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Original paper

A fuzzy logic-based extremal optimization approach for enhancing energy efficiency in wireless sensor networks

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Abstract

A wireless sensor network (WSN) consists of a collection of sensor nodes that collaboratively perform monitoring and data acquisition tasks. Considering the strict resource limitations of sensor nodes, achieving high energy efficiency is a critical requirement. In WSNs, it is essential to minimize data collection delay to ensure that sensed information remains current, while simultaneously maximizing the number of collected data samples to enhance accuracy and reliability. To address these conflicting objectives, this paper proposes a clustering-based routing protocol that simultaneously maximizes packet delivery, minimizes energy consumption, and reduces end-to-end delay. The proposed protocol integrates extremal optimization with fuzzy logic to dynamically form clusters, selecting cluster heads based on two primary criteria: residual energy and distance to the sink. The elected cluster heads then construct a minimum spanning tree (MST) to serve as an efficient multi-hop communication backbone toward the sink. The proposed method, termed the Extremal Optimization Fuzzy-Based Clustering Algorithm (EOFBCA), was implemented and evaluated using the OPNET 11.5 simulation platform. Performance is compared against three state-of-the-art protocols: AFSRP, BFOABMS, and NODIC. Simulation results demonstrate that EOFBCA achieves superior performance across multiple metrics, including energy consumption, end-to-end delay, throughput, packet delivery ratio, and signal-to-noise ratio.

Keywords: Wireless sensor networks, energy efficiency, clustering, extremal optimization, fuzzy logic, minimum spanning tree.

1 Introduction

A wireless sensor network (WSN) is composed of hundreds or even thousands of small, cost-effective electronic devices, known as sensor nodes. Each sensor node typically comprises a microcontroller, a sensing unit, and a wireless transceiver. The sensing unit measures environmental parameters such as temperature, pressure, humidity, and motion. The measured data is then transmitted to a central unit, referred to as the sink, via the communication module [17]. WSNs are applied in a wide range of domains, including healthcare systems, entertainment, games, environmental monitoring, and military applications. However, like other wireless devices, sensor nodes face several challenges, including unreliable communication links, limited communication range, and security vulnerabilities. In many deployment scenarios, such as environmental monitoring and military operations, sensor nodes are deployed in remote or hostile areas, making battery replacement difficult or even impossible. Therefore, designing energy-efficient protocols is crucial to prolong the operational lifetime of WSNs. To manage the energy consumption associated with communication, various protocols and techniques have been proposed for WSNs. A significant number of these protocols are based on clustering techniques [14], in which the network is divided into smaller regions, known as clusters. Within each cluster, one node is designated as the cluster head (CH), responsible for managing both intra-cluster and inter-cluster communication. In clustering protocols, time is typically divided into discrete slots. During each time slot, non-CH nodes transmit their collected data

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to the CH, which then aggregates the data and forwards the results either to the next CH (via multi-hop communication) or directly to the sink (via single-hop communication) [7]. Given that the data measured by sensors within a cluster are often highly correlated, effective clustering methods can significantly reduce the energy consumption required for data transmission [5]. This paper proposes a novel clustering and routing protocol that integrates extremal optimization with fuzzy logic for optimal cluster formation and CH selection in WSNs. The proposed method reduces energy consumption and extends the lifetime of the WSN. In particular, it replaces direct single-hop communication between CHs and the sink with an efficient multi-hop backbone based on a MST. Additionally, the optimal number of clusters is dynamically determined, and the network is partitioned into approximately equally sized regions to further optimize energy usage. The contributions of this work are summarized as follows:

- A novel hybrid clustering protocol that combines extremal optimization and fuzzy logic to form balanced clusters while considering residual energy and distance to the sink.
- The extremal optimization algorithm selectively removes the most detrimental aspects of a solution and substitutes them randomly, allowing for a dynamic and thorough exploration of the solution space to identify optimal configurations.
- The proposed clustering algorithm incorporates both the remaining battery energy and the distance to the sink when selecting cluster heads.
- Simulation results demonstrate that the proposed approach significantly improves network lifetime, energy consumption, end-to-end delay, throughput, packet delivery ratio, and signal-to-noise ratio (SNR), compared with existing state-of-the-art approaches.

This article is organized as follows. Section 2 provides a comprehensive review of the related literature. Section 3 details the proposed EOFBCA clustering and routing protocol. Section 4 presents the simulation setup and performance evaluation conducted using the OPNET simulator. Finally, Section 5 summarizes the key findings and outlines potential directions for future research.

2 Related works

In recent years, advancements in WSNs have generated substantial interest among researchers, manufacturers, and users. These technological improvements have contributed to addressing key challenges, such as deployment, connectivity, routing, and information security. Nevertheless, significant challenges remain, particularly in the area of energy management. A WSN consists of a collection of sensor nodes, each equipped with a battery, responsible for receiving, processing, and transmitting data via radio communication links. Consequently, enhancing the network's lifespan is achievable through the optimization of energy consumption. One effective method for achieving this is clustering, which involves partitioning sensor nodes into smaller, geographically close groups. Clusters enable the aggregation of sensed data, which is then sent to the base station through the cluster head (CH), thereby reducing the energy expenditure compared to individual transmission by each node. The clustering technique is inherently linked to routing protocols, as routing plays a critical role in optimizing the network's performance in terms of power consumption, energy efficiency, and data delivery rate. Recent research has focused extensively on improving clustering and routing protocols in WSNs to address these issues. For example, in [8], a routing protocol designed for energy-efficient networks is presented, which operates in three phases: (1) the initial phase, (2) the setup phase, and (3) the routing phase. The protocol begins with two primary operations: (1) dividing the network area into equal-sized partitions, and (2) determining the position of the sink node. Subsequently, the nodes are distributed within these partitions based on their geographical positions. In each partition, a CH is selected based on two key criteria: (1) the node should be centrally located in relation to other nodes, and (2) its energy level must exceed a specific threshold. This paper introduces a multi-hop routing approach, where, in the final step, each CH identifies its neighboring CHs and selects the one with the shortest distance to the sink for data transmission. In [3], a clustering model is proposed for circular sensor networks, designed to minimize energy consumption through efficient multi-hop communication. In this model, the sink is placed at the center of a circular deployment area, and cluster formation is governed by single-hop distance, clustering angle, and CH transmission range. In [18], an energy-aware routing method for WSNs is proposed, utilizing the Bacteria Foraging Optimization Algorithm with a mobile sink (BFOABMS). This method enhances energy efficiency within the network. In this approach, specific sensor nodes are selected as CHs based on two criteria: (1) the energy level of the node's battery, and (2) the distance from the node to the sink. These selected nodes form regular clusters within the network, facilitating more efficient data transmission. In WSNs that employ a fixed sink, nodes located near the sink consume their battery energy at a faster rate due to the increased volume of data they transmit compared to nodes located farther away. This disproportionate energy consumption can lead to node depletion, resulting in topology failure and disruption in data reporting. To address this issue, [18] introduced the concept of a mobile sink, which helps balance the energy consumption across the network, thereby extending the overall network lifetime. As previously mentioned, clustering is an effective strategy for optimizing energy consumption in WSNs. In [6], a fish swarm algorithm is applied to clustering, specifically using the Artificial Fish Swarm Optimization Algorithm (AFSRP). This algorithm, inspired by the social behavior of fish, is known for its high convergence speed, insensitivity to initial values, and flexibility, making it well-suited for solving complex optimization problems. Furthermore, the algorithm demonstrates fault tolerance, which is essential for maintaining network stability under variable conditions. Simulation results indicate that the proposed method outperforms the Energy Routing Algorithm (ERA). Specifically, it improves the energy consumption of sensor nodes by 40In [10], to enhance energy efficiency in wireless sensor networks, the Adaptive Remora Optimization Algorithm (AROA) was employed for clustering and selecting efficient cluster heads. AROA selects cluster heads based on the remaining energy of sensor nodes while considering the trade-off between inter-cluster and intra-cluster distances. During clustering, optimal clusters are formed with an appropriate number of nodes in each iteration. Despite its effectiveness in balancing energy consumption and extending network lifetime, the method involves higher computational complexity during cluster-head selection and relies on accurate knowledge of the network state, which may limit its scalability in large or highly dynamic networks. In [9], the genetic algorithm and krill herd optimization algorithm were employed to optimize energy consumption by clustering and selecting efficient CHs in WSNs. The genetic algorithm selects CHs based on the remaining energy of the nodes. In this method, a trade-off is considered between inter-cluster distance and intra-cluster distance, aiming to balance energy consumption and communication efficiency. Additionally, the Krill Herd algorithm is employed to form clusters with optimal nodes, ensuring an efficient number of nodes in each iteration. In [2], a hybrid Butterfly Optimization Algorithm (BOA) and Ant Colony Optimization (ACO) approach is proposed for clustering and routing in both static and mobile sink scenarios. The butterfly colony optimization algorithm determines the optimal CHs, while the ant colony optimization algorithm performs energy-aware routing. This hybrid approach improves the network lifetime by reducing energy consumption, demonstrating significant efficiency in the routing process. In [13], a fault-tolerant clustering method with energy-aware routing is proposed, which effectively reduces energy consumption in sensor networks and extends their operational lifetime. The protocol optimizes CH selection and routing paths while incorporating fault-tolerance mechanisms. The approach consists of three primary stages: (1) Moth Flame Optimization (MFO) for CH selection and cluster formation, (2) fault-tolerant operation to enhance node lifetime, and (3) Social Spider Optimization (SSO)-based routing for determining the most efficient paths. Simulation results show significant network lifetime improvement over several state-of-the-art protocols, including EAFTC-RIS, UCCAR-GWSO, FBECS, MLSLEEP, and bee-colony-based methods. In [11], a novel routing method based on clustering is proposed to maximize the lifetime of a WSN. The method involves two key phases: (1) selection of the optimal cluster head using a novel Artificial Electrical Field Algorithm (ML-AEFA), and (2) data transmission facilitated by the Gray Wolf Optimization algorithm. The CH selection considers various factors, including the node's energy, degree, the distance between sensor nodes, the distance to the base station, and the expected node lifetime. Simulation results show that the proposed method outperforms several baseline algorithms (MSA, AEFA, and BOA+ACO) in terms of network lifetime for a 100-node network. In [15], a hybrid clustering and routing scheme combining Gray Wolf Optimization (GWO), fuzzy logic, and multi-criteria decision-making (MCDM) is proposed for WSN-IoT environments. The GWO algorithm is used to select candidate cluster heads by considering factors such as node energy, distance, and connectivity, while fuzzy logic further refines the cluster-head selection by assessing various performance criteria. MCDM is applied to prioritize routing decisions, balancing energy consumption and improving the reliability of data transmission. Although it achieves substantial gains in network lifetime, energy efficiency, and throughput, the approach suffers from increased computational complexity and longer execution times owing to the integration of multiple optimization and decision-making techniques. In [19], a fuzzy multi-objective optimization scheme utilizing Particle Swarm Optimization (PSO) was developed to improve both energy efficiency and routing reliability in wireless sensor networks. The proposed approach combines the adaptive capabilities of PSO with fuzzy logic to address parameter uncertainties and optimize multiple objectives, including minimizing energy consumption, extending network lifetime, and enhancing data transmission reliability. A fuzzy inference system evaluates routing metrics, while PSO searches for optimal paths based on the resulting fitness values. The method achieves notable improvements in energy balance, packet delivery, and network stability. In [16], a fuzzy sink-based routing strategy was developed to improve energy efficiency and enhance reliable data delivery in wireless sensor networks. The proposed model utilizes a fuzzy inference mechanism at the sink node to assess factors such as remaining energy, communication distance, and network traffic, enabling the selection of the most efficient data transmission routes. By dynamically distributing the communication load and minimizing redundant data transfers, the approach contributes to lower energy consumption and longer network lifetime. In [20], a memetic-based adaptive clustering and routing technique was proposed to improve energy efficiency and resource utilization in wireless sensor networks. This approach combines memetic optimization with dynamic cluster formation to select cluster heads and establish routing paths, considering metrics such as residual energy, node density, and inter-node distance. The clustering and routing configurations are updated iteratively to balance energy consumption across the network and extend its operational lifetime. However, its higher computational overhead and dependency on accurate global network information may restrict scalability in large-scale or highly dynamic deployments. In [12], an energy-efficient routing strategy for wireless sensor networks was proposed by integrating Adaptive Entropy Bald Eagle Search Optimization (EBES) with density-based adaptive soft clustering. The approach applies EBES to optimize cluster-head selection and routing paths based on metrics such as residual energy, node density, and communication distance, while density-based soft clustering dynamically organizes clusters to evenly distribute network load. Clustering and routing decisions are updated iteratively to reduce energy consumption and prolong network lifetime. While effective in improving energy efficiency, network lifetime, and packet delivery ratio, the method incurs high computational overhead and requires accurate network state information.

3 Proposed method

This section first introduces the extremal optimization (EO) algorithm and then describes its application to cluster formation in wireless sensor networks. Extremal optimization is a meta-heuristic algorithm with the approach of local search, first proposed by Boettcher and Percacci in 2001 [4]. This algorithm has some applications in solving NP-hard combined optimization problems.

Extremal optimization is inspired by the physics of self-organized criticality (SOC). SOC refers to a system's ability to evolve naturally toward a critical state without relying on external control parameters or modifications to its initial conditions. The extremal optimization algorithm is also inspired by the Bak-Sneppen (BS) model in biological evolution. In the BS model, components have fitness values between 0 to 1, which represents the relative adaptability (or survival probability) of each species. Components with higher fitness have a higher chance of survival.

The components of this model are placed in the cells of a network. Each component has a random fitness with uniform distribution. In each update step, the worst component has to mutate. This mutation affects both the fitness of the selected species and its neighbors. It means that the fitness of components around the worst component is randomly changed. After many iterations, the system reaches a highly correlated state known as self-organized criticality (SOC). In this status, all components have fitness higher than a pre-defined threshold.

In SOC, small changes in a component lead to a set of co-evolutionary chain reactions called the avalanche. The size distribution of these avalanches follows a power-law distribution:

$$P(k) \propto k^{-\tau}, \tag{1}$$

where τ is a positive exponent. As a result, a small avalanche has a higher chance of occurring than a great avalanche. However, great avalanches must also be addressed because they affect the whole system, although with low probability. Thus, large avalanches consist of any possible change in the solution.

In contrast with the genetic algorithm, which deals with all genes of possible solutions and a population of candidate solutions, the extremal optimization algorithm iteratively eliminates the worst-performing component of a single solution S and evolves it toward better configurations. Each decision variable in solution S is considered a component in extremal optimization. The only operation used in extremal optimization is the mutation operator. By repeatedly mutating the worst component and its neighbors, the algorithm drives the solution toward high-quality configurations.

Therefore, a proper representation should be used to assign a quality criterion (fitness) to each component. This is in contrast to population-based evolutionary algorithms, which typically assign and evaluate a single fitness value to an entire solution [4]. In the proposed method, sensor nodes are randomly distributed in the environment and clustered using extremal optimization, considering both residual energy and distance to the sink. The steps of the extremal optimization algorithm are mentioned below:

Step 1: First, the sink sends a route request message to all sensor nodes, and the physical location of the sink is mentioned in this message. Each sensor node that receives this message will calculate its distance from the sink and sends its remaining energy value and ID in the form of an ACK packet in response to the sink request. After receiving this information, the sink registers them in its table. Given a network of 50 nodes, five cluster heads are selected. The EO algorithm maintains a population of 10 candidate solutions, each being a 5-element array of node IDs. The optimum solution as the initial population ($S_{best} = S_{current}$) is considered. The initial population is shown in Figure 1. Figure 1 illustrates an example of a candidate solution containing node IDs 30, 10, 5, 14, and 50 as potential cluster heads.

Table 1: Example of a candidate solution in the initial population

Cluster Head Candidates Solution	1	10	30	5	14	50

Until the termination condition, which is the completion of 100 repetitions, is reached, steps 2-1 to 2-4 are carried out.

Step 2.1: For each sensor node whose ID is in the initial population array, the fitness of each solution is calculated by fuzzy logic. The process of fitness calculation is explained in the following. The sink looks up the residual energy and distance of each candidate node ID in its local table and feeds these values into the fuzzy inference system. Figure 2 shows a block diagram of fuzzy logic for the proposed method.

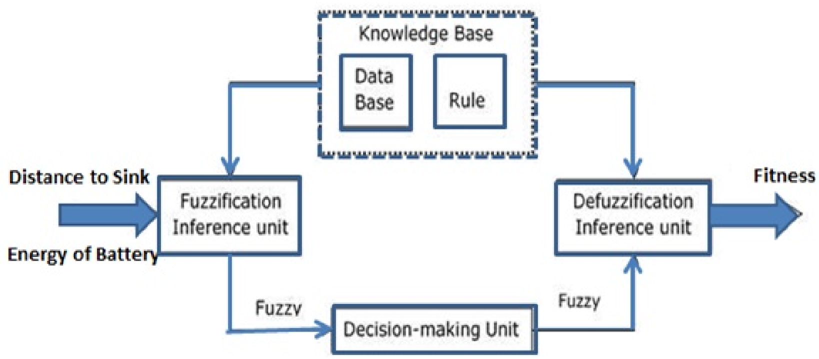


Figure 1: Block diagram of the proposed fuzzy inference system

Both input variables (residual energy and distance to the sink) are normalized to $[0, 1]$. Three triangular membership functions (Low, Medium, High) are used for each input, and five triangular membership functions (Very Low, Low, Medium, High, Very High) for the output (fitness), as shown in Figures 3–5. Equation (1) defines the membership function:

$$\mu(x) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x \leq b \\ \frac{c-x}{c-b} & b < x \leq c \\ 0 & x > c \end{cases} \tag{2}$$

where x represents the normalized input level of a sensor node. The parameters for the lower (a), middle (b), and upper (c) points of each triangular fuzzy set for the energy variable are summarized in Table 1.

Table 2: Parameters of the triangular fuzzy sets for residual energy

Fuzzy Set	**a**	**b**	**c**
Low (L)	0.00	0.01	0.25
Medium (M)	0.25	0.49	0.74
High (H)	0.74	0.99	1.00

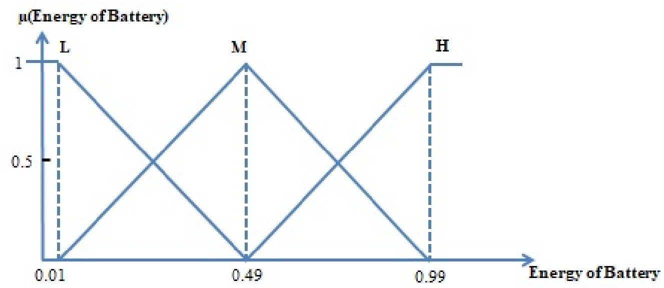


Figure 2: First input variable of the fuzzy system

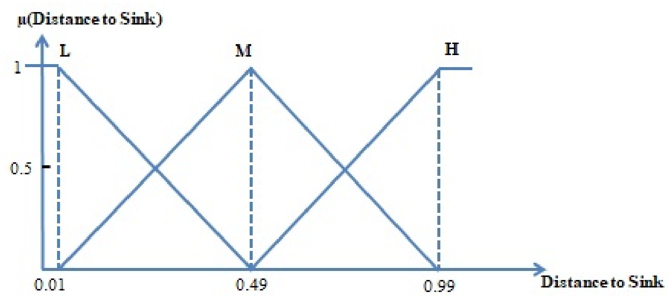


Figure 3: Second input variable of the fuzzy system

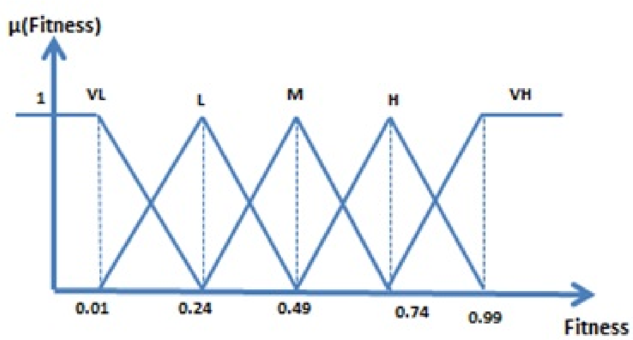


Figure 4: Output variable of fuzzy system

At the inference step, using nine fuzzy rules, fitness is calculated based on considered parameters: the distance of the sensor to the sink and the battery energy of the node. Each fuzzy rule consists of an antecedent (IF-part) such as "If the remaining energy level of a node is high and distance to sink is low" and a consequent (THEN-part) such as "Then fitness is very high." The proposed method employs the **Mamdani minimum** as the fuzzy inference engine.

Three fuzzy sets are defined for each of the two input parameters, resulting in a total of nine fuzzy rules ($3 \times 3 = 9$), as detailed in Table 2. The defuzzifier translates the fuzzy output into a numeric value, defined by Equation 3:

$$\text{Fitness}_i = \frac{\sum_{i=1}^{m} \mu_i \cdot z_i}{\sum_{i=1}^{m} \mu_i}, \tag{3}$$

where:

- i is the rule index.
- m is the number of fuzzy rules (here $m = 9$).
- n is the number of membership functions of input variables (here $n = 2$).

- μ_i is the fuzzy value (firing strength) of the membership function for rule i.
- z_i is the centroid of the corresponding output fuzzy set.

The overall fitness of the solution is then calculated as the average of the local fitness values:

$$\text{Fit} = \frac{1}{k}\sum_{i=1}^{k} \text{Fitness}_i. \tag{4}$$

where Fitness_i denotes the local fitness of the i-th candidate Cluster Head (CH), and Fit represents the overall fitness (the average of the five local fitness values, where $k = 5$).

Table 3: Fuzzy Rules

Rules #	**Inputs**		**Output**
i	**Distance to Sink**	**Remaining Energy Level**	**Fitness**
1	Low	Low	Medium
2	Low	Medium	High
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

Step 2.2: In each candidate solution, the Cluster Head (CH) candidate with the lowest local fitness is identified. Its neighbors are then evaluated, and the neighbor with the highest local fitness replaces the weakest node. The modified solution becomes the new candidate solution.
Step 2.3: The fitness function of the candidate population is recalculated using Equation (3). If the fitness of the candidate population is higher than that of the initial population (prior to the replacement of the weak node), the candidate population is designated as the new initial population.
Step 2.4: If the fitness of the candidate population exceeds the fitness of the current optimum solution, the optimum solution is replaced by the candidate population.
Step 3: Upon reaching the 100th iteration, the five node IDs in the best-found solution are officially designated as cluster heads.
Step 4: The sink node transmits a *cluster-selecting* message based on the node IDs in the best solution array, notifying them of their CH status. Subsequently, each CH generates an *Advertisement* message, including its physical coordinates and ID, and broadcasts it within its neighborhood. Non-CH nodes join the nearest CH by transmitting a *Join-Request* message containing their ID, residual energy, and location. The pseudocode and flowchart of the EOFBCA are illustrated in Figures 6 and 7, respectively. The process initiates when the sink node disseminates a *route-request* signal across the network to acquire the spatial location and remaining energy of each sensor node. Using this collected data, the extremal optimization algorithm constructs an initial set of potential cluster-head configurations. In every iteration, the fuzzy inference engine computes a fitness score for each candidate CH by considering two essential attributes: the node's energy reserve and its distance to the sink. The candidate exhibiting the weakest fitness performance is substituted with a neighboring node that demonstrates a higher suitability level. Whenever this modification leads to an improvement in the global fitness score, the updated configuration becomes the current optimal solution. This evolutionary process proceeds until the predefined stopping criterion is fulfilled. Subsequently, the nodes with the highest fitness values are elected as CHs and issue announcement messages to nearby nodes, initiating cluster organization. Each ordinary node then affiliates with its closest and most energy-efficient CH, resulting in a well-balanced cluster structure and reduced energy expenditure during data routing.

The pseudocode and flowchart of the EOFBCA are illustrated in Figures 6 and 7, respectively. The process initiates when the sink node disseminates a *route-request* (RREQ) signal across the network to acquire the spatial location and remaining energy of each sensor node.

```
Function EO(problem) returnsa state that is a local maximum
Input:Problem_size,iterations_max,τ
Output:S_best
S_current ← CreateInitialSolution(Problem_size);
S_best ← S_current;
for k=1 to iterations_max do
  foreach Component_i ∈ S_current do
    Component_i^fitness ← Fitness(Component_i,S_current);
  end
  RankedComponents ← Rank(S_current^components)
  Component_i ← SelectWeakComponent(RankedComponents,Component_i,τ);
  Component_j ← SelectReplacementComponent(RankedComponents,τ);
  S_candidate ← Replace(S_current,Component_i,Component_j);
  if Fitness(S_candidate) ≥ Fitness(S_current) then
    S_current ← S_candidate;
    if Fitness(S_candidate) ≥ Fitness(S_best) then
      S_best ← S_candidate;
    end
  end
end
return S_best;
```

Figure 5: pseudo-code of extremal optimization for the proposed method.

3.1 Computational complexity analysis

The computational complexity of the proposed EOFBCA algorithm primarily depends on the number of sensor nodes (N), the population size (P), and the number of iterations (T). In each iteration, the algorithm evaluates the fitness of candidate nodes using the fuzzy inference system, which requires O(N) operations. The extremal optimization phase then identifies the least-fit CH candidate and replaces it with a higher-fitness neighbor, also incurring O(N) cost. Consequently, the total computational complexity of EOFBCA is $O(P \times N \times T)$. Consequently, the total computational complexity of the EOFBCA algorithm can be expressed as: $O(P \times N \times T)$. This complexity level is comparable to, and often lower than, that of other metaheuristic-based clustering protocols such as AFSRP, BFOABMS, and NODIC.

3.2 Convergence justification

The convergence behavior of the proposed EOFBCA algorithm has been analyzed to confirm its stability and reliability.The extremal optimization–based selection mechanism progressively eliminates low-fitness components and substitutes them with higher-quality alternatives, thereby directing the search process toward near-optimal cluster configurations. This iterative refinement strategy facilitates steady convergence while minimizing the risk of premature stagnation. Simulation results (Section 4.2) show that the global fitness value stabilizes after approximately 70–80 iterations, indicating that the algorithm consistently converges to a stable clustering configuration within a limited number of iterations. This observed convergence behavior validates the robustness, efficiency, and practical applicability of the proposed EOFBCA approach in dynamic wireless sensor network environments. Compared with other hybrid metaheuristic-fuzzy approaches (e.g., ACO–Fuzzy, PSO–Fuzzy, GA–Fuzzy), the integration of extremal optimization with fuzzy logic in EOFBCA provides unique advantages. Unlike population-based algorithms that rely on crossover or velocity updates, EO focuses on improving a single solution by repeatedly replacing its weakest component. Embedding fuzzy inference into the fitness evaluation enables flexible, multi-criteria assessment of node suitability (residual energy and distance to sink) without requiring explicit tuning parameters. The fuzzy system also introduces controlled uncertainty that balances exploration and exploitation, thereby mitigating the risk of premature convergence often observed in pure EO. This complementary synergy (efficient local improvement from EO and adaptive multi-criteria reasoning from fuzzy logic) results in faster convergence, lower computational overhead, and superior performance in energy consumption, network stability, and lifetime.

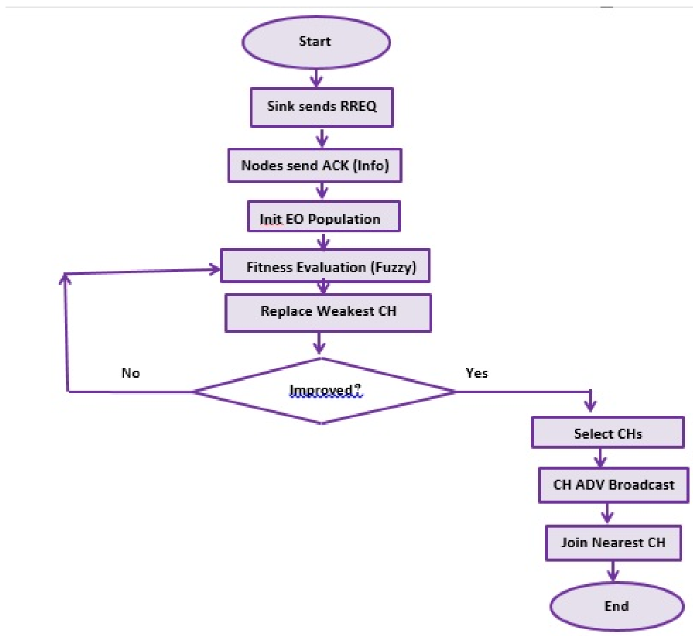


Figure 6: Flowchart of the EOFBCA process.

3.3 Processing time evaluation

In addition to the theoretical analysis presented in Section 3.1, the practical processing time of the proposed EOFBCA algorithm was examined to verify its computational efficiency. The simulation experiments were carried out in the OPNET 11.5 environment on a system equipped with an Intel® Core™ i3-6100U processor (2.3 GHz) and 8 GB of RAM. For a network topology consisting of 50 sensor nodes and 100 iterations, the average processing time per iteration was approximately 0.012 seconds, yielding a total clustering time of about 1.2 seconds. This low execution time confirms that EOFBCA is computationally lightweight and well-suited for real-time or near-real-time clustering in medium-scale wireless sensor networks.

4 Simulation of the proposed method

4.1 Simulation environment

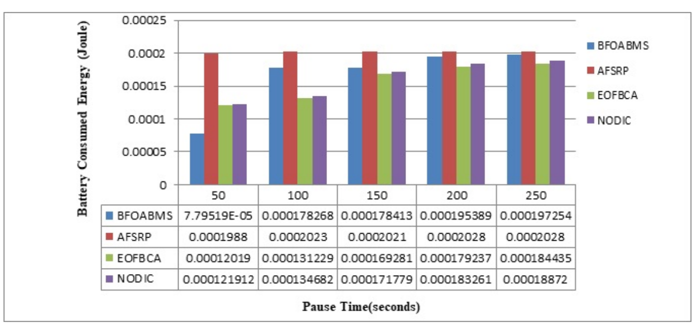
OPNET Modeler 11.5 is used in this study to simulate the suggested approach and compare it to the AFSRP, BFOABMS, and NODIC protocols. This software allows network designers and researchers to anticipate the performance of protocols and equipment with good accuracy through simulation. In the simulation environment, 50 sensor nodes are randomly deployed within a 1000 × 1000 m area to emulate a realistic and unbiased network scenario. The same network topology is used for all four protocols (EOFBCA, AFSRP, BFOABMS, and NODIC) to ensure that performance comparisons were conducted under identical conditions. The random deployment of nodes allows for a fair evaluation of clustering efficiency and energy consumption under non-deterministic spatial distributions, while maintaining consistent topological parameters across all protocols guarantees reliable comparative results. The communication model in OPNET was configured according to the IEEE 802.15.4 standard, which is widely adopted in low-power wireless sensor networks. Each node was equipped with a transceiver operating at 2.4 GHz and a maximum transmission range of 100 m. The free-space propagation model was employed to simulate signal attenuation, and the CSMA/CA medium access mechanism defined by IEEE 802.15.4 was used for channel coordination. Each node is initialized with a random initial energy uniformly distributed between 200 J and 400 J. All nodes generate data packets of 1024 bytes. This configuration realistically emulates the energy-constrained nature of WSNs and enables reliable evaluation of connectivity, throughput, and energy efficiency. Also, to ensure a fair and unbiased comparison of the evaluated protocols, several key factors were standardized across all simulations. A consistent network topology, consisting of 50 nodes randomly deployed within a 1000x1000m area, was employed for all protocols to eliminate any bias stemming from variations in network layout. Additionally, each protocol was simulated for an identical duration of 150 seconds, with uniform initial energy levels (ranging from 200 to 400 Joules per node), ensuring consistency in both operational time and energy configuration. The node setup, including the use of a Random Waypoint mobility model, was also kept consistent across all protocols. Simulation parameters are shown in Table 3. This paper considers a network with a 50-nodes topology based on four scenarios. In this regard, the first scenario works based on the NODIC protocol; the second scenario works based on the proposed method (EOFBCA protocol), the third scenario works based on the AFSRP protocol, and the fourth scenario works based on the BFOABMS scenario. The same topology is considered for each of our scenarios.

Table 4: Simulation Parameters

Parameter	**Value**
Nodes' distribution in the area	Random
Size of simulation area	$1000\,m \times 1000\,m$
Simulation time	150 seconds
Initial energy	200–400 Joules
Packet size	1024 bytes
Number of nodes	50
Radio transmission range	100 meter
Mobility Model	Random Waypoint

4.2 Simulation results

Figure 8 compares total network energy consumption over simulation time for the four protocols. The vertical axis represents the consumed energy, while the horizontal axis indicates simulation time. As depicted in Figure 8, In AFSRP [6], CHs often experience rapid energy depletion after cluster formation due to heavy data forwarding loads, which can lead to early node failure. Similarly, in the BFOABMS protocol [18], if a node with the shortest distance to the sink and sufficient remaining energy is unavailable, the clustering process will not be repeated. This algorithm also employs direct data transmission for cluster heads located closer to the sink. Consequently, when a high data volume exists, these cluster heads must consume more energy to transmit the data, causing them to deplete their energy and shut down. In the NODIC protocol [1], if a node with a sufficient number of neighbors and remaining energy above the threshold is not present, reclustering will not occur. As a result, the cluster heads will deplete their energy rapidly in subsequent iterations. In contrast, EOFBCA consistently selects CHs with high residual energy and short distance to the sink using extremal optimization and fuzzy logic. As a result, member nodes are more likely to connect to the nearest cluster head within their vicinity, reducing the energy required to send data from the member node to its cluster head. This approach leads to a noticeable improvement in energy consumption. EOFBCA reduces total energy consumption by 22.24% compared to AFSRP, 5.18% compared to BFOABMS, and 1.99% compared to NODIC.

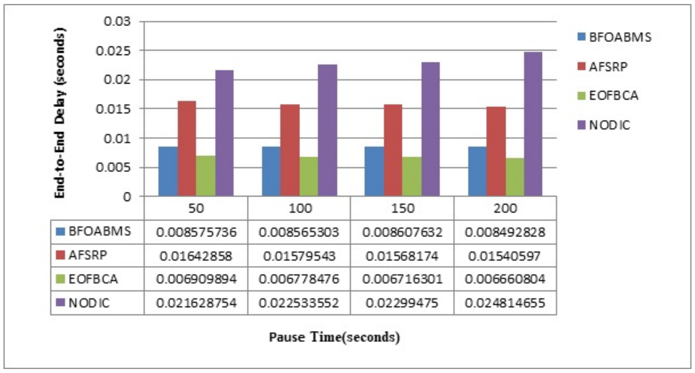


	50	100	150	200	250
BFOABMS	7.79519E-05	0.000178268	0.000178413	0.000195389	0.000197254
AFSRP	0.0001988	0.0002023	0.0002021	0.0002028	0.0002028
EOFBCA	0.00012019	0.000131229	0.000169281	0.000179237	0.000184435
NODIC	0.000121912	0.000134682	0.000171779	0.000183261	0.00018872

Figure 7: Average of network consumed energy.

Figure 9 compares end-to-end delay for the four protocols over simulation time. The vertical axis represents the end-to-end delay, while the horizontal axis indicates simulation time. As shown in Figure 9, the NODIC protocol exhibits the highest end-to-end delay among the protocols. This is due to the rapid depletion of energy in the cluster heads during the initial iterations, which prevents them from transmitting sensed data. Consequently, the end-to-end delay increases as a result of the network's inability to forward data efficiently. Similarly, in the AFSRP protocol, the energy of the cluster heads decreases in the early iterations, which can cause transmission failures. Moreover, due to the absence of a reclustering mechanism, new cluster heads are not selected, further exacerbating the delay. In the

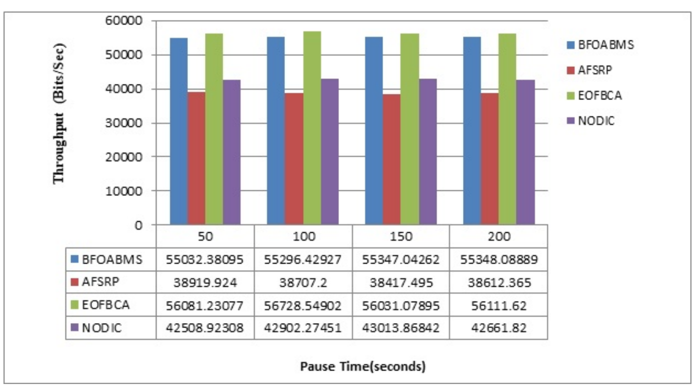
BFOABMS protocol, cluster heads located near the sink may be turned off early in the simulation due to the high volume of data being transmitted. This forces the protocol to artificially increase end-to-end delay to preserve near-sink CHs. In contrast, the EOFBCA method utilizes fuzzy logic to accurately evaluate the fitness of each candidate cluster head based on two critical factors: distance to the sink and remaining energy. This method ensures the selection of optimal cluster heads, which rarely deplete their energy during data transmission. As a result, the end-to-end delay is significantly reduced. EOFBCA reduces average end-to-end delay by 57% relative to AFSRP, 20.95% relative to BFOABMS, and 70.75% relative to NODIC.



	50	100	150	200
BFOABMS	0.008575736	0.008565303	0.008607632	0.008492828
AFSRP	0.01642858	0.01579543	0.01568174	0.01540597
EOFBCA	0.006909894	0.006778476	0.006716301	0.006660804
NODIC	0.021628754	0.022533552	0.02299475	0.024814655

Figure 8: End-to-end delay.

Figure 10 compares network throughput (successfully delivered bits per second) over time. As shown in Figure 10, the AFSRP protocol exhibits a lower transfer rate compared to the proposed method and the other protocols. Specifically, the number of successfully delivered packets to the sink node is significantly lower relative to the total number of transferred packets. Similarly, the NODIC protocol demonstrates a reduced transfer rate, as it may fail to complete data transfer in the event of errors. The BFOABMS protocol, utilizing a mobile sink and data transmission through cluster heads near the sink, shows an improved transfer rate compared to the other protocols. However, cluster heads near the sink node are susceptible to the hotspot problem, where they may be unable to complete data transmission, resulting in a reduced transfer rate compared to the proposed method. As a result, the EOFBCA method consistently outperforms the other protocols in terms of transfer rate, as shown in Figure 10. This performance can be attributed to two key factors: (1) during the clustering process, nodes are optimally selected based on their path energy and proximity to the sink, leveraging the combined capabilities of the Extremal Optimization algorithm and fuzzy logic, and (2) the method generates stable and reliable routes, which remain static until the data transfer phase is completed. EOFBCA improves throughput by 31% over AFSRP, 1.74% over BFOABMS, and 23.94% over NODIC. Figure 11 shows the average signal-to-noise ratio (SNR) over simulation time. The horizontal axis represents



	50	100	150	200
BFOABMS	55032.38095	55296.42927	55347.04262	55348.08889
AFSRP	38919.924	38707.2	38417.495	38612.365
EOFBCA	56081.23077	56728.54902	56031.07895	56111.62
NODIC	42508.92308	42902.27451	43013.86842	42661.82

Figure 9: Transferring rate.

simulation time, while the vertical axis shows the signal-to-noise ratio. As observed, the AFSRP protocol exhibits a lower SNR compared to the other protocols. This is because, during data transmission, the error rate may increase due to disturbances, which consequently reduces the SNR. Furthermore, in the NODIC protocol, if no node with a high number of neighbors and remaining energy above the threshold exists, reclustering may not occur to select new cluster heads. This leads to energy depletion in the cluster heads, resulting in a reduction in the SNR. As a result, the SNR in the NODIC protocol is lower compared to the BFOABMS and EOFBCA protocols. In the BFOABMS protocol, cluster heads located near the sink node may be turned off due to the hotspot problem, leading to a further decrease in the SNR. In contrast, the EOFBCA method benefits from the selection of stable routes, which are ensured by the use of fuzzy logic and the extremal optimization algorithm. These routes remain stable throughout the data transfer phase, thus maintaining a higher SNR. As a result, EOFBCA demonstrates significant SNR improvements over AFSRP, BFOABMS, and NODIC, achieving gains of 47%, 20.73%, and 45.72%, respectively. Figure 12 compares packet delivery

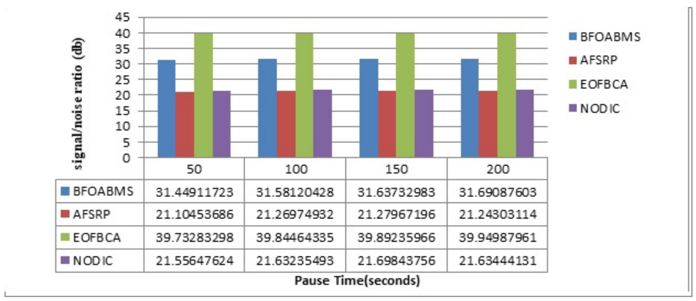


Figure 10: Signal-to-noise ratio.

ratio (PDR) to the sink for the four protocols. As shown in Figure 12, the NODIC protocol exhibits a lower success probability for data transmission compared to the other three methods. This is primarily due to the fact that in the NODIC protocol, each cluster head node transmits data directly to the base station in a single hop. This approach is energy-intensive, particularly for nodes that are located farther from the sink, leading to faster energy depletion and a reduction in network lifetime. In the AFSRP protocol, the success probability of data transmission is lower than that of the BFOABMS and EOFBCA protocols, as some network nodes may shut down due to errors or battery depletion, preventing the successful transfer of data to the sink node. In the BFOABMS protocol, the success probability is further reduced by the hotspot problem, where cluster head nodes near the sink may deplete their energy rapidly due to the high volume of data they handle. In contrast, the proposed EOFBCA method enhances the success probability of data transmission to the sink by selecting stable routes composed of nodes with higher energy reserves. This approach ensures more reliable transmission, leading to an increase in the success probability. EOFBCA improves PDR by 1% over AFSRP, 57% over BFOABMS, and 2.29% over NODIC. To ensure statistical reliability, each simulation scenario

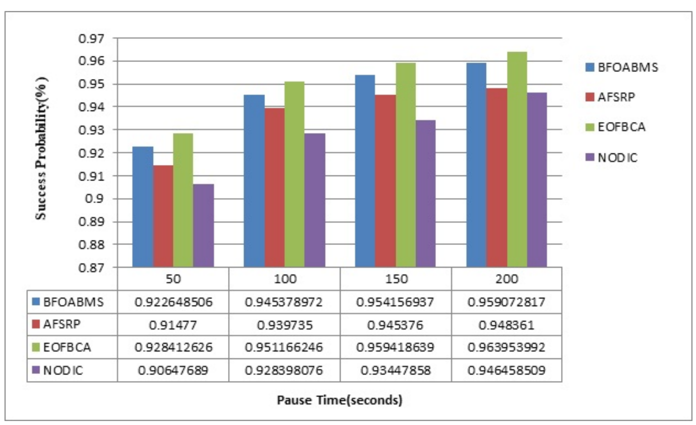


Figure 11: The success probability of data transmission to the sink.

was executed five independent times using different random seeds (128, 256, 384, 512, and 640). Figures 13–16 present the mean performance metrics across five independent runs, with error bars indicating the standard deviation (Mean $\pm$ SD).

In addition, a one-way analysis of variance (ANOVA) was conducted to examine the presence of statistically significant variability among the independent runs. The resulting p-values were as follows: End-to-End Delay, $p = 0.0632$; SNR, $p = 0.4813$; Success Probability, $p \approx 8.21 \times 10^{-44}$; and Throughput, $p \approx 1.14 \times 10^{-7}$.

These findings confirm that the End-to-End Delay and SNR metrics remain statistically consistent across simulation replications (i.e., no significant differences at $\alpha = 0.05$). Conversely, the Success Probability and Throughput metrics exhibit statistically significant run-to-run variations, which can be attributed to stochastic data traffic patterns and transient routing dynamics inherent in wireless sensor networks. Overall, the use of multiple replications, error-based variability analysis, and ANOVA strengthens the robustness and credibility of the experimental results.

Figure 13 illustrates the End-to-End Delay performance of the proposed EOFBCA protocol over the simulation duration. The plotted curve represents the mean delay across five independent simulation runs, while the error bars indicate the corresponding standard deviation (Mean ± SD). The results show that EOFBCA consistently maintains low latency throughout the network lifetime, demonstrating its capability to establish efficient routing paths and minimize both propagation and queuing delays. Moreover, the narrow error margins confirm the protocol's robustness and reliability under stochastic network conditions, reflecting stable performance despite random variations in traffic and topology dynamics. Figure 14 depicts the average Signal-to-Noise Ratio (SNR) obtained across five independent simulation replications, with error bars representing the corresponding standard deviation (Mean ± SD). The consistently stable trend in SNR indicates that the EOFBCA protocol sustains strong and interference-resilient communication links throughout the simulation period. The minimal variability observed between runs further verifies the effectiveness and robustness of the protocol's link-quality estimation mechanism under dynamic wireless channel conditions. Figure 15

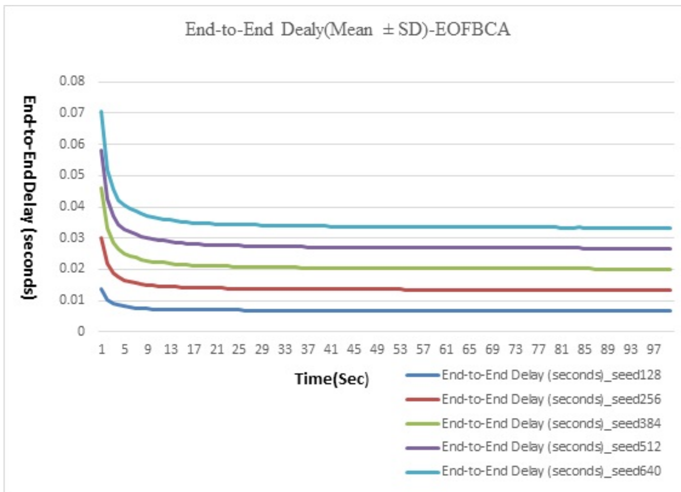


Figure 12: Average end-to-end delay vs. simulation time (5 runs).

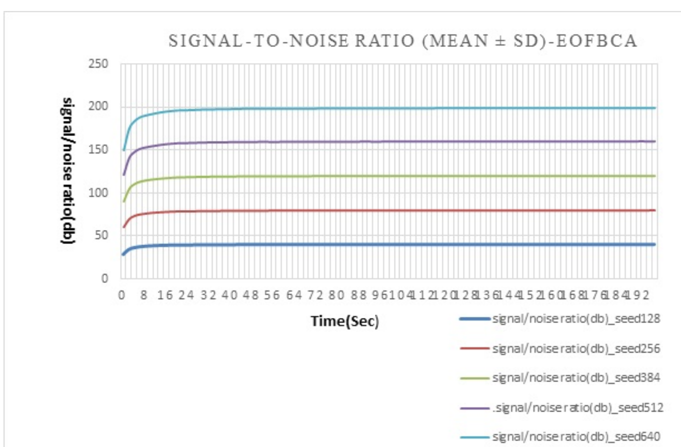


Figure 13: Average SNR vs. simulation time (5 runs).

presents the mean packet success probability measured across five independent simulation runs, with error bars indicating the corresponding standard deviation (Mean ± SD). Although slight fluctuations are observed—primarily due to stochastic traffic variations and occasional congestion—the overall trend demonstrates that the EOFBCA protocol sustains a high packet delivery ratio throughout the simulation. The observed variability aligns with transient changes in network topology and traffic conditions, further confirming the protocol's adaptability in dynamic wireless sensor network environments. Figure 16 illustrates the throughput performance over the simulation duration, where the plot-

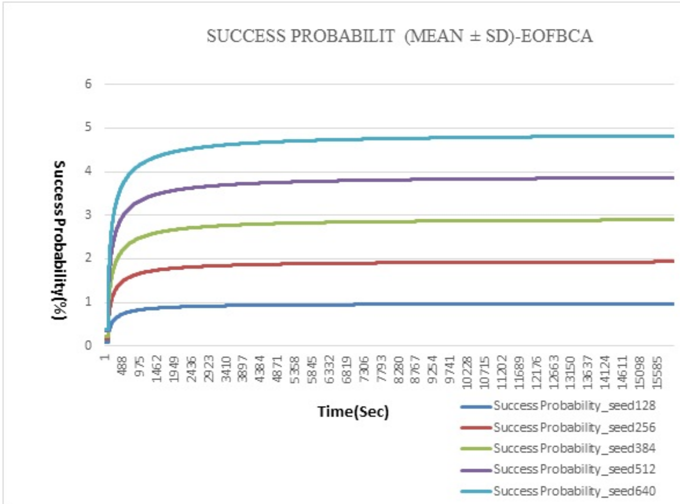


Figure 14: Average packet delivery ratio vs. simulation time (5 runs).

ted values represent the mean throughput derived from five independent simulation runs, and the error bars correspond to the standard deviation (Mean ± SD). The results demonstrate the capability of the EOFBCA protocol to sustain a high data delivery rate while effectively adapting to dynamic network conditions. Although some variability is observed among different runs, the overall trend confirms robust bandwidth utilization and efficient congestion-handling mechanisms, highlighting the protocol's effectiveness in enhancing data transmission efficiency in wireless sensor networks.

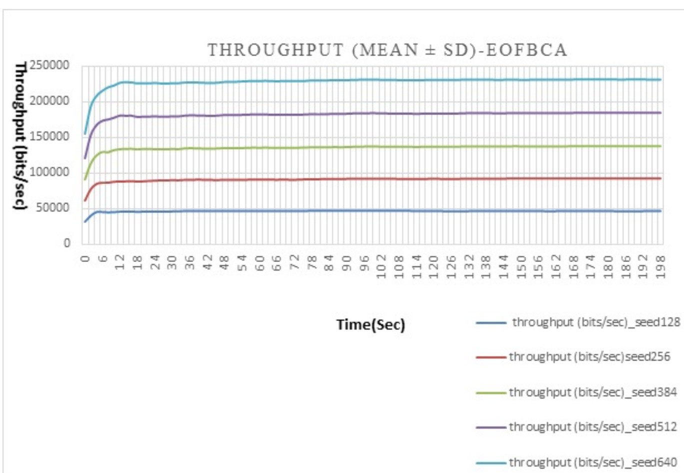


Figure 15: Average throughput vs. simulation time (5 runs).

5 Conclusions

This paper proposes EOFBCA, a novel clustering and routing protocol that integrates extremal optimization with fuzzy logic to improve energy efficiency in wireless sensor networks. The performance of EOFBCA is evaluated using OPNET Modeler 11.5 and compared with three state-of-the-art protocols: AFSRP, BFOABMS, and NODIC. Simulation results demonstrate superior performance across all key metrics: energy consumption, end-to-end delay, signal-to-noise ratio (SNR), packet delivery ratio, and throughput. EOFBCA consistently outperforms the benchmark protocols, primarily due to its effective selection of CHs based on residual energy and distance to the sink. Furthermore, the construction of stable multi-hop routes via a minimum spanning tree significantly enhances overall network lifetime and reliability.

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This study has received no funding from any organizations.

Conflicts of interest

All of the authors declare that they have no conflict of interest.

Availability of data and material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Code availability

All code for data analysis associated with the current submission is available from the corresponding author upon reasonable request.

Ethical approval

This article does not contain any studies with human par- ticipants or animals performed by any of the authors.

Consent to participate

This article does not contain any studies with human par- ticipants or animals performed by any of the authors.

Consent for publication

This article does not contain any studies with human par- ticipants or animals performed by any of the authors.

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