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iPAFAR: An Adaptive Pareto-Based NS-AAA Energy-Stable Fuzzy Clustering and Routing Framework for Smart City IoT-Enabled WSNs

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ABSTRACT: Wireless Sensor Networks (WSNs) play a vital role in smart city Internet of Things (IoT) applications, including environmental monitoring, intelligent transportation, and infrastructure management. However, limited battery capacity, uneven energy consumption, and inefficient clustering and routing mechanisms significantly reduce network lifetime, reliability, and scalability, especially in large-scale IoT deployments. Traditional routing protocols often rely on single-objective optimization or static clustering strategies, which fail to maintain long-term energy balance and stable communication performance. To address these challenges, this paper proposes iPAFAR, a Pareto-based multi-objective clustering and routing framework designed for IoT-enabled WSNs. The proposed model formulates cluster-head selection as a multi-objective optimization problem that considers residual energy, node centrality, load variance, and fairness. A Non-Dominated Sorting Artificial Algae Algorithm (NS-AAA) is used to obtain Pareto-optimal cluster-head configurations, followed by a fuzzy inference system for refined decision-making. To ensure long-term energy stability, a Lyapunov-based routing model is incorporated, and an adaptive re-clustering mechanism is introduced to reduce unnecessary control overhead under dynamic network conditions. The performance of the proposed framework is evaluated through MATLAB-based simulations and compared with existing protocols, including LEACH-M, ME-LEACH, FQA, MKNDPC, RANP-PSO, and BKA-TOA. Experimental results show that iPAFAR achieves approximately 40% lower end-to-end delay, 15%–20% higher packet delivery ratio, and 45%–50% improvement in residual energy while maintaining nearly twice the number of active nodes after 1000 simulation rounds. These results confirm that the proposed framework provides improved energy efficiency, load balancing, and routing stability, making it suitable for long-term smart city IoT deployments.

KEYWORDS: Wireless sensor networks; smart cities; multi-objective optimization; artificial algae algorithm; energy-aware clustering; pareto optimization; IoT routing

1 Introduction

Large-scale deployments of the Internet of Things (IoT) in smart city environments, such as intelligent transportation systems, environmental monitoring, smart grids, and urban infrastructure management, have become essential, enabled by Wireless Sensor Networks (WSNs) [1]. These applications demand

scalable communication architectures, high-quality data transmission, and autonomous operation over long durations under strict energy constraints. Nonetheless, the small size of sensor node batteries, energy dissipation asymmetry, and ineffective clustering/routing schemes [2] impose significant limitations on network lifetime, stability, and sustainability. Routing using clustering has gained significant popularity to improve scalability and reduce communication overhead in WSNs [3]. In this type of architecture, data stored by the member nodes is sent to the sink via multi-hop communication, with the chosen cluster heads (CHs) combining the information and transmitting it to the sink. Although clustering is more energy-efficient than flat routing schemes, inappropriate CH choice and workload imbalances often lead to untimely node exhaustion [4]. Nodes that repeatedly assume the CH role are depleted faster, leading to network fragmentation, delays, packet losses, and reduced network lifetime [5]. In recent studies, optimization-based clustering and routing techniques have been investigated to address these shortcomings.

Nevertheless, most available methods use single-objective or weighted-sum models, which can mask trade-offs among conflicting measures of residual energy, node centrality, sink distance, load variance, and fairness. There is also neglect of long-term energy-stability mechanisms, where progressive imbalance builds up over extended operational rounds. Consequently, many protocols exhibit good initial behaviour but degrade sharply in subsequent network phases [6]. To overcome these issues, this study proposes iPAFAR, an energy-aware Pareto-based Artificial Algae Algorithm (AAA) fuzzy clustering and routing framework for static IoT-enabled WSNs [2,3]. In contrast to traditional weighted-aggregation methods, the new framework treats cluster-head selection as a genuine multi-objective problem and uses non-dominated sorting to maintain trade-offs among Pareto-optimal solutions across conflicting objectives. A fuzzy refinement mechanism is used to increase CH resilience to small energy missteps, and a Lyapunov-based stability model is used to control the long-term energy imbalance [7]. Moreover, an adaptive re-clustering policy is presented to control unnecessary control overhead and ensure fairness and stability in the network. An overall architectural overview of the proposed iPAFAR framework is illustrated in Fig. 1, showing the interactions among network initialization, Pareto-based cluster-head selection, fuzzy refinement, Lyapunov-stable routing optimization, and adaptive re-clustering for energy-balanced smart city IoT deployments.

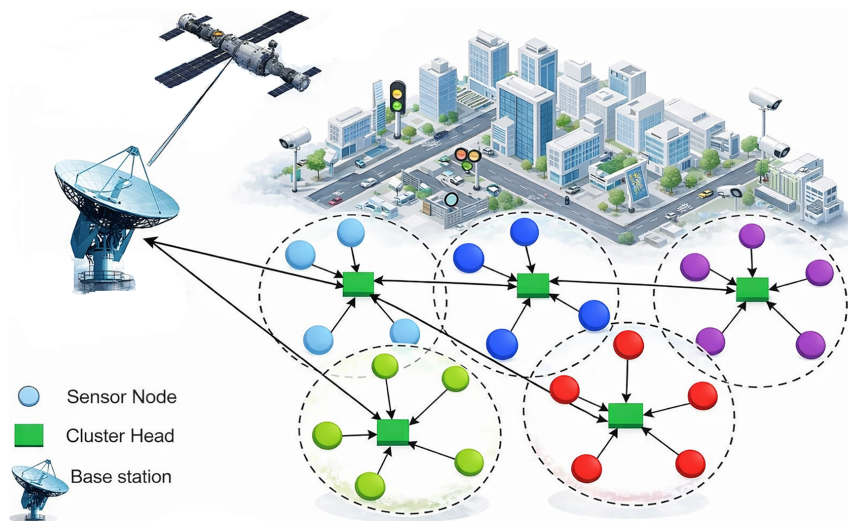


Figure 1: Clustering and routing framework for smart city IoT-Enabled WSNs.

Relative analysis with LEACH-M, ME-LEACH, FQA, MKNDPC, RANP-PSO and BKA-TOA indicates significant gains in delay, packet delivery reliability, residual energy conservation, load-balancing efficiency,

and network lifetime. These findings confirm that iPAFAR is a scalable, energy-efficient, and stability-enhancing routing solution suitable for long-term smart city IoT applications. The rest of this paper is structured as follows. Part 2 is the review of the related work, Part 3 is the proposed methodology, Part 4 is the discussion of the simulation results and comparative analysis, and Part 5 is the final section of the study with future research directions.

Our Contributions

1. We propose iPAFAR, an energy-aware clustering–routing framework for static IoT-enabled Wireless Sensor Networks that dynamically balances node workload and prolongs network lifetime through optimized multi-hop communication.
2. Cluster-head selection is formulated as a Pareto-based multi-objective optimization problem that incorporates residual energy, spatial centrality, sink distance, load variance, and energy fairness (Jain's index). The problem is solved using a Non-Dominated Sorting Artificial Algae Algorithm (NS-AAA) to preserve optimal trade-offs without weighted aggregation.
3. A Lyapunov drift-based stability mechanism is integrated into routing decisions to regulate long-term energy imbalance, mathematically constraining energy deviation and preventing premature node depletion.
4. A residual-energy-ratio-based re-clustering trigger is introduced to reduce unnecessary control overhead while maintaining fairness and sustainable operation across extended simulation rounds.
5. Extensive MATLAB simulations over 1000 rounds demonstrate that iPAFAR significantly outperforms LEACH-M, ME-LEACH, FQA, MKNDPC, RANP-PSO, and BKA-TOA in terms of delay reduction, improved packet delivery ratio, preserved residual energy, load-balancing efficiency, and extended network lifetime.

2 Literature Review

Much of the literature has focused on energy-efficient clustering and routing protocols for WSNs, since these mechanisms strongly influence network lifetime and load balancing. However, existing methods still face challenges such as energy imbalance, overhead, and scalability issues. A summary of representative approaches and their limitations is presented in [Table 1](#), highlighting the need for a more stable, energy-balanced clustering and routing framework.

Table 1: Summary of existing WSN clustering and routing methods.

Author	Method/Algorithm	Key contribution	Limitation/Issue
Cao et al. [5]	Improved DV-Hop localization	Used node negotiation and multiple radii to improve distance estimation	Accuracy is still affected by irregular node distribution
Sun et al. [6]	DV-Hop + Adaptive Genetic Algorithm	Reduced localization error using optimization	Increased computational complexity
Wang et al. [8]	DV-Hop with hop-loss optimization	Improved position estimation using multinode distance calculation	Requires more anchor information

(Continued)

Table 1 (continued)

Author	Method/Algorithm	Key contribution	Limitation/Issue
Zhao et al. [9]	LEACH-M	Improved cluster-head selection to enhance energy balance and network lifetime	Does not consider distance to the base station, distance between cluster members, and previous round energy consumption in CH selection
Zamry et al. [10]	LEACH-CR	Improved energy efficiency using hierarchical routing	Not suitable for large-scale networks
Phoemphon et al. [11]	Hybrid PSO localization	Obstacle-aware localization improvement	Complex implementation
Han et al. [12]	DV-Hop + Differential Evolution	Reduced hop distance error	Increased processing overhead
Smaragdakis et al. [13]	SEP protocol	Energy-aware CH selection in heterogeneous WSN	Uneven load in later rounds
Jia et al. [14]	BKA-TOA	Bio-inspired CH selection and routing optimization	High optimization overhead
Kaur et al. [15]	Weighted centroid localization	Improved accuracy in random deployment	Sensitive to node density variation
Abdurohman et al. [16]	Modified E-LEACH	Improved fairness in CH selection	Needs further validation in large networks
Hada and Srivastava [17]	Dynamic CH selection	Uses connectivity and energy for CH selection	Scalability issues in dense WSN
Sadek [18]	Hybrid energy-aware clustering	Balanced energy consumption in IoT WSN	Limited adaptability in dynamic networks
Haseeb et al. [19]	RCER routing	Multi-criteria next-hop selection	Increased routing complexity
Chang et al. [20]	Density-based clustering	Improved load balancing	Extra computation for threshold calculation
Mansour et al. [21]	APSO-EARPT routing	Optimization-based route planning	Higher optimization time
Abdulzahra et al. [22]	Unequal clustering + sleep scheduling	Reduced energy consumption	Additional control overhead

Despite these developments, several limitations still exist. Most existing protocols rely on weighted-sum objective functions, which may hide trade-offs among residual energy, load balance, centrality, and fairness. In addition, long-term energy stability is rarely considered, and frequent re-clustering may introduce unnecessary overhead. These limitations indicate the need for a Pareto-based multi-objective clustering and routing framework that can balance conflicting objectives while maintaining energy stability. Therefore, this paper proposes an adaptive Pareto-driven Artificial Algae Algorithm-based clustering and routing model to improve energy fairness, reliability, and scalability in smart city IoT-enabled WSNs.

3 Proposed Methodology

The suggested iPAFAR framework proposes a Pareto-optimal, energy-conscious fuzzy clustering and routing solution for a static IoT sensor network using the AAA for optimization. The main aim of the framework is to increase the network lifetime, ensure energy egalitarianism among the nodes, and enable stable multi-hop communication to the sink. Such features are especially relevant in smart city IoT applications, where sensor devices are permanently installed and can operate for long periods without battery changes. Unlike a traditional clustering scheme, which may be based on single-objective or weighted-sum optimization, the proposed scheme formulates cluster-head selection as a multi-objective optimization problem. It combines non-dominated sorting, fuzzy logic refinement, Lyapunov-based stability modelling, and adaptive re-clustering to balance energy consumption with the long-term sustainability of operations. The stepwise operational structure of the proposed iPAFAR protocol is formally presented in Algorithm 1, while its detailed control-flow representation is illustrated in Fig. 2.

Algorithm 1: iPAFAR (PD-AAA-EAFCR)

Input:

N sensor nodes
 Initial energy E_{init}
 Transmission radius R
 Threshold θ
 AAA parameters (Population P, Generations G)
 Maximum rounds R_{max}

Output:

Optimal cluster heads
 Stable multi-hop routes

Begin

Step 1: Initialize network parameters

Step 2: Deploy sensor nodes N randomly in the sensing area

For each node i:

Step 3: Compute residual energy and inter-node distances

Set residual energy $E_i = E_{init}$

 Compute distances d_{ij}

 Compute Deg_i^{2hop}

 Compute centrality C_i

EndFor

Round = 1

While (Alive nodes > 0) AND (Round ≤ R_{max})

 Compute E_{min} and E_{avg}

(Continued)

Algorithm 1 (continued)

If (Round == 1) OR ($E_{\min}/E_{\text{avg}} < \theta$) **Then**

Step 4: Perform cluster head selection using NS-AAA optimization

Initialize CH population

For generation = 1 to G:

Evaluate objectives f1–f5

Perform non-dominated sorting

Apply AAA growth phase

Apply AAA adaptation phase

Apply sigmoid binary mapping

Preserve Pareto solutions

EndFor

Select Pareto CH configuration

Step 5: Apply fuzzy-based refinement to selected cluster heads

For each candidate CH:

Normalize metrics

Compute fuzzy Chance score

EndFor

Select final CHs per 2-hop region

Step 6: Optimize multi-hop routing using Lyapunov-based model

For each CH:

Initialize routing population

For generation = 1 to G:

Evaluate routing cost $R(P)$

Apply Lyapunov drift penalty

Apply AAA update operators

EndFor

Select optimal route

EndFor

EndIf

Step 7: Transmit sensed data to base station

Perform data transmission (CM → CH → Sink)

Step 8: Update residual energy of nodes

Step 9: Repeat the process until termination criteria is met

Update residual energy using radio model

Round = Round + 1

EndWhile

Return final CH set and routing paths

End

End

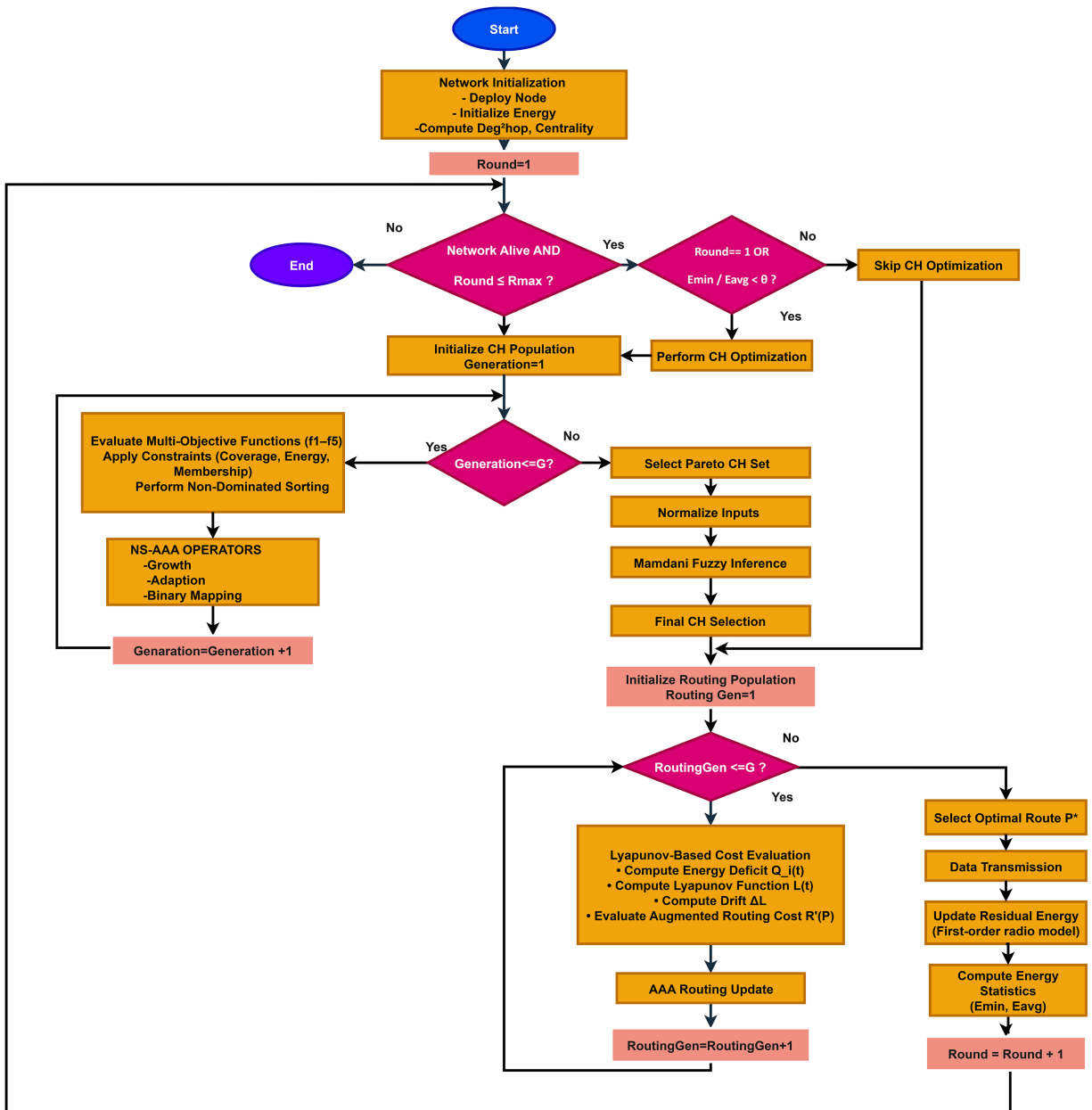


Figure 2: Proposed algorithm iPAFAR (PD-AAA-EAFCR).

3.1 Network Model

Consider a static IoT sensor network modeled as an undirected graph:

$$G = (V, E)$$

where:

- $V = \{v_1, v_2, \dots, v_N\}$ represents sensor nodes
- $E = \{(v_i, v_j) \mid d_{ij} \leq R\}$ represents communication links
- R is the transmission radius

- V_s is the sink or $V_s = \{s_1, s_2, \dots, s_m\}$

In a large-scale smart city implementation, several edge gateways or sinks can be installed to minimize communication latency and reduce backbone overload. The suggested framework facilitates the selection of the multi-sink, allowing the heads of the clusters to be linked to the closest best sink for routing optimization.

Node attributes:

$$v_i = (x_i, y_i, E_i^{res}, Deg_i^{2hop}, C_i, w_i) \quad (1)$$

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

In smart city IoT deployments, sensing traffic may have different priority levels depending on application criticality (e.g., emergency monitoring, traffic control, environmental sensing). Therefore, each node v_i is additionally associated with a priority weight w_i , representing data urgency, where S_i represents the set of one-hop neighboring nodes of the sensor node v_i , *i.e.*,

$$S_i = \{v_j \in V \mid d_{ij} \leq R\}$$

3.2 Energy Model

The first-order radio energy model is adopted in the framework to capture communication energy expenditures precisely. Transmission energy is a function of transmission distance and packet size, with short-range transmission following the free-space model and long-range transmission following the multi-path fading model. The energy received is represented as a linear function of packet size. Once transmission and reception are in operation, the residual energy is continuously updated. This energy formulation ensures that decisions on clustering and routing are made to capture realistic battery-depletion dynamics in IoT nodes.

First-order radio model:

$$E_{tx}(k, d) = \begin{cases} kE_{elec} + k\epsilon_{fs} d^2, & d < d_0 \\ kE_{elec} + k\epsilon_{mp} d^4, & d \geq d_0 \end{cases} \quad (3)$$

$$E_{rx}(k) = kE_{elec} \quad (4)$$

Residual energy update:

$$E_i^{res}(t+1) = E_i^{res}(t) - E_{tx} - E_{rx} \quad (5)$$

3.3 System Assumptions and Design Challenges

The proposed framework is developed based on several key assumptions while addressing key design challenges inherent to IoT-enabled wireless sensor networks. Sensor nodes are randomly deployed in a two-dimensional sensing area and remain static after deployment. Each node is initialized with equal energy to ensure uniform initial conditions. The base station is assumed to be fixed and may be located either inside or outside the sensing region. Furthermore, nodes can estimate inter-node distances from received signal strength, and the communication links between nodes are assumed to be symmetric. Despite these assumptions, several challenges must be addressed to ensure efficient network operation. One of the primary issues is uneven energy dissipation across nodes, which leads to premature node failures and reduced network lifetime. Frequent re-clustering further increases control overhead and affects overall efficiency.

Additionally, maintaining stable and reliable multi-hop routing paths in dynamic network conditions remains a complex task. The framework must also address scalability concerns as node density increases in large-scale deployments. Moreover, there is an inherent trade-off among energy efficiency, latency, and load balancing, making it difficult to optimize all performance metrics simultaneously. These considerations motivate the need for a multi-objective optimization-based clustering and routing framework, which is formally described in the subsequent sections.

3.4 Two-Hop Degree and Centrality

The proposed method uses both the two-hop neighborhood degree and spatial centrality measures to enhance the quality of cluster-head selection. The two-hop degree has a broader influence on connectivity and can select nodes that are highly topologically important to the algorithm, even if they are not immediate neighbors. Centrality is used to show the extent to which a node is spatially balanced in its neighborhood, thereby minimizing intra-cluster transmission distance when a node is chosen as a cluster head. All these measures improve load allocation and minimize communication cost within clusters.

$$Deg_i^{2hop} = |\{vj \in V \mid d_{ij} \leq 2R\}| \quad (6)$$

$$C_i = \frac{1}{|S_i|} \sum_{j \in S_i} d_{ij}^2 \quad (7)$$

3.5 Multi-Objective Cluster Head Selection

The cluster-head selection is formulated as a Pareto-based multi-objective optimization problem with binary decision variables. This goal is achieved by reducing the inverse residual energy, spatial centrality cost, distance to the sink, cluster load variance, and energy unfairness, as measured by the Jain fairness index. Rather than integrating goals into a single weighted objective, non-dominated solutions are determined to maintain trade-offs between conflicting goals. Several constraints are implemented, including minimum cluster-head count, energy threshold eligibility, and unique cluster membership, which ensure viable and balanced clustering configurations.

Define binary CH variable:

$$x_i \in \{0, 1\} \quad (8)$$

We formulate CH selection as a Pareto multi-objective optimization problem:

$$\min F(X) = \{f1(X), f2(X), f3(X), f4(X), f5(X)\} \quad (9)$$

where:

Energy objective:

$$f1 = \sum_{i=1}^N \frac{x_i}{E_i^{res}} \quad (10)$$

Centrality objective:

$$f2 = \sum_{i=1}^N x_i C_i \quad (11)$$

Sink distance objective:

$$f3 = \sum_{I=1}^N x_i \frac{\min_{s_j \in V_s} d_{is}}{d_{is}} \quad (12)$$

Load variance:

$$f4 = Var(L) = \frac{1}{K} \sum_{k=1}^K (Lk - \bar{L})^2 \quad (13)$$

Energy fairness (Jain index): The Jain fairness index ensures uniform energy consumption across nodes and penalizes imbalance.

$$J = \frac{(\sum_{i=1}^N E_i^{res})^2}{N \sum_{i=1}^N (E_i^{res})^2} \quad (14)$$

Fairness objective:

$$F_5 = \frac{1}{J} \quad (15)$$

Constraints Coverage:

$$\sum_{i=1}^N x_i \geq K_{Min} \quad (16)$$

where K_{Min} denotes the minimum required number of cluster heads to guarantee network coverage

$$\forall region r_k, \exists CH_i \in rk$$

This constraint ensures that every sensing region in the smart city deployment maintains at least one active cluster head, guaranteeing continuous urban monitoring coverage even as energy depletion progresses.

Energy threshold:

$$E_i^{res} \geq E_{th}, \forall i, \text{ where } x_i = 1 \quad (17)$$

Unique membership:

$$\sum_{i=1}^N a_{ij} = 1, \forall j \quad (18)$$

3.6 Non-Dominated Sorting Artificial Algae Algorithm (NS-AAA)

To solve the multi-objective cluster-head selection problem, an NS-AAA is employed. Each algae individual represents a potential cluster-head configuration. The population evolves through growth and adaptation phases, where candidate solutions move toward better-performing individuals while maintaining diversity. Continuous position updates are converted to binary decisions using a sigmoid function. Pareto dominance ranking and elitist preservation ensure that high-quality non-dominated solutions are retained across generations. This approach enables efficient exploration of the solution space without premature convergence.

Each algae individual:

$$X^p = [x_1^{(p)}, x_2^{(p)}, \dots, x_N^p] \quad (19)$$

Pareto dominance:

$$X_a < X_b \iff \forall k, f_k(X_a) \leq f_k(X_b)$$

and $\exists k$ such that

$$f_k(X_a) < f_k(X_b) \quad (20)$$

The population is ranked using non-dominated sorting. The elitist preservation mechanism ensures that non-dominated solutions are retained across generations, guaranteeing monotonic improvement of the Pareto front. The stochastic growth and adaptation operators maintain diversity, reducing premature convergence and enabling efficient exploration of the solution space.

AAA Phases

$$\text{Growth: } X_i^{new} = X_i + \alpha r(X_{best} - X_i) \quad (21)$$

$$\text{Adaptation: } X_i^{new} = X_i + \beta r(X_j - X_k) \quad (22)$$

Binary mapping:

$$x_i = 1 \text{ if } \sigma(X_i) > 0.5 \quad (23)$$

0 otherwise

$$\sum_{i=1}^N a_{ij} = 1, \forall j \quad (24)$$

$$\sigma(X_i) = \frac{1}{1 + e^{-X_i}} \quad (25)$$

Elitist selection retains Pareto front solutions.

3.7 Fuzzy-Based CH Refinement

After Pareto-optimal cluster-head candidates are generated, a fuzzy inference system is applied for final refinement. Residual energy, two-hop degree, and centrality are normalized and provided as inputs to a Mamdani-type fuzzy system. The system outputs a suitability score indicating the likelihood that a node will serve as a stable cluster head. Within each two-hop neighborhood, the node with the highest fuzzy score is selected. This refinement stage enhances robustness against minor energy fluctuations and improves cluster stability. Triangular membership functions are used for the input values (Low, Medium, High). A rule base of 9 rules is defined that combines residual energy, centrality, and degree. Defuzzification is performed using the centroid method.

Normalized inputs:

$$E'_i = \frac{E_i^{res}}{E_{max}}, D'_i = \frac{Deg_i^{2hop}}{N}, C'_i = \frac{C_i}{C_{max}} \quad (26)$$

Mamdani inference:

$$Chance_i = F(E'_i, D'_i, C'_i) \quad (27)$$

Final CH:

$$CH_i = 1 \text{ if } Chance_i = \max(Chance_j), j \in 2-hop \quad (28)$$

3.8 Lyapunov-Based Stability Modeling

The framework uses the Lyapunov drift analysis to avoid the long-term energy imbalance. Each node has an energy deficit queue, which is the difference between the initial and residual energy. A Lyapunov function is defined in such a way as to quantify the deviation of system energy with time. A drift penalty term is also added to the routing objective, which discourages pathways in routing that increase the energy imbalance. This mechanism mathematically guarantees limited energy variation and enables sustainable network operation across multiple rounds. The energy deficit queue is defined as $Q_i(t) = E_{initial} - E_i(t)$, representing the cumulative energy consumption of node i , enabling monitoring of long-term imbalance.

$$Q_i(t) = E_{init} - E_i^{res}(t) \quad (29)$$

Lyapunov function: The drift control parameter η is empirically set to 0.1 in simulations to balance routing optimality and energy stability.

$$L(t) = \frac{1}{2} \sum_{i=1}^N Q_i^2(t) \quad (30)$$

Drift:

$$\Delta L = L(t+1) - L(t) \quad (31)$$

Routing objective augmented:

$$R'(P) = R(P) + \eta \Delta L \quad (32)$$

This ensures energy stability over time.

3.9 AAA-Based Multi-Hop Routing

Multi-hop routing paths between cluster heads and the sink are established after cluster formation. The routing goal minimizes a weighted sum of transmission energy, the number of hops, the inverse residual energy, and the path load. To ensure long-term energy sustainability, the Lyapunov drift component is factored into the final routing cost. The AAA optimization process selects the optimal path that uses energy resources in the most balanced way, without compromising communication reliability.

Path:

$$P = \{v_{i1}, v_{i2}, \dots, v_s\} \quad (33)$$

Routing objective:

$$R(P) = \lambda_1 \sum_{(i,j) \in P} E_{tx}(d_{ij}) + \lambda_2 |P| + \lambda_3 \sum_{i \in P} \frac{1}{E_i^{res}} + \lambda_4 Load(P) + \lambda_5 \sum \frac{w_i}{E_i^{res}} \quad (34)$$

The weights are set as: $\lambda_1 = 0.25$ (energy), $\lambda_2 = 0.20$ (hop count), $\lambda_3 = 0.20$ (residual energy), $\lambda_4 = 0.20$ (load), $\lambda_5 = 0.15$ (priority)

The priority term ensures that delay-sensitive smart city data is routed through energy-stable paths, improving Quality of Service for critical applications.

Optimal route:

$$P^* = \arg \min R'(P) \quad (35)$$

Priority term guarantees that delay-sensitive smart city traffic is routed along energy-stable paths and enhances the quality of service for essential applications. The routing optimization problem is solved using the AAA framework; the set of candidate solutions is encoded as viable multi-hop paths between the cluster head and the sink. At each iteration, the candidate paths are updated using the growth and adaptation operators, and infeasible paths are repaired via connectivity validation. The route with the lowest augmented routing cost is chosen as the best path.

3.10 Adaptive Re-Clustering Trigger

Re-clustering is not performed in all rounds to minimize unnecessary control overhead. The protocol, on the other hand, checks the ratio of minimum residual energy over the average network energy. A drop in this ratio to a predetermined level will result in re-clustering. This control strategy helps prevent overcomputing and ensures the network imbalance is corrected before critical nodes fail.

Re-clustering is activated if:

$$\frac{E_{min}}{E_{avg}} < \theta \quad (36)$$

This strategy enhances scalability and extends network lifetime by avoiding redundant optimization cycles while preserving global energy stability.

4 Results and Experimentation

The performance of the proposed iPAFAR protocol was evaluated using MATLAB R2023a simulation environment. All competing algorithms (LEACH-M, ME-LEACH, FQA, MKNDPC, RANP-PSO, and BKA-TOA) were implemented under identical network conditions to ensure a fair and unbiased comparison. The simulation was executed for 1000 rounds to assess long-term stability, energy efficiency, and routing performance. To ensure the reliability and consistency of the obtained results, all simulations were independently executed 10 times under identical parameter settings. The reported results represent the average performance across these runs. The network configuration and simulation parameters used in this study are summarized in [Table 2](#).

Table 2: Simulation parameters.

Parameter	Value
Simulation tool	MATLAB R2023a
Network area	100 m × 100 m
Simulation rounds	1000
Number of sensor nodes	100
Initial energy per node	0.5 J
Base station location	(50, 50 m)
Transmission range	25 m
Packet size	4000 bits
Energy model	First-Order Radio Model
elec	50 nJ/bit
amp	100 pJ/bit/m ²
Simulation rounds	0–1000

(Continued)

Table 2 (continued)

Parameter	Value
Population size (P) =	30
Number of generations (G)	50
Growth rate (α) = 0.5	Growth rate (α) = 0.5
Adaptation rate (β) = 0.3	Adaptation rate (β) = 0.3
Performance metrics	Hop count, delay, PDR, residual energy, alive nodes

All nodes were randomly deployed within the sensing field, and the base station was centrally positioned to minimize extreme-distance bias. The first-order radio energy model was adopted to calculate transmission and reception energy consumption.

4.1 End-to-End Delay Analysis

The comparison of the mean end-to-end delay across all simulated routing protocols over the course of the simulation rounds is shown in Fig. 3. iPAFAR has the lowest end-to-end delay across all simulation rounds. iPAFAR achieves around 39 ms at 1000 rounds and is much lower than LEACH-M (66 ms on average), FQA (53 ms on average), and MKNDPC (55 ms on average). This can be credited to the effective cluster-chain routing strategy and the zed next-hop selection, which minimize transmission distance and reduce buffering delays at intermediates. LEACH-M has the highest delay during the simulation. Its deterioration is more evident beyond 500 rounds, where the delay rises rapidly from 45 ms to 66 ms at 1000 rounds. BKA-TOA exhibits lower delay than RANP-PSO or ME-LEACH but it still cannot achieve the same delay efficiency as iPAFAR.

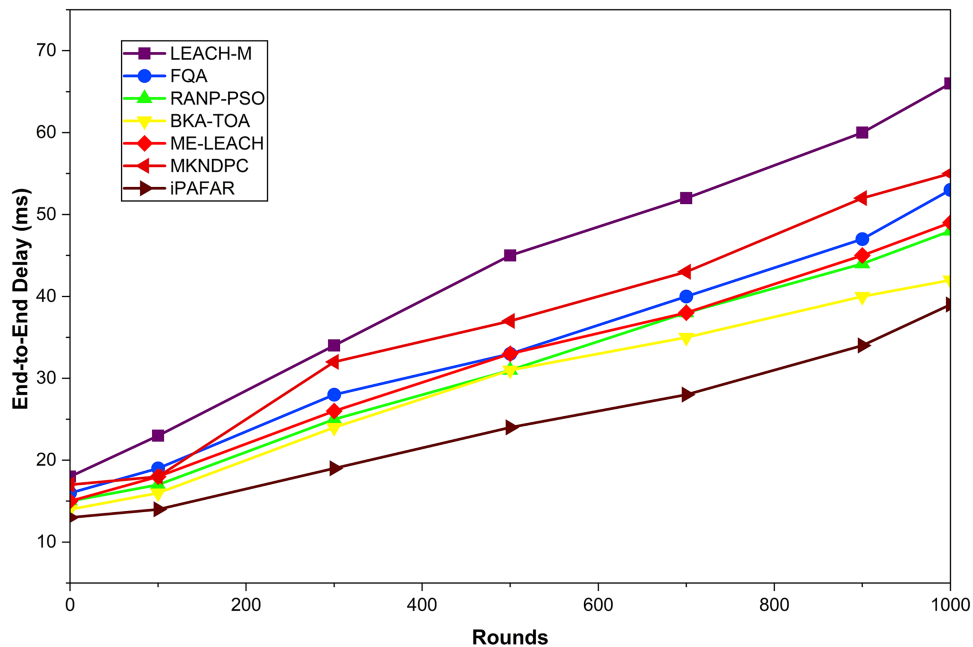


Figure 3: Comparative end-to-end delay analysis over 1000 simulation rounds.

4.2 Packet Delivery Ratio (PDR) Analysis

The Packet Delivery Ratio (PDR) represents the reliability of data transmission. It is defined as the ratio of successfully received packets at the sink to the total packets transmitted by sensor nodes. Fig. 4 illustrates the PDR performance of all protocols over 1000 simulation rounds.

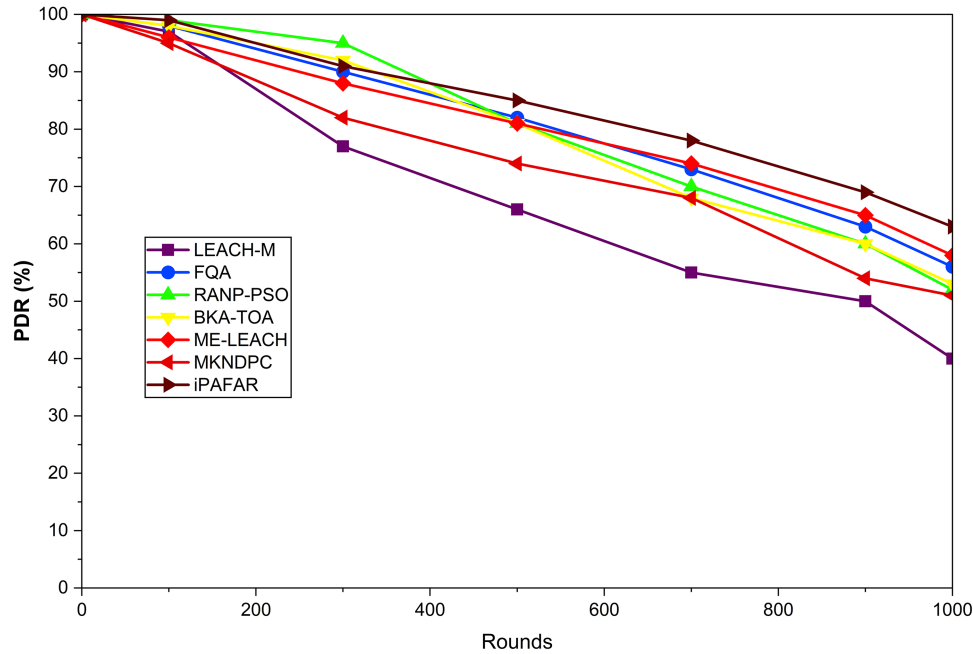


Figure 4: Comparative packet delivery ratio (PDR) performance over 1000 rounds.

It is observed that PDR gradually decreases with increasing rounds due to node failures and energy depletion. However, the proposed iPAFAR framework consistently maintains a higher PDR than existing protocols. At 1000 rounds, iPAFAR achieves approximately 63%–68% packet delivery, whereas LEACH-M drops below 40%, and FQA and MKNDPC show moderate performance around 50%–55%. The incorporation of energy fairness and Lyapunov-based stability reduces packet drops and improves route reliability, particularly in later stages of network operation.

4.3 Residual Energy Analysis

Residual energy is the energy left in the network and directly affects network lifetime and stability.

Energy-saving measures ensure a long network lifetime. Based on Fig. 5, all protocols exhibit a decrease in residual energy with increasing rounds. LEACH-M has a high energy consumption rate and almost reaches zero J after 1000 rounds, indicating premature network failure. DV-HOP-DNN and RANP-PSO have around 5–10 J of energy, and BKA-TOA has around 17 J at the conclusion of the simulation. Conversely, the proposed iPAFAR conserves about 43 J of residual energy at 1000 rounds, which is much higher than that of any other protocol.

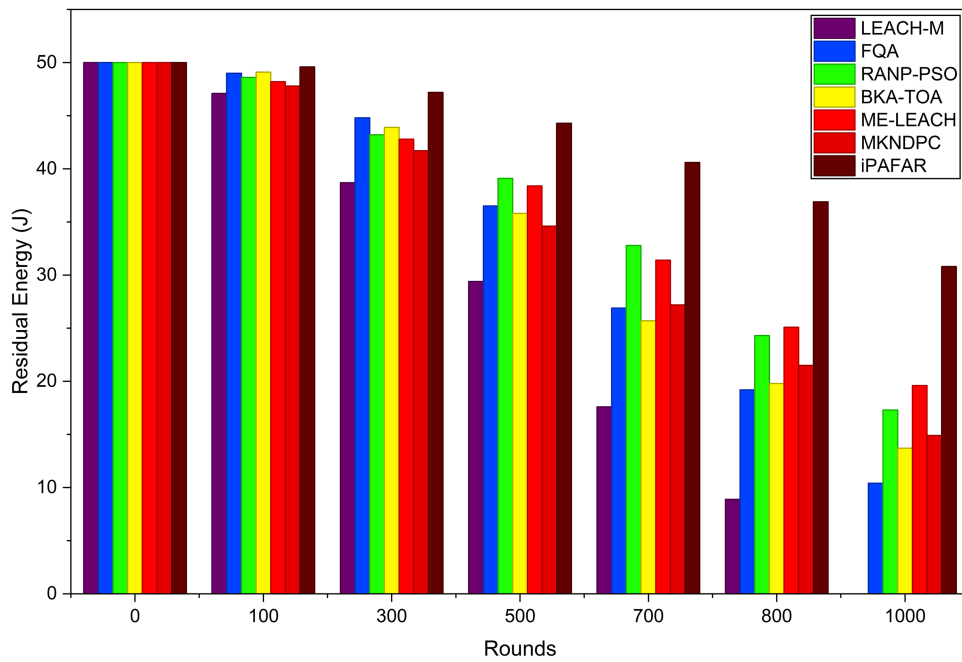


Figure 5: Residual energy trends across 1000 simulation rounds.

4.4 Alive Nodes Analysis

Fig. 6 shows the alive nodes at the 1000th simulation round for all the routing protocols examined.

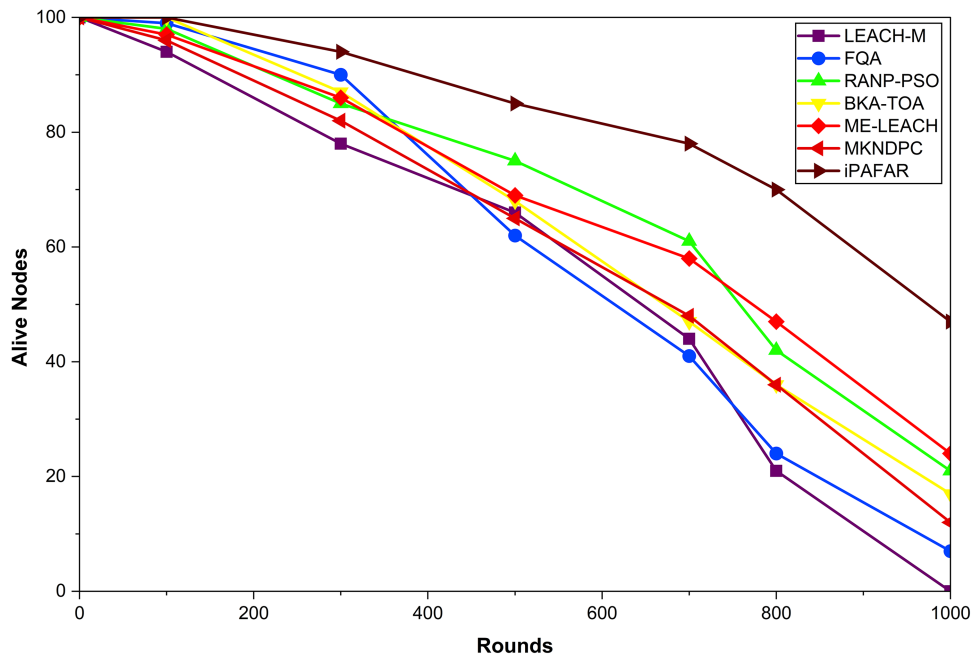


Figure 6: Number of alive nodes over 1000 simulation rounds.

As anticipated, the active nodes decrease gradually over time due to energy loss and the load on the cluster head. Nevertheless, the node death rates across different protocols differ significantly. The iPAFAR

method suggested shows the greatest network survivability throughout the simulation. At 1000 rounds, iPAFAR still has about 47 live nodes, whereas LEACH-M has none, and FQA has fewer than 10. LEACH-M has the greatest node depletion. At 500 rounds, the number of alive nodes reduces drastically, and by the conclusion of the simulation, the number of alive nodes is almost 0. The survivability of RANP-PSO and ME-LEACH among intermediate protocols is relatively high compared with FQA and MKNDPC. Nevertheless, their node survival rate after 700 rounds drops by several folds, indicating minimal long-term load balancing. In general, the findings indicate that iPAFAR substantially increases network lifetime and stability, reducing premature node death and sustaining the cluster balance.

4.5 Load Balance Index Analysis

Fig. 7 provides the results of the Load Balance Index (LBI). As the number of network rounds increases, LBI values increase progressively across all protocols due to uneven residual energy use.

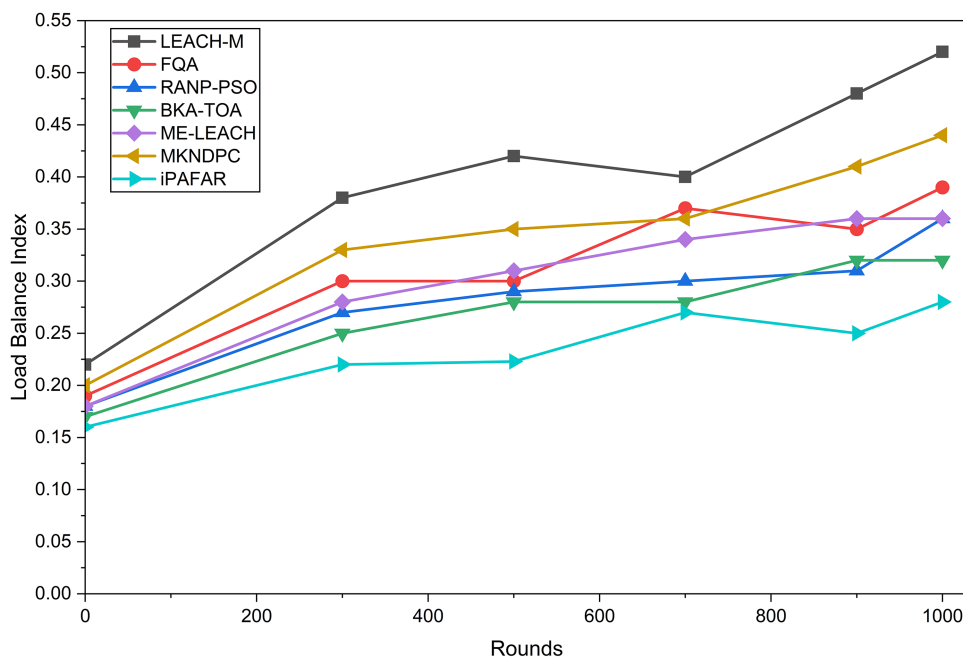


Figure 7: Load balance index (LBI) comparison among routing protocols.

The Load Balance Index (LBI) measures the variation in residual energy across sensor nodes. It is computed as the average squared deviation of individual node energy from the network's mean energy. A lower LBI value indicates better load balancing, as it reflects a more uniform energy distribution among nodes. However, iPAFAR consistently has the lowest LBI values throughout the simulation, indicating better workload distribution among the cluster heads. LEACH-M exhibits the greatest imbalance, especially at 300 rounds, which is why its nodes were quickly depleted, and, as shown in the earlier analysis, the network lifetime was shorter. Similarly, MKNDPC and FQA energy-adaptation strategies are inefficient.

4.6 Clustering Time Analysis

The clustering time of the considered protocols varies across simulation rounds, as shown in Fig. 8. The offered iPAFAR algorithm maintains a relatively low, constant average clustering time of 5–6 ms, indicating that it is very efficient and consistent in creating clusters. Conversely, MKNDPC cluster heads and node

assignment. LEACH-M has the shortest absolute clustering time (approximately 45 ms); however, this is due to the random selection of cluster-heads, which can affect the quality of the clusters and the energy balance. FQA and RANP-PSO have moderate clustering times, with minor variations across rounds, whereas BKA-TOA has a relatively stable, slightly higher value than iPAFAR. On balance, the findings show that iPAFAR can achieve a good trade-off between computational complexity and clustering efficiency. It is not the minimum, but its clustering time is always low, providing better network stability and energy balancing, making it more appropriate for long-term WSN deployments than traditional methods.

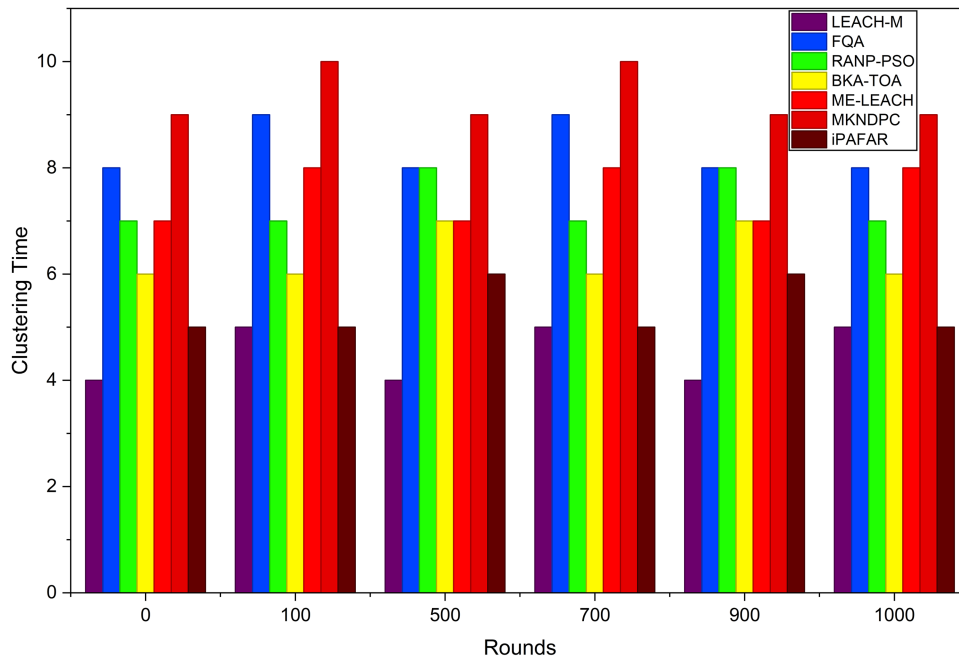


Figure 8: Clustering time comparison across simulation rounds.

4.7 Jitter Analysis

The jitter performance, as shown in Fig. 9, increases gradually with the number of rounds across all routing protocols as nodes lose energy and experience greater traffic congestion in the latter phases of the simulation. Nevertheless, the iPAFAR scheme always has the minimum jitter in all rounds. iPAFAR has a jitter of approximately 3.5 ms at 1000 rounds, and LEACH-M has the largest delay variation of more than 6 ms. The sharp increase in LEACH-M after 500 rounds indicates irregular routing paths and an uneven workload distribution among cluster heads. Conversely, iPAFAR exhibits smoother growth, better controls fluctuations, and indicates improved congestion management and adaptive routing.

The relatively stable protocols, like FQA and RANP-PSO, perform moderately and only become evidently unstable after 700 rounds. The findings verify that iPAFAR provides more stable timing and consistent transmission in dense WSN environments. The overall computational complexity of the proposed framework is approximately $O(P \times G \times N)$, where P is population size, G is generations, and N is number of nodes. Additional overhead from fuzzy refinement and routing optimization remains linear, making the approach computationally feasible.

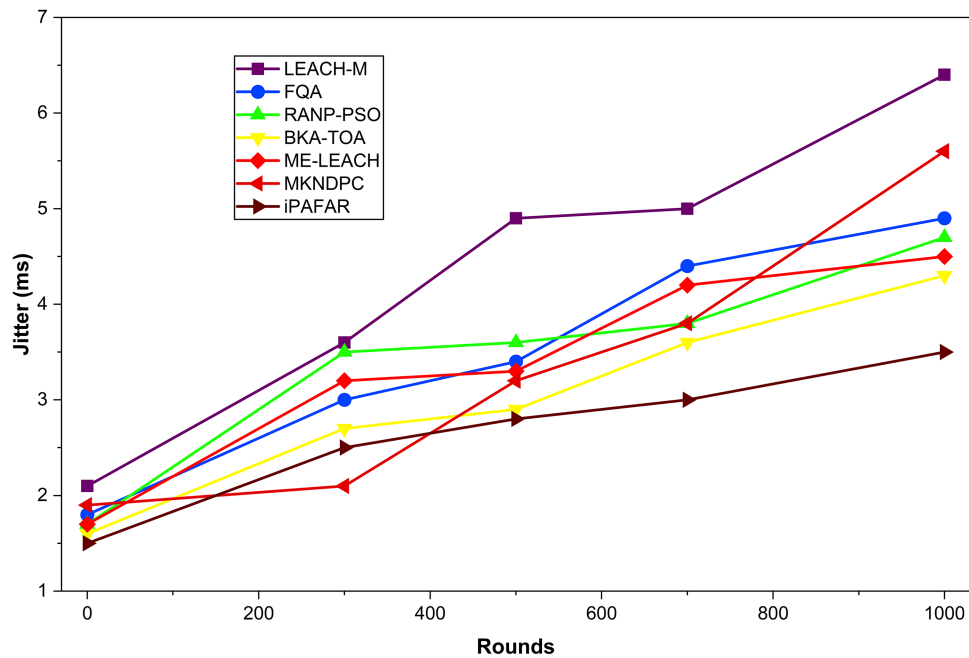


Figure 9: Jitter performance over 1000 simulation rounds.

5 Discussion

Comparative protocols show rapid performance degradation after approximately 700 simulation rounds due to node failures and unstable routing paths. In contrast, the proposed iPAFAR framework maintains higher delivery availability, exceeding 63% even after 1000 rounds. The integration of energy fairness and load variance in cluster-head selection reduces packet loss and improves network stability across different operational phases. The improvement in network lifetime is supported by the residual energy and alive-node analysis, which indicates more balanced energy consumption among sensor nodes. The Lyapunov-based stability control further limits long-term energy imbalance, thereby improving delay, reliability, and survivability. Moreover, the jitter and clustering-time results demonstrate that the proposed method achieves a practical balance between routing stability and computational overhead. Although the clustering time is not the lowest, it remains stable across simulation rounds, indicating good scalability for long-term smart city IoT deployments. Overall, the experimental results confirm that iPAFAR's performance improvement is consistent across multiple metrics. The combination of Pareto-based multi-objective optimization, fuzzy refinement, Lyapunov stability modeling, and adaptive re-clustering provides a robust and energy-efficient routing framework for static IoT-enabled wireless sensor networks.

6 Conclusion and Future Scope

In this paper, the iPAFAR, a Pareto-driven Artificial Algae Algorithm-based energy-sensitive clustering and routing framework of smart city Wireless Sensor Networks, was introduced. The proposed method successfully addresses the issues of uneven energy dissipation and early node exhaustion by leveraging non-dominated sorting as an effective tool, the fuzzy refinement tool, and Lyapunov-based energy-stability modelling to formulate cluster-head selection as a real multi-objective optimization problem. The existing model presupposes a fixed, homogeneous network condition; thus, extending it to a heterogeneous, mobile WSN would also demonstrate its flexibility. Lightweight security can also be included in future research to address routing attacks and malicious node behavior. In addition, machine learning-assisted adaptive

parameter tuning should be integrated to improve dynamic optimization across varied traffic and energy conditions. Practical applicability can be validated using real sensor testbeds or advanced simulators.

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