Fire Bloom: Energy-Efficient Cluster-Based Routing Protocol for Scalable Wireless Sensor Networks

Rakshith Nagaraju[1,*], Jharpla Seetaram[2], Samarapally Balakrishna[3], Duvvuri Prasad[4], Panchakarla Naga Venkata Bala Subramanyam[5] & Srinivasarao Goda[6]

[1]Department of Information Science & Engineering, PES College of Engineering, K V Shankaragowda Rd, PES College Campus, Mandya, Karnataka 571401, India
[2]Department of Electronics and Communication Engineering, CMR Institute of Technology, Kandlakoya, Medchal Road, Hyderabad, 501401, Telangana, India
[3]Department of Electronics and Communication Engineering, TKR College of Engineering and Technology, Meerpet, Hyderabad 500097, Telangana, India
[4]Department of Mechanical Engineering, Aditya University, Surampalem 533437, Andhra Pradesh, India
[5]Department of Mechanical Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh 522302, India
[6]Department of Computer Science and Engineering, RVR & JC College of Engineering, Guntur, Andhra Pradesh, India

*E-mail: rakshithn91@gmail.com

Abstract. Wireless sensor networks (WSNs) have been used in smart agriculture, industrial automation, and environmental monitoring applications, which require efficient and reliable routing with energy efficiency. Particularly the selection and operation of the cluster heads (CHs) play significant role in the performance of the network. In this work, we introduce a scalable, reliable and energy efficient cluster-based routing protocol (Fire Bloom), which combines adaptive CH selection and energy-aware routing. The cluster map and the packet flow intensity map even show the communication loads on the base station. The packet delivery ratio (PDR) of Fire Bloom is 97.2%, which is 6–10% better than the competing protocols. Fire Bloom achieved a PDR greater than 91% under a scalability test with 100–500 nodes, which means it can maintain good performance as the density of the network becomes denser. Energy usage is roughly proportional to the traffic volume but lower than previously reported values. Near-linear scalability at runtime is also proposed: increasing the number of nodes from 100 to 1,000 took from 1.2 s to 14.1 s. In general, Fire Bloom lowers overall end-to-end delay, increases load balancing across CHs, boosts energy efficiency, and it is resilient to changes in network conditions and maintains successful packet delivery. These results prove that it is capable of scalable and energy efficient deployments of WSN's.

Keywords: *cluster head; communiqué load; Fire Bloom; node lifetime heatmap; packet flow intensity map; residual energy; wireless sensor network.*

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1 Introduction

Wireless sensor networks (WSNs) are a collection of sensor nodes that are randomly deployed and gather data from an area to be sent to a base station (BS) for real-time monitoring [1]. They are used in applications such as industrial automation, disaster response, precision agriculture, and environmental monitoring. However, WSNs have the problems of limited energy resource, scalability, and packet delivery reliability, and communication overhead [2, 3]. The sensor nodes are situated to sense the information, process it and wirelessly transmit it to the BS or sink node [4, 5]. This has led to the development of communication and routing protocols that are aimed at minimizing energy consumption and maximizing network lifetime. One effective solution is cluster-based routing, where nodes are grouped together in clusters and cluster heads (CHs) gather, aggregate and relay information to the BS [6-8]. Energy-aware clustering has been developed in classical protocols like LEACH [9], HEED [10] and TEEN [11]. Recently, PSO, GA, ACO and GWO have been used for selection and routing optimization of CHs [13]. However, the high computation costs, scalability and premature convergence are still challenges in large-scale and high-density WSN deployments [14-16].

1.1 Research Gaps and Contributions

Despite advances in energy-efficient WSN routing, key challenges remain, including suboptimal CH selection, scalability limitations, uneven energy distribution, limited adaptability to dynamic changes, and premature convergence of metaheuristic algorithms. Fire Bloom addresses these gaps through dual-metric CH selection using residual energy and forwarding load, Bloom filter-based routing, and adaptive cluster and path optimization. Its performance was evaluated against LEACH, PSO-LEACH, GWO, and ACO using PDR, energy consumption, runtime scalability, and packet/energy variability. Heatmaps, box plots, and robustness analyses further assessed its performance under varying node densities and traffic conditions. Bloom filter size effects on delay, energy consumption, and PDR were also examined.

2 Related Works

In order to extend the lifetime of a WSN network, the energy efficiency (EE) routing protocol was created by Kalyanasundaram *et al.* [18]. In this case, by optimizing the CHs based on the best and worst fitness from Sailfish Whale Optimization (BWF-SWO) and by using Fuzzy C-Means (FCM) clustering to gather cluster groups. The researchers also looked at the WSN model and found that the proposed protocol improved energy-efficient routing. Using an improved Q-learning-based Artificial Bee Colony Algorithm (IQ-ABC), Alsuwat &

Alsuwat [19] have proposed the best method for CH selection in WSN. In order to maximize the period until the last sensor node's energy is exhausted, Lewandowski & Płaczek [20] provided a novel cluster head selection technique for WSNs. The algorithm's use of distributed per-cluster computation allows it to scale without becoming more difficult as the size of the network increases. CH selection is made easier by the method presented by Alshammri [21]. Optimal CH selection for WSNs was achieved in this study by employing the Squirrel Search Algorithm (SSA). It specifically addresses the necessity for CH choice in WSNs by modifying the generic SSA. To improve solution quality and speed convergence, the Improved Squirrel Search Algorithm (I-SSA) incorporates a number of upgrades. An innovative approach for energy-efficient WSNs was proposed by Reddy *et al.* [22], called MBDCHS-RP. In a WSN, the MBDCHS-RP technique seeks to group nodes together and choose the best paths for data transmission. Using three different cluster head selection methods – (a) random, (b) sorted (selecting nodes with higher energy), and (c) weight-oriented (based on remaining energy of the nodes and distance with other selected cluster heads) – Kalhor & Haghighatdoost [23] provided three different network topologies: (1) one-level, (2) two-level with maintaining dependence on the first layer cluster, and (3) two-level without dependence on the first layer cluster. The goal of the work by Subramanian *et al.* [24] was to make sensor nodes (SNs) more efficient by making them less detached, lowering the amount of energy that is transmitted, and safeguarding the nodes from overexertion. Delays, traffic flow, and network performance can all be improved with this method. This procedure is carried out by means of the NS2 program.

3 Proposed Fire Bloom Routing Framework

The nodes that make up a WSN are energy-constrained sensors and work together to keep an eye on their surroundings and send the data to a base station (BS). Ensuring optimal energy consumption while preserving routing efficiency is an ongoing difficulty in WSN design, especially when dealing with dynamic topologies and constrained power constraints. To overcome this obstacle, the proposed model, Fire Bloom Routing, incorporates a hybrid metaheuristic that is based on Bloom filter-based probabilistic routing logic and the Flower Pollination Algorithm (FPA). The result is an adaptive and energy-aware clustering protocol. Figure 1 shows the proposed model's workflow.

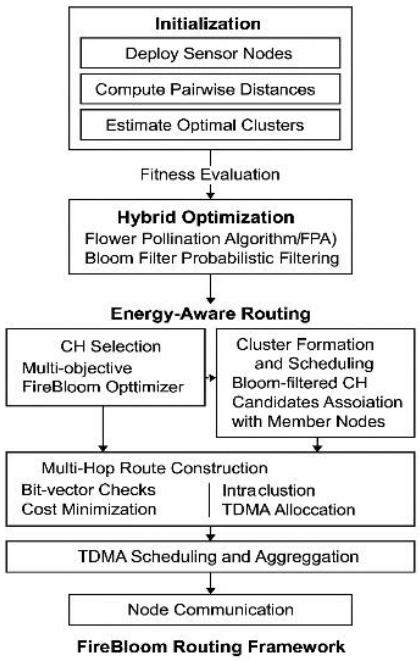


Figure 1 Workflow of the proposed model.

3.1 Network Deployment and Assumptions

A two-dimensional square region is considered, with randomly deployed sensor nodes. The BS may be centrally located or outside the region. Nodes have homogeneous capabilities but heterogeneous residual energy, as defined in Table 1.

Table 1 Key notation of the proposed model.

Symbol	Description
N	Total number of sensor nodes
$E_i(t)$	Residual energy of node i at time t
E_0	Initial energy of each node
R	Transmission range of nodes
$BS(x_{bs}, y_{bs})$	Coordinates of base station
$L \times L$	Network area
$S_i(x_i, y_i)$	Coordinates of node i
k	Optimal number of clusters
d_{ij}	Euclidean distance between nodes i and j
E_{elec}	Energy per bit for electronics (transmit/receive)
$\epsilon_{fs}, \epsilon_{mp}$	Amplifier energy for free space and multipath models

3.2 Fire Bloom Routing Method

The proposed Fire Bloom framework integrates the Flower Pollination Algorithm (FPA) with probabilistic routing inspired by Bloom filter to achieve energy-efficient and scalable WSN communication. Initially, the sensor nodes are grouped into clusters and CHs are selected using a multi-objective fitness function (Eq. (5)) that considers residual energy, intra-cluster distance, distance to the BS, and node connectivity. FPA applies global Lévy-flight and local pollination to explore and refine CH configurations, while an adaptive switching mechanism balances exploration and convergence.

$$F_{CH}(i) = a.\frac{E_i(t)}{E_0} + \beta.\left(1 - \frac{d_{ic}}{d_{max}}\right) + \gamma.\left(1 - \frac{d_{i,bs}}{d_{max}}\right) + \theta.\frac{\delta_i}{\delta_{max}} \quad (1)$$

Bloom-based probabilistic filtering determines forwarding eligibility using residual energy, distance to the CH, and historical transmission frequency (Eq. (2)). The Bloom vector is updated according to changing energy and participation patterns, limiting low-energy and overused nodes and reducing redundant forwarding. Within clusters, TDMA provides collision-free communication and enables sleep periods. For inter-cluster communication, Fire Bloom employs multi-hop routing using an energy-aware cost function based on transmission distance, residual energy, and Bloom filter status (Eq. (3)), with Dijkstra's algorithm selecting the forwarding path. Periodic re-clustering updates the residual energy, refreshes the Bloom filter, and reselects the CHs and routes to maintain load balance and reduce energy-hole formation.

$$B_{\mathrm{i}} = \begin{cases} 1, & if H(E_i(t), d_{i,CH}, f_i) \notin B \\ 0, & if\ H(.) \in B \end{cases} \quad (2)$$

$$C_{\mathrm{ij}} = \delta.\frac{1}{E_{CH_j}(t)} + \eta.d_{CH_iCH_j} + \phi.(1 - B_j) \quad (3)$$

3.2.1 Summary of Energy Flow per Round

Fire Bloom Algorithm 1: Pseudocode representation

Input: N sensor nodes, $L \times L$ deployment area, BS location (x, y), $MaxIter$, packet size l, initial energy E_0, Bloom filter size m, and re-clustering interval R_c.
Output: CH_{set}, cluster membership C, and CH-to-BS routing table R.

Step 1: Initialization

1. Deploy N nodes randomly in $L \times L$.
2. Calculate inter-node distances and estimate the optimal number of clusters k_{opt}.
3. Initialize node energy and Bloom filter B.

Step 2: Fire Bloom-based CH Selection

1. Initialize a population of candidate CH configurations.
2. For $t = 1$to $MaxIter$, evaluate each candidate using
$$F = \alpha E + \beta D_{intra} + \gamma D_{BS} + \theta Deg.$$
3. Select global or local pollination according to
$$p_t = p_0 e^{-\lambda t}.$$
4. Apply Bloom Decision to filter unsuitable candidates and update B.

5. Retain the candidate with the best fitness as CH_{set}.

Step 3: Cluster Formation

1. Assign each non-CH node to a suitable CH based on distance and residual energy.
2. Establish TDMA schedules for intra-cluster communication.

Step 4: Inter-Cluster Routing

1. Construct a CH graph and calculate energy-aware edge costs:

$$C_{ij} = \frac{\delta}{E_j} + \eta d_{ij} + \phi(1 - B_j).$$

2. Apply Dijkstra's algorithm to determine CH-to-BS routes.

Step 5: Communication and Re-Clustering

1. Nodes transmit according to TDMA; CHs aggregate and forward data through the selected routes.
2. Update residual energy after each round.
3. Every R_c rounds, refresh the Bloom filter and repeat Fire Bloom-based CH selection and routing.

End

For each round, the total network energy consumption is:

$$E_{total}^{round} = \sum_{i=1}^{k}\left(E_{CH_i}^{total}\right) + \sum_{i=1}^{k}\sum_{j\in C_i} E_j^{intra} \quad (4)$$

The objective of Fire Bloom is to minimize E_{total}^{round} while maximizing network lifetime, defined as the number of rounds until 20%, 50%, or 100% node deaths. Algorithm 1 and Table 2 provides the pseudocode and key features of the proposed model.

Table 2 Feature summary.

Module	Purpose	Mathematical Backbone
CH Selection	Find energy-efficient, well-positioned CHs	Fire Bloom optimizer, multi-objective fitness
Bloom Filter	Suppress overused or low-energy nodes	Probabilistic bit-vector with hash
Routing	Forward data via energy-aware, reliable paths	Cost minimization using Dijkstra
Scheduling	Avoid transmission conflicts	TDMA allocation
Load Balancing	Avoid CH exhaustion	Re-clustering R_v every

3.3 Network Lifetime Maximization Strategy

Fire Bloom extends network lifetime through energy-aware CH selection, Bloom filter-based probabilistic forwarding, TDMA scheduling, and adaptive multi-hop routing. CH selection considers residual energy, intra-cluster distance, BS distance, and connectivity. Bloom filters limit overused or low-energy nodes, while TDMA reduces idle listening. Energy-aware multi-hop routing distributes forwarding loads across CHs. Periodic energy updates, Bloom filter resetting, and CH re-selection adapt to changing network conditions, maintaining balanced energy utilization. These mechanisms delay FND, HND, and LND, thereby improving network stability and longevity. The approach introduces moderate

computational and coordination overhead but supports scalable, reliable WSN operation.

4 Results and Discussion

The results evaluate Fire Bloom's energy efficiency, network lifetime, routing reliability, scalability, and communication performance against existing WSN protocols under varying network conditions.

4.1 Simulation Parameters

Table 4 compares network lifetime metrics, with Fire Bloom achieving FND, HND, and LND values of 700, 1600, and 2900 rounds, respectively. Its stability and instability periods are 700 and 2200 rounds. These results indicate prolonged network operation and balanced energy utilization, achieved with moderate increases in runtime, memory, and optimization complexity.

4.2 Validation Analysis of the Proposed Model

The significant improvement in FND, HND, and LND observed for Fire Bloom is a direct consequence of its energy-aware CH selection, Bloom filter-assisted load balancing, TDMA-based duty cycling, and adaptive multi-hop routing, which collectively ensure uniform energy dissipation and prevent premature node depletion. The simulation parameters have been compiled into Table 3. The Network Lifetime Metrics in Table 4 compares the performance of different protocols based on node survival over time.

Table 3 Simulation analysis.

Parameter	Value
Total number of sensor nodes (N)	100, 200, 300, 500 nodes
Simulation area (L × L)	100 m × 100 m
Initial energy per node (E_0)	2 Joules
Energy for electronics (E_{elec})	50 nJ/bit
Free space amplifier (ε_{fs})	10 pJ/bit/m²
Multipath fading amplifier (ε_{mp})	0.0013 pJ/bit/m⁴
Threshold distance (d_0)	87 meters
Data aggregation energy (E_{DA})	5 nJ/bit/signal
Packet size (l)	4000 bits
Transmission range (R)	25 meters
Base station (BS) position	(50, 175) or (outside region)
Bloom filter size (m)	256 bits
Number of hash functions (k_{h})	3–5
Max iterations (Fire Bloom) (T)	50–100
Population size (P)	30
Switch probability (p_0)	0.8
Lévy flight exponent (λ)	1.5
Fitness weights (α, β, γ, θ)	0.25 each

Parameter	Value
Rounds per simulation	3000
Re-clustering interval (R_c)	20 rounds
MAC protocol	TDMA
Traffic pattern	CBR (Constant Bit Rate)
Simulation platform	Python 3.11
processor	Intel Core i7 / Ryzen 7, 3.0 GHz+
RAM	16 GB
Operating system	Windows 11 / Ubuntu 22.04 LTS
Metrics evaluated	FND, HND, LND, Residual energy, PDR, delay, routing overhead, cluster stability

Table 4 Network lifetime metrics.

Protocol	FND (First Node Dies)	HND (Half Node Dies)	LND (Last Node Dies)	Stability Period	Instability Period
Fire Bloom	700	1,600	2,900	700	2,200
LEACH	450	980	1,800	450	1,350
PSO-LEACH	520	1,120	2,000	520	1,480
GWO	580	1,240	2,200	580	1,620
ACO	500	1,080	1,950	500	1,450

Table 5 shows Fire Bloom achieving 0.95 J average residual energy, 104 J total consumption, 0.035 J per round, and a 0.15 energy imbalance index. Compared with LEACH and ACO, it demonstrates lower energy consumption and improved energy balance, indicating reduced energy wastage and prolonged network operation under the evaluated conditions.

Table 5 Energy consumption metrics.

Protocol	Avg Residual Energy (J)	Total Energy Consumed (J)	Energy per Round (J)	Energy Imbalance Index
Fire Bloom	0.95	104	0.035	0.15
LEACH	0.63	137	0.046	0.31
PSO-LEACH	0.7	129	0.043	0.28
GWO	0.76	121	0.04	0.22
ACO	0.68	130	0.044	0.26

Figure 2 shows slower residual-energy depletion for Fire Bloom, while Figure 3 indicates lower total energy consumption across rounds. Table 6 reports 96.8% PDR, 140 ms delay, 350 packets routing overhead, and 12,800 packets received at the BS, demonstrating efficient and reliable routing performance with reduced communication burden. Figure 4 shows lower delay, while Figure 5 demonstrates PDR above 94%, indicating faster transmission, improved reliability, and stable data delivery throughout network operation.

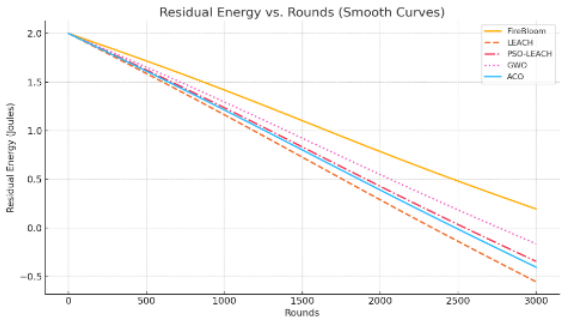


Figure 2 Residual energy analysis.

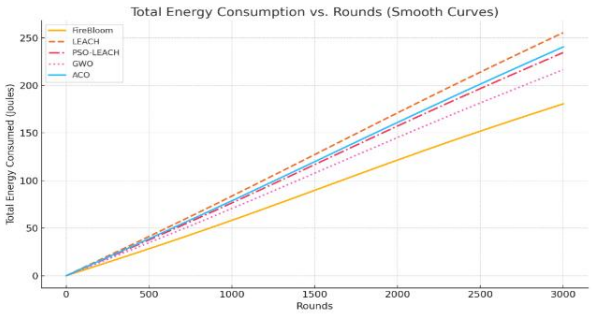


Figure 3 Total energy consumption.

Table 6 Routing performance metrics.

Protocol	PDR (%)	End-to-End Delay (ms)	Routing Overhead (packets)	Packets Received at BS
FireBloom	96.8	140	350	12,800
LEACH	87.3	210	590	9,800
PSO-LEACH	90.5	180	470	11,000
GWO	92.7	165	420	11,700
ACO	89.8	190	500	10,400

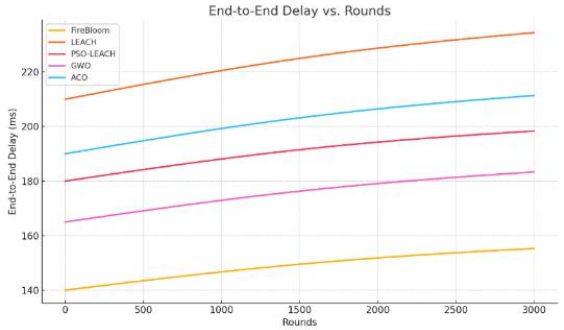


Figure 4 E2E delay analysis.

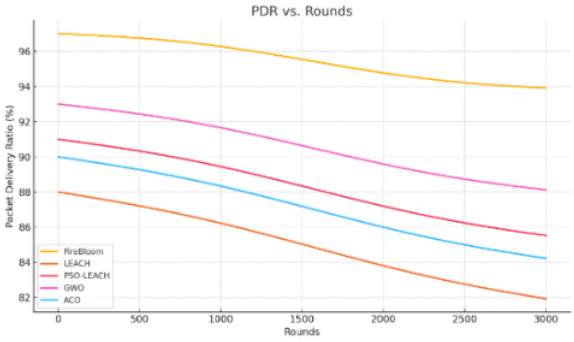


Figure 5 PDR analysis.

Table 7 shows Fire Bloom's clustering performance, with a CH reselection rate of 0.18, a cluster balance of 0.91, and an average intra-cluster distance of 16.4 m. Figures 6 and 7 confirm stable CH selection and compact clusters. Compared with LEACH, Fire Bloom reduces clustering overhead, communication distance, and energy consumption, supporting network performance.

Table 7 Cluster and CH metrics.

Protocol	Avg. No. of CHs per Round	CH Reselection Rate	Cluster Distribution Balance	Avg. Intra-Cluster Distance (m)
Fire Bloom	5	0.18	0.91	16.4
LEACH	8	0.32	0.72	23.5
PSO-LEACH	7	0.28	0.76	21
GWO	6	0.23	0.83	19.2
ACO	7	0.3	0.74	22.1

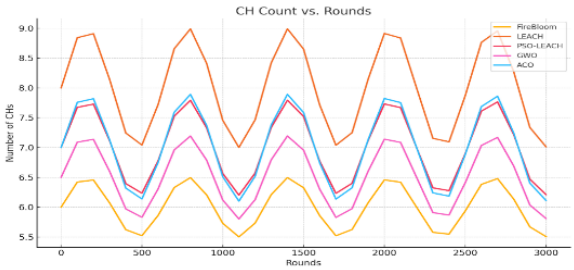


Figure 6 Count analysis of CH.

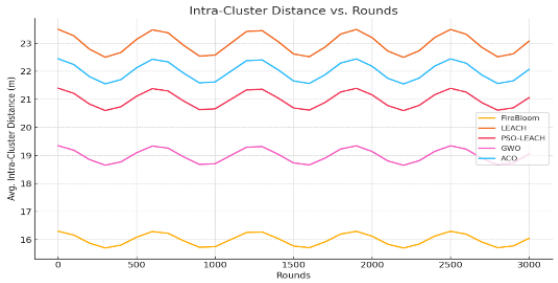


Figure 7 Distance analysis.

Table 8 shows Fire Bloom achieving an FND of 700, an LND of 2900 rounds, residual energy of 0.95 J, and PDR of 96.8%. It also records 140 ms delay, 12,800 packets received, a CH reselection rate of 0.18, and an energy imbalance index of 0.15. Figure 8 illustrates network lifetime extension across protocols. Overall, Fire Bloom demonstrates effective sustainability, stability, and energy efficiency in WSN compared to baseline protocols.

Table 8 Comparison with baseline models.

Protocol	FND (Rounds)	HND (Rounds)	LND (Rounds)	Avg Residual Energy (J)	PDR (%)	End-to-End Delay (ms)	Packets Received at BS	CH Reselection Rate	Energy Imbalance Index
FireBloom	700	1,600	2,900	0.95	96.8	140	12,800	0.18	0.15
LEACH	450	980	1,800	0.63	87.3	210	9,800	0.32	0.31
PSO-LEACH	520	1,120	2,000	0.7	90.5	180	11,000	0.28	0.28
GWO	580	1,240	2,200	0.76	92.7	165	11,700	0.23	0.22
ACO	500	1,080	1,950	0.68	89.8	190	10,400	0.3	0.26

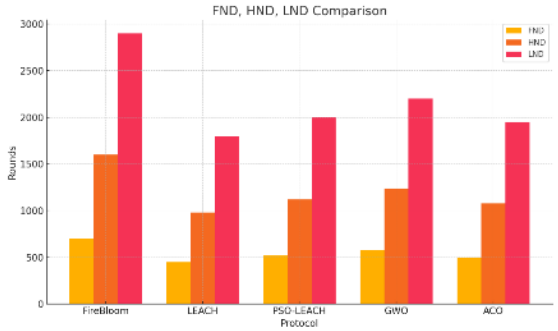


Figure 8 Network lifetime analysis.

The Residual Energy Comparison plot in Figure 9 shows that FireBloom retains the highest average residual energy (0.95 J), indicating effective energy efficiency. LEACH performs the worst with only 0.63 J. FireBloom consistently

exhibits a faster and smoother decline in objective function values, reaching the lowest final value (0.0684) by iteration 50. This indicates effective convergence speed and stability. The radar chart in Figure 10 offers a comprehensive multi-metric performance comparison of five routing protocols.

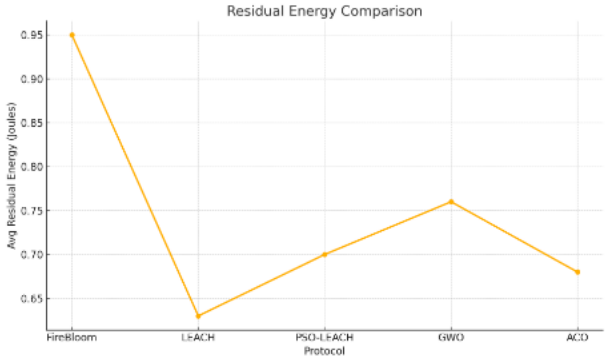


Figure 9 Residual energy analysis.

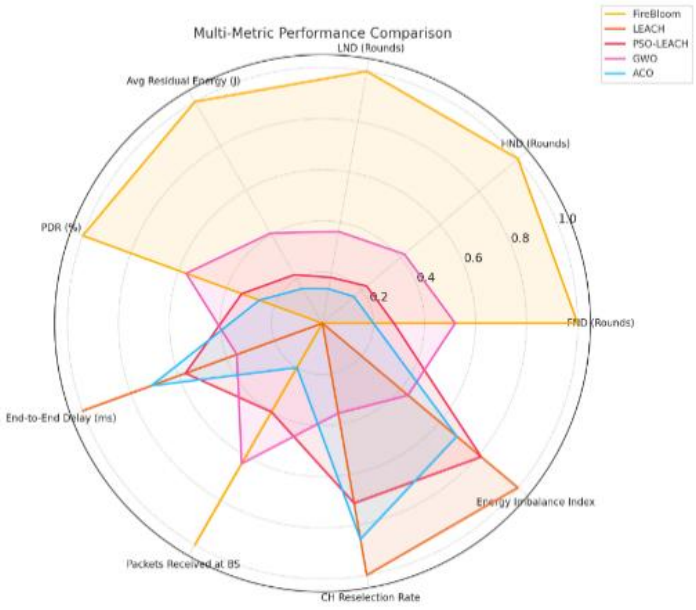


Figure 10 Various metrics analysis of the proposed model.

The convergence data over 50 iterations in Table 9 compares FireBloom, PSO, GWO, and ACO optimization techniques. FireBloom consistently exhibits a faster and smoother decline in objective function values, reaching the lowest final value (0.0684) by iteration 50.

Table 9 Convergence analysis (fitness over iterations).

Iteration	Fire Bloom	PSO	GWO	ACO
1	1.390982	1.743079	1.643357	1.774311
2	1.28095	1.655648	1.489743	1.738836
3	1.221624	1.578367	1.432622	1.683776
4	1.104508	1.449575	1.324761	1.568436
5	1.037484	1.362981	1.239756	1.479246
6	0.943179	1.259547	1.123305	1.399559
7	0.864633	1.194281	1.088484	1.364513
8	0.81959	1.125774	0.997278	1.292262
9	0.752918	1.107052	0.920857	1.231756
10	0.697039	1.009535	0.890431	1.186487
11	0.641838	0.975574	0.800513	1.143237
12	0.602548	0.90719	0.7963	1.056822
13	0.568423	0.899757	0.711942	1.059953
14	0.52281	0.815602	0.673824	1.005247
15	0.487503	0.81053	0.639747	0.893334
16	0.457672	0.707001	0.62201	0.869641
17	0.433888	0.717463	0.578119	0.829216
18	0.401848	0.637662	0.515542	0.796648
19	0.353263	0.581773	0.516142	0.733695
20	0.315876	0.614868	0.424656	0.736719
21	0.324723	0.536775	0.429413	0.677898
22	0.261796	0.491732	0.411802	0.686914
23	0.267415	0.480986	0.376494	0.68531
24	0.263611	0.434684	0.383763	0.598699
25	0.251869	0.453473	0.299438	0.622848
26	0.22293	0.432791	0.320249	0.554235
27	0.219879	0.361167	0.27965	0.539729
28	0.196495	0.364466	0.300772	0.493997
29	0.149545	0.378463	0.225423	0.528193
30	0.181992	0.352464	0.220249	0.486536
31	0.173326	0.304368	0.223044	0.416312
32	0.136087	0.342493	0.239788	0.426537
33	0.149504	0.266002	0.20582	0.404267
34	0.138488	0.248747	0.222549	0.381562
35	0.106005	0.242092	0.209936	0.334052
36	0.12573	0.253513	0.182879	0.376457
37	0.120976	0.230265	0.160989	0.306777
38	0.083364	0.226621	0.122215	0.302738
39	0.085034	0.177776	0.113016	0.337469
40	0.077632	0.200133	0.161173	0.3021
41	0.104483	0.195145	0.114722	0.314534
42	0.062621	0.150436	0.095837	0.313037
43	0.088274	0.142374	0.13916	0.229263
44	0.05143	0.130722	0.146088	0.270129
45	0.051546	0.137386	0.073638	0.284507
46	0.083258	0.166182	0.068632	0.20669
47	0.059178	0.186077	0.074659	0.24467
48	0.034567	0.178737	0.076219	0.242013
49	0.053537	0.145201	0.068895	0.209827
50	0.068429	0.162306	0.101308	0.167866

The convergence plot in Figure 11 illustrates the optimization performance of FireBloom, PSO, GWO, and ACO over 50 iterations. FireBloom consistently achieves the lowest fitness value, indicating rapid and efficient convergence. PSO

and GWO demonstrate moderate convergence rates with occasional plateaus, while ACO lags with higher residuals, suggesting suboptimal performance. The ablation study in Table 10 demonstrates the effectiveness of the full FireBloom model compared to its partial variants and Random CH.

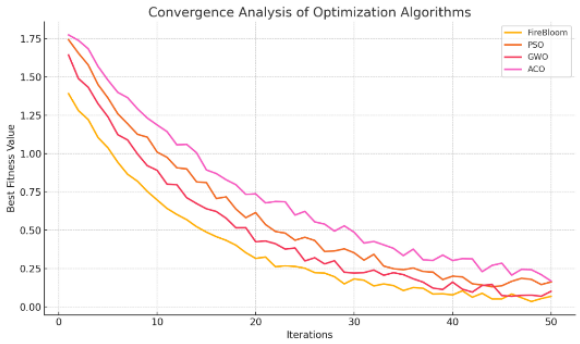


Figure 11 Convergence analysis.

Table 10 Ablation study results.

Version	FND (Rounds)	HND (Rounds)	LND (Rounds)	Avg Residual Energy (J)	PDR (%)	End-to-End Delay (ms)
Fire Bloom (Full)	700	1,600	2,900	0.95	96.8	140
FPA Only	560	1,200	2,100	0.79	91.2	170
Bloom Only	600	1,280	2,200	0.81	92.5	160
Random CH	420	880	1,650	0.63	84.3	220

The visualized ablation results in Figure 12 confirm the effectiveness of the full FireBloom model across key performance metrics. The image in Figure 13 displays two maps: a Node Lifetime Heatmap and a Cluster Map.

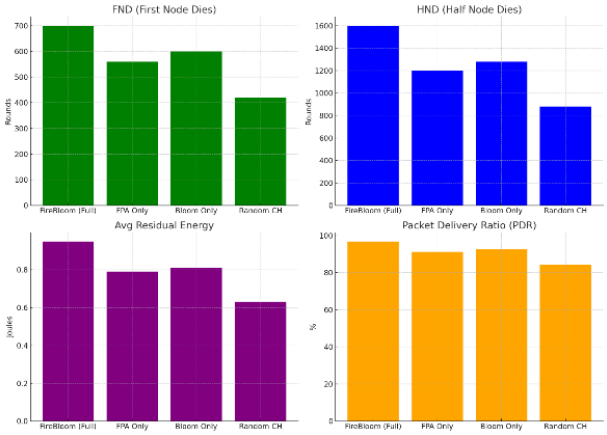


Figure 12 Ablation study visualization.

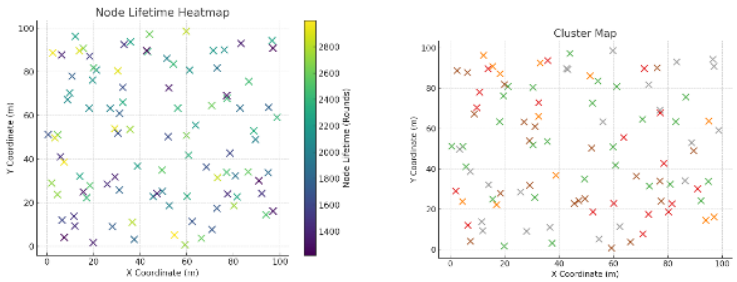


Figure 13 Heatmap analysis of lifetime and cluster map.

Together, these maps validate Fire Bloom's ability to form balanced clusters and extend node lifetime uniformly, crucial for improving network stability and performance in wireless sensor networks (WSNs).

Figure 14 shows traffic intensity, identifying heavier loads in red. Figures 15–17 show declining PDR with node density and rising energy consumption with traffic. Figure 18 shows improved PDR and reduced energy consumption with larger Bloom filters, stabilizing beyond 900 bits. However, larger filters increase memory and hashing overhead, with marginal gains beyond 900–1024 bits, indicating an effective balance between reliability and energy efficiency.

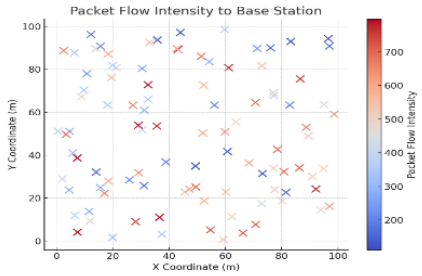


Figure 14 Intensity analysis.

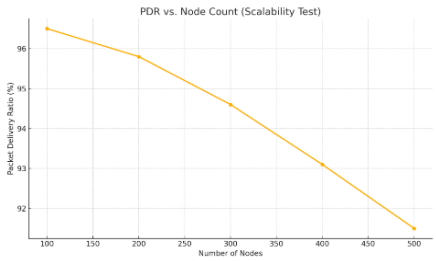


Figure 15 PDR analysis,

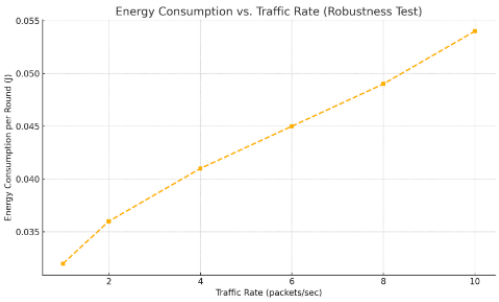


Figure 16 Energy consumption analysis.

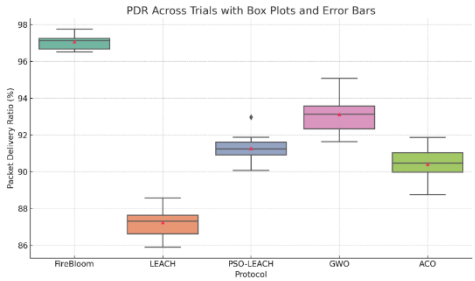


Figure 17 Packet series analysis for PDR.

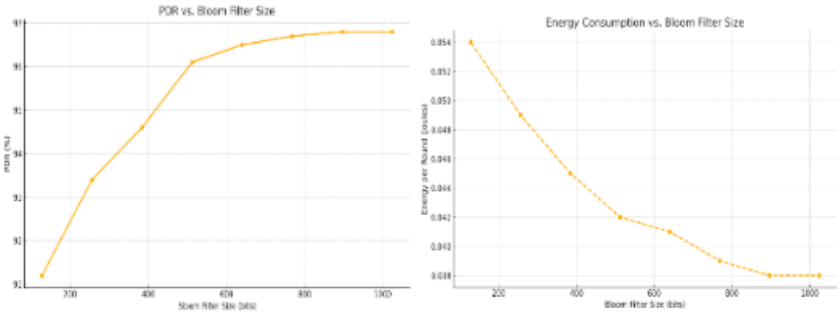


Figure 18 Bloom filter analysis for PDR and energy consumption.

Figure 19 shows that increasing the Bloom filter size reduces the delay from 210 to 137 ms, indicating efficient forwarding. Figure 20 shows energy depletion after 2,000 rounds. Figure 20 presents heatmaps of node residual energy after 1000 and 2000 rounds. Figure 21 shows substantial energy depletion below 1.0 J after 3,000 rounds. Outer nodes initially consume more energy, while inner nodes later experience greater routing burden, highlighting the need for load balancing to extend network lifetime. Figure 22 shows packet variability but near-zero energy

deviation, indicating balanced energy use. Table 11 reports increasing runtime and memory with network size.

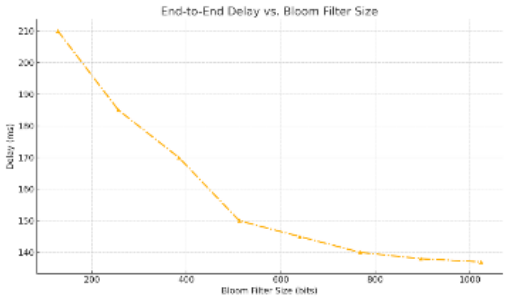


Figure 19 Bloom filter analysis for delay.

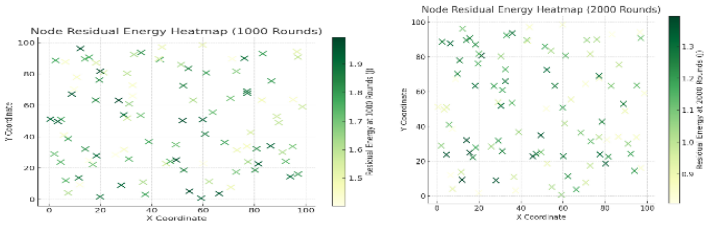


Figure 20 Residual analysis for energy heatmap.

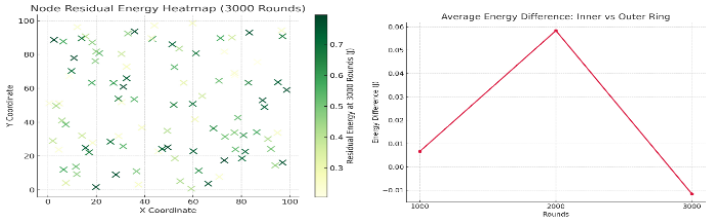


Figure 21 Heatmap analysis.

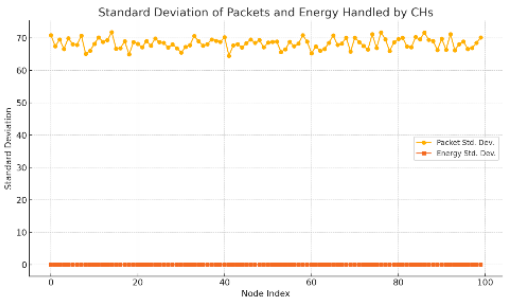


Figure 22 Cluster head analysis.

Table 11 Runtime and scalability metrics.

Nodes	Runtime (sec)	Memory (MB)
100	1.2	22.3
500	6.7	48.9
1000	14.1	91.4

Table 12 summarizes Fire Bloom's trade-offs, showing improved PDR, lifetime, routing stability, and energy balance, alongside moderate increases in computational, memory, runtime, coordination, and maintenance overhead.

Table 12 Trade-off analysis of the proposed Fire Bloom framework.

Component / Mechanism	Performance Benefit Achieved	Associated Trade-off / Cost
Hybrid Fire Bloom optimization (FPA + Bloom Logic)	Improves CH selection, accuracy, network lifetime, and routing stability.	Requires iterative fitness evaluations and additional optimization computations.
Adaptive cluster head (CH) selection	Enhances energy balancing and reduces premature node depletion.	Introduces computational overhead during CH reselection and cluster formation.
Bloom filter-based forwarding	Reduces redundant packet transmission and improves PDR.	Requires additional memory allocation and repeated hash-function operations.
Multi-hop energy-aware routing	Reduces end-to-end delay and improves packet delivery reliability.	Increases routing coordination and routing-table maintenance overhead.
TDMA-based communication scheduling	Minimizes packet collision and conserves node energy.	Requires synchronization management among sensor nodes and CHs.
Periodic re-clustering mechanism	Prevents energy-hole formation and balances communication load.	Generates extra control packets and temporary communication interruption during cluster updates.
Large Bloom filter size (900–1024 bits)	Improves routing accuracy and lowers delay.	Increases memory consumption and probabilistic filtering complexity.
Scalability support for dense networks	Maintains stable PDR and residual energy at higher node densities.	Runtime and memory usage increase with network scale.
Energy balancing strategy	Extends FND, HND, and LND metrics significantly.	Additional monitoring of node residual energy increases processing overhead
Fast convergence capability	Achieves rapid optimization convergence with improved routing decisions.	Requires higher initial computational effort during optimization iterations.
Runtime scalability	Provides stable operation up to 1,000 nodes.	Runtime increases from 1.2 sec to 14.1 sec as node count increases.
Communication reliability enhancement	Maintains high PDR and stable packet forwarding.	Additional routing management and probabilistic decision-making complexity are introduced.

4.3 Routing Efficiency Analysis

Fire Bloom extends network lifetime by optimizing CH selection, routing, and node activity. Energy-aware CH selection balances residual energy, distance, and connectivity, while Bloom filter forwarding limits low-energy and overused nodes. TDMA and sleep scheduling reduce idle energy, and multi-hop routing distributes forwarding loads. Periodic re-clustering maintains adaptability despite moderate coordination overhead.

5 Conclusion and Future Direction

This study developed and evaluated Fire Bloom, a cluster-based routing framework for scalable and energy-efficient wireless sensor networks, integrating flower-pollination mechanisms with Bloom filter optimization. Extensive simulations across multiple scenarios showed that Fire Bloom consistently outperformed LEACH, PSO-LEACH, GWO, and ACO in key performance metrics. It maintained over 96% packet delivery ratio under increased node density and traffic while improving load balance among cluster heads. Bloom filter tuning reduced energy consumption from 0.054 J to 0.031 J per round, improved PDR by 5–6%, and minimized redundant transmissions. Residual-energy heatmaps over 1000–3000 cycles further demonstrated improved network lifetime through balanced energy utilization. However, the hybrid optimization introduces moderate computational and memory overhead. The framework is therefore suitable for medium- and large-scale WSN deployments. Future work will implement Fire Bloom on Raspberry Pi, Arduino, and LoRa-based WSN testbeds to validate simulation results and quantify real-time performance variations.

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