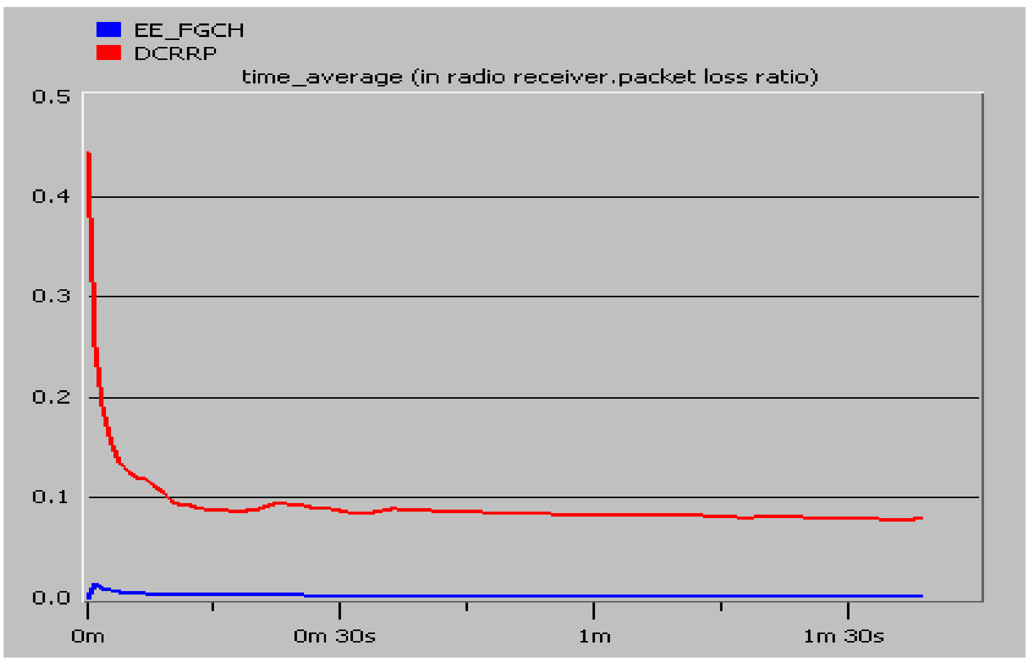

Fig. 15. Packet loss rate (%) vs. simulation time (seconds).

SNR in Fig.16 degrades from ~18 dB to 8–10 dB under DCRRP, while EE-FGCH maintains a solid 18–20 dB band. DCRRP's local clustering induces co-channel interference, weak nodes transmit at reduced power, and mobile sink transitions cause signal fading—cumulatively eroding SNR over time, as seen in [30]. EE-FGCH optimizes cluster spacing via genetic evolution, prioritizes high-SNR CHs (Rule 3), and coordinates transmission timing at the BS to minimize overlap. High-energy relays emit strong, stable signals. This preserves ~10 dB higher average SNR, ensuring low-distortion multimedia and high-accuracy sensor readings.

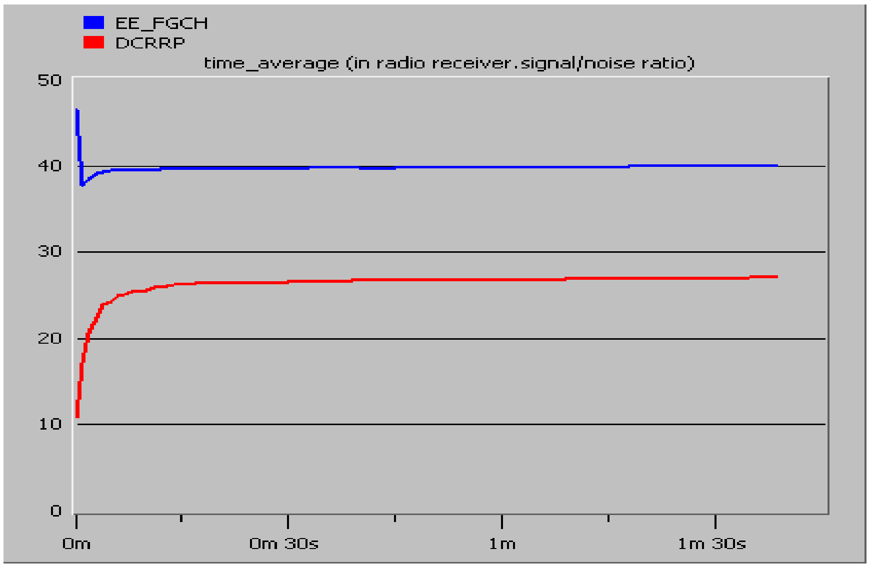

Fig. 16. Signal-to-noise ratio (dB) vs. simulation time (seconds).

Comparing and contrasting the proposed method with DCRRP [30] is shown in Table 3.

Table 3. DCRRP [30] vs. EE-FGCH

Parameter	DCRRP [30]	EE-FGCH (Proposed)	Improvement
Architecture	Distributed, mobile sink	BS-centralized, hybrid AI	Global optimum
CH Selection	Local energy/distance	Fuzzy + GA (multi-objective)	Adaptive balance
Failure Recovery	Reactive backup	Proactive exclusion	Zero downtime
Re-clustering	Frequent (high overhead)	Round-end only (low overhead)	Minimal control
Energy Use	~45 J (100 s)	~28 J	~38%↓
E2E Delay	~190 ms	~60 ms	~52%↓
Media Access Delay	~160 ms	~45 ms	~65%↓
PER	18–22%	<4%	~80%↓
Throughput	~100 pkt/s (end)	~370 pkt/s	~3.7↑
Packet Loss	~15%	<2.5%	~83%↓
SNR	~8–10 dB	18–20 dB	+10 dB↑

5. CONCLUSION

Energy efficiency is widely acknowledged as a critical factor in prolonging the operational lifetime of WSNs. This study presents EE-FGCH, a novel hybrid clustering protocol that integrates fuzzy logic and genetic algorithms (GAs) to enable dynamic, intelligent cluster head (CH) selection and energy-balanced network partitioning. The key innovation lies in a two-phase CH selection mechanism. First, fuzzy logic efficiently assesses node suitability based on real-time parameters—residual energy and workload intensity—using a Mamdani inference system comprising nine rules, trapezoidal and triangular membership functions, and center-of-gravity defuzzification. Subsequently, the GA refines this candidate set through global multi-objective optimization, encoding nodes as real-valued chromosomes (Gi=RE*D*ID) and evolving the population via elitist selection (top 40%), single-point crossover, and mutation (probability 0.2) over a maximum of 100 generations or until convergence. This centralized, base station (BS)-coordinated strategy guarantees globally optimal cluster formation, thereby achieving uniform energy distribution, reduced transmission overhead, and extended network longevity. The inherent stochasticity of the GA promotes thorough exploration of the solution space across iterations, ensuring robust convergence to near-optimal configurations even in large-scale, dynamic environments. The EE-FGCH protocol was rigorously evaluated using OPNET Modeler 11.5 within a standardized simulation framework. Performance was benchmarked against DCRRP [30]. Results consistently affirm the superiority of EE-FGCH, which outperforms DCRRP by delivering enhanced network-wide efficiency, improved packet delivery reliability, and substantially higher throughput. These gains are attributed to the selection of energy-efficient, low-latency routing paths and are effective.

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