

## Enhancing Sensor Network Lifetime through Optimal Path Selection and Cluster Head Optimization using Energy-Aware Routing

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### Abstract:

Effective routing strategies are crucial for prolonging the lifespan of wireless sensor networks (WSNs) while maintaining effective data transmission. In densely deployed WSNs, interference and channel congestion can degrade communication quality and increase energy consumption. A fundamental challenge in WSNs is to ensure a prolonged network lifetime while maintaining efficient data transmission. This research presents a novel approach to address this challenge through a framework designed to optimize routing paths, ultimately maximizing the operational lifetime of sensor networks. Motion and Energy Distribution Modelling involves comprehending the motion of the sink nodes and the evolution of their energy levels. The performance metrics related to motion and energy density is calculated using the bee algorithm. A key aspect of the framework is the formation of clusters facilitated by fuzzy logic-based techniques. Additionally, an Energy-aware routing algorithm is employed to select Cluster Heads (CHs) depend on a holistic assessment of various parameters, including trust, resource availability, spatial positioning, neighbouring nodes, and energy profiles. The proposed BA-EAIOR obtained values of 50 nodes is 7, 0.43, 0.22, 0.806 and 100 nodes is 25, 0.0308, 0.34, 0.566, which shows significant improvements in network efficiency and longevity.

**Keywords:** Wireless Sensor Networks, Cluster Head, Fuzzy Logic, BA-EAIOR, Fitness Evaluation.

## 1. Introduction

The utilization of WSN has introduced numerous conveniences into our daily lives. WSN play a vital role in gathering and transmitting data from remote environments. WSNs consist of numerous sensor nodes capable of wireless communication, information sensing, and environmental event detection [1] [2]. In conventional WSN transmission, sensor nodes are tasked not only with transmitting their data but also with relaying data generated by other nodes to the sink [3]. Consequently, sensor nodes near the sink tend to expend more energy compared to those located farther away, giving rise to a significant sinkhole issue [4]. Nonetheless, sensor nodes operate on limited battery power and are frequently not feasible to recharge. This limitation implies that the lifespan of WSNs is bound by the finite energy of

the sensor nodes. Consequently, conserving sensor node energy emerges as the paramount concern for ensuring the extended operation of WSNs [5]. Enhancing energy efficiency and extending network longevity involve the utilization of a clustering-based hierarchical routing protocol. This protocol minimizes total transmission distance and effectively distributes energy consumption among nodes throughout the network's lifespan [6].

WSNs are characterized by resource-constrained sensor nodes, dynamic network topologies, and stringent energy constraints. These characteristics necessitate innovative approaches to ensure sustainable and efficient network operation. In this context, optimal routing strategies play a pivotal role in achieving a balance between data transmission efficiency and energy conservation. Enhancing the operational lifespan of WSNs through the integration of a mobile sink represents a significant and complex challenge that has garnered growing interest within the research community. Numerous researches have delved into the routing challenges within Wireless Sensor Networks (WSNs), resulting in the proposal of various routing methodologies, including flat, clustering, hierarchical, and location-based algorithms. These investigations have consistently shown that cluster-based routing protocols surpass alternative approaches in terms of enhancing the scalability and longevity of WSNs [7],[8],[9]. Consequently, the practice of clustering sensor nodes emerges as a pragmatic approach to curbing energy consumption in WSNs. To collect data from the non CHs, clustering techniques segregate sensor nodes into clusters. Furthermore, the critical process of CH selection and cluster formation significantly contributes to reducing energy consumption in WSNs. Therefore, an efficient clustering strategy not only conserves energy in sensor nodes but also extends the network's lifespan.

In this exploration of routing algorithms, we delve into the diverse array of research conducted by various scholars, shedding light on their innovative contributions to this critical field of computer science. Hui Wang [5]. Enhancing the path of the sink node using an EHMO-based routing algorithm extends its lifespan and significantly balances the energy consumption of the sensor nodes. When a large number of impractical solutions combine to form a big infeasible region, the metaheuristics algorithm EHMO finds it challenging to discover a workable solution. Ramin Yarinezhad and Seyed Naser Hashemi [10] employed an EB-CRP routing protocol to increase the life span of sensor networks which results in improved network efficiency compared to other protocols. Speeding up the suggested fpt-approximation algorithm's execution time is a challenging task. Kongara Mahesh Chowdry and Venkastanareshbabu Kuppili [8] modeled a JayaX-LSM-CHS algorithm to choose a useful collection of CHs. Performance analysis demonstrates superior results compared to existing algorithms for LN. However, the method's efficiency might decrease when applied to large-scale sensor networks, as the complexity of path planning and communication management could grow substantially. Xiuwen Fu and Xiaolin H [4] e used a clustering algorithm named energy-balanced data collection. This method improves the path length and decreases energy consumption. But this method will give rise to certain sub-problems, including the distribution of load among individual mobile sinks and the establishment of their cooperative mechanisms. S.Prithi and S.Sumathi [6] modeled a hybrid algorithm for optimal and energy-efficient routing in WSN which is used for secured data transmission. The integration of multiple optimization algorithms and automata-based mechanisms can increase the complexity of the overall algorithm, making it challenging to implement, debug, and maintain.

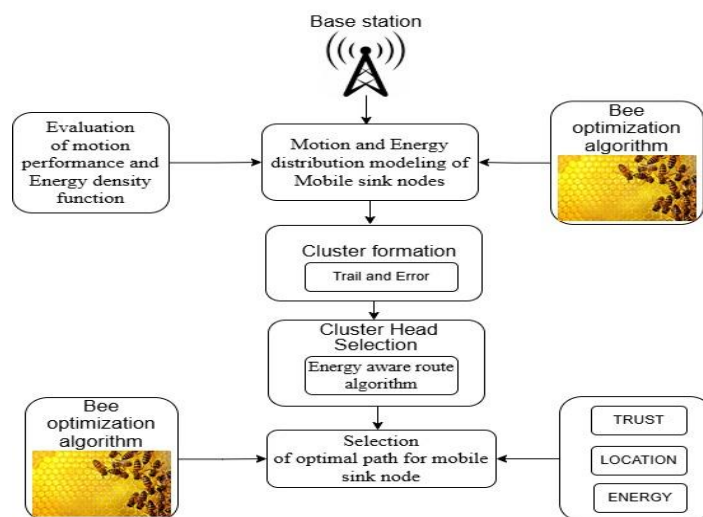
Challenges in existing researches:

1. While the hybrid PSO-GWO algorithm aims to achieve both security and energy efficiency, there might be trade-offs between these objectives. Strengthening security measures could potentially lead to increased energy consumption [6].
2. The effectiveness of mobile sink path construction heavily depends on accurate mobility prediction and real-time adaptation. If the mobility patterns are unpredictable or hard to estimate, it might result in suboptimal path choices [4].
3. In cases where a substantial number of infeasible solutions cluster to create extensive infeasible regions, the metaheuristics algorithm EHMO faces challenges in locating feasible solutions. Consequently, this could result in the potential omission of optimal next address for the sink node [5].
4. The FPT-approximation algorithm's performance could heavily depend on the specific topology of the sensor network, potentially leading to variations in effectiveness across different network configurations. The algorithm might require parameter tuning to achieve optimal performance, and selecting suitable parameter values could be non-trivial and time-consuming [10].
5. Integrating enhanced clustering and mobile sink path construction algorithms could increase the complexity of the system, potentially making it challenging to implement, maintain, and troubleshoot [8].

In this research, a framework for optimal routing to prolong the lifetime of the sensor network using energy-aware algorithm is introduced. The main goal of the research is to choose the best route for mobile sink nodes to extend lifespan of the sensor network. To do this, data collected from the BS is subjected to modelling of the sink nodes' motion and energy distribution, and the performance of motion and energy density is then calculated using Bee optimization to halt the motion of the data. Fuzzy logic is used to create clusters from the measured data to reduce BS traffic. Then, using an Energy-aware routing method, the CH is chosen in consideration of the trust, resource, location, number of neighbours, and energy. The chosen cluster head is then put through the process of choosing the best route for the mobile sink node, which is optimized using the Bee optimization to select feasible path. The following is a presentation of the research's main contribution:

## 2. Methods

The (EAIOR) framework for optimal routing utilizing energy aware algorithm to extending the sensor networks' lifespan is founded on a systematic and iterative approach that integrates various stages. Each stage contributes to the overall effectiveness of the routing strategy and ultimately aims to prolong the operational lifespan of the network. This involves analysing the data collected from the Base Station (BS) and applying motion and energy distribution models to the sink nodes. Specifically, the performance of motion and energy density is quantified through Bee optimization, which aids in halting data movement when required. The collected data is then subjected to a clustering process that leverages fuzzy logic to establish clusters, thereby alleviating congestion at the BS and optimizing data flow. Subsequently, the selection of CH is conducted using an Energy-aware routing algorithm. The criteria for CH selection encompass factors such as trust, resource, location, Number of neighbors, and energy. Once the CH is identified, the focus shifts to identifying the optimal paths for mobile sink nodes. Bee optimization [11] techniques are utilized to achieve this, ensuring that the selected paths are the most efficient.



**Figure 1: Block diagram for Energy aware algorithm-based optimum routing**

**2.1 Mathematical representation of the sensor networks:**

A uniform collection of sensor nodes is strategically positioned within the designated region. Once deployed and fully encircling the target area, all of the sensor nodes become static, upon deployment all sensor nodes assume a stationary state within the target area, effectively converging in its entirety. The central sink, which is also stationary, is positioned beyond the confines of the target area. All sensor nodes are endowed with an equivalent initial energy supply and each sensor node is individually label with a distinct identification number. Furthermore, each sensor node possesses a defined sensing range  $\alpha$  and communication range  $A$ . In WSNs, the predominant energy-consuming tasks encompass data transmission and reception. The energy expenditure associated with transmitting or receiving data is contingent on both the distance,  $d$ , separating the communicating entities, and the dimensions of the data packet. Given these premises, the energy required to transmit a data packet of size  $\alpha$  bits is quantified as:

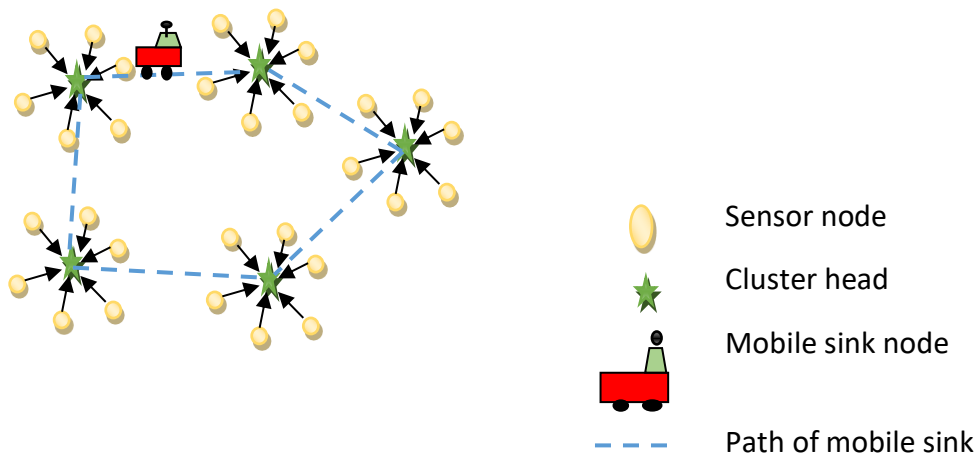
$$E_{tx} = (\alpha, \beta) = \begin{cases} \beta E_{ds} + \beta \xi_{FS}, & \alpha \leq \alpha_{th} \\ \beta E_{ds} + \beta \xi_{MP}, & \alpha > \alpha_{th} \end{cases} \quad (1)$$

Here,  $E_{tx}$  denotes the energy utilization for data transmission, the parameter  $\alpha$  corresponds to length of the data, while  $E_{ds}$  denotes the amount of energy required to send or receive a single bit of data,  $\xi_{FS}$  denotes energy dissipation coefficient according to the free space propagation model,  $\xi_{MP}$  signifies energy dissipation coefficient in the context of the multi-path attenuation model, and  $\alpha_{th}$  signifies the transmission distance threshold, as stipulated in the equation.

$$\alpha_{th} = \sqrt{\frac{\xi_{FS}}{\xi_{MP}}} \quad (2)$$

Explaining research chronological, including research design, research procedure (in the form of algorithms, Pseudocode or other), how to test and data acquisition [12], [13], [14]. The description of the course of research should be supported references, so the explanation can be accepted scientifically [15], [16]. Figures 2 are presented center, as shown below and cited in the manuscript [12], [17], [18],

[19], [20], [21], [22]. The variation of average repeater spacing RR, km against number of links and initial Raman pump wavelength shown in Figure 1.



**Figure 2: Sample of mobile-sink WSN model.**

## 2.2 Cluster formation using Fuzzy logic technique

Creation of clusters using the fuzzy logic technique involves categorizing data elements into groups in a way that allows for degrees of membership to multiple clusters, considering the fuzzy nature of relationships between elements. Distance-based grouping, often associated with clustering, is a technique used to group similar data points based on their proximity or similarity in a multidimensional space. Fuzzy logic can be incorporated into distance-based grouping methods to handle uncertainty in assigning data points to clusters. One popular approach that combines distance-based clustering with fuzzy logic is the Fuzzy C-Means (FCM) algorithm [23].

The algorithm reduces an objective function that accounts for the distances between data points and cluster centroids, as well as the degree of membership of each data point to every cluster. The equation for the objective function in the FCM algorithm is as follows:

$$I_n = \sum_{x=1}^M \sum_{y=1}^l V_{xy}^n \|k_x - l_y\|^2, \quad 1 \leq n \leq \infty \quad (3)$$

Where  $I_n$  is the objective function to be minimized,  $M$  represents the number of data points, number of clusters is illustrated as  $l$ ,  $V_{xy}$  represents the degree of membership of data point  $k_x$  to cluster  $l_y$ ,  $n$  is a fuzziness exponent, typically set to a value greater than 1 to control the degree of fuzziness,  $k_x$  is the  $x$  th data point,  $l_y$  denotes the centroid of the cluster  $y$ , and  $\|k_x - l_y\|$  represents the Euclidean distance between the data point  $k_x$  and  $l_y$ . The cluster centroids  $l_y$  and membership degrees  $V_{xy}$  are iteratively updated by the FCM method until convergence. The subsequent equation can be utilized to compute the degree of membership  $V_{xy}$  which indicates how closely data point  $k_x$  relates to cluster  $l_y$ :

$$V_{xy} = \frac{1}{\sum_{i=1}^l \left( \frac{\|k_x - l_y\|}{\|k_x - l_i\|} \right)^{\frac{2}{n-1}}} \quad (4)$$

Where  $i$  iterates the overall cluster.

### 2.3 Decision of the cluster head using energy-aware route algorithm

Enhancing data aggregation and communication, extending network longevity, and improving energy efficiency are the key objectives of CH selection. Data from member nodes must be collected by cluster heads before being transmitted to the BS. By using cluster heads, the network can reduce the energy consumption associated with direct transmissions from all sensor nodes to the BS.

Due to the need for proximity to both cluster members and BS, along with maintaining high residual energy ( $E_{RES}$ ) for efficient energy consumption, a fitness function-based algorithm for selecting CH known as the FCH-based CH selection algorithm is introduced. This algorithm's design also takes into account factors such as a node's separation from the BS  $D_{2bs}$ , the distance of the node from its centroid  $D_{2l}$ , the initial energy  $E_{int}$  of the nodes, and their  $E_{RES}$ ,  $D_{2bs}$  and  $D_{2l}$  represent the Euclidean distances of a node from the BS and its centroid ( $l^1$ ) respectively.

$$F_{CH} = \begin{cases} \alpha x_1 + (1 - \alpha)x_2, & (E_{RES} \geq E_{th}) \& (D_{2bs} > D_{2l}) \\ x_1 & (E_{RES} < E_{th}) \& (D_{2bs} = D_{2l}) \\ \alpha x_1 + (1 - \alpha)x_2', & (E_{RES} \geq E_{th}) \& (D_{2bs} < D_{2l}) \end{cases} \quad (5)$$

Where  $x_1$  represents relative energy of the node to its starting energy,  $x_2$  and  $x_2'$  denotes the ratio of the relative Euclidean distance of the node from cluster centroid and BS.

### 2.4 Bee algorithm for optimal path selection

#### Motivation

The Bee Algorithm draws inspiration from the foraging and information sharing behaviour of honeybees which is often used to solve optimization problems, including path selection problems. The algorithm divides the optimization process into several phases, mimicking the behaviours of bees in a hive. The utilization of an efficient search process during the population initialization phase contributes to a rapid convergence speed and is one of the major advantages of this optimization.

#### Inspiration

The optimization algorithm takes inspiration from the foraging behaviour of honey bees, where bees explore the environment to discover food sources and communicate their findings to the hive. A group of bees can execute intricate tasks by following relatively uncomplicated rules governing the behaviour of individual bees. Examples of these intelligent behaviour include gathering, processing, and promoting nectar sources. In this algorithm, potential solutions to an optimization problem are analogously represented as food sources. Bees are emulated through employed, onlooker, and scout roles. Employed bees exploit existing solutions (food sources), onlooker bees select sources based on their quality through stochastic sampling, and scout bees explore new solution candidates. This approach simulates the natural process of bees searching for food. Unemployed bees transition into foragers upon discovering better solutions, while scout bees facilitate global exploration. The various searching behaviours encompass random exploration, hill-climbing, and guided search. The bee waggle dance conveys information about the direction and distance of food sources. The algorithm strives to achieve an equilibrium replicating information-sharing dynamics found in real honey bee colonies [24]. In this research the optimization is employed for clustering and path selection for routing.

2.4.1 Solution Initialization: Solution initialization stands as the inaugural step in the process, the objective function might represent the quality of a path based on certain criteria, such as distance, cost, or other relevant factors.

$$C = \{c_1, c_2, \dots, c_i, \dots, c_n\} \quad (6)$$

$$P = \{p_1, p_2, \dots, p_j, \dots, p_m\} \quad (7)$$

$$P = \{CH_1, H_2, \dots, H_k, \dots, H_D\} \quad (8)$$

Where  $C_n$  represents total number of clusters,  $P_j$  indicates  $j$ th path, cluster head is denoted as CH,  $H_k$  represents  $K_{th}$  intermediate node, and  $H_D$  is BS.

2.4.2 Fitness Evaluation: This evaluation provides a quantitative measure of the solution's quality, guiding the algorithm's search towards more promising solutions. By assigning fitness scores to solutions, the algorithm can make informed decisions about which solutions to select, modify, and explore further during the optimization process [25].

The clustering fitness is evaluated as

$$F_c^{\max} = \{T_c, R, L, N, E\} \quad (9)$$

Trust of a node  $T_c$  should be high, Resonance  $R$  must high so that throughput remains high, location of node  $L$  to be near with the head, Energy  $E$  should be high so that the data transfer is not interrupted.

The routing fitness is evaluated as

$$F_R = \max(\text{Thr}, Li, E, T) \quad (10)$$

Where Thr indicates throughput and Li represents lifetime of the node.

### 2.4.3 Rule for cluster update

This process may involve adjusting the cluster's centroid or representative based on the disseminated information, along with potential adaptations to the cluster's dimensions.

$$C_i^{\text{tH}} = C_i^t + \frac{[\rho_{li}] \left[ \frac{1}{d_{li}} \right]}{\sum_{\text{all nodes}} [\rho_{li}] \left[ \frac{1}{d_{li}} \right]} + r_i (C_i^t - C_p^t) \quad (11)$$

Where trust rating between node  $l$  and  $CH_i$  is represented as  $\rho_{li}$ , distance between node  $l$  and  $CH_i$  is  $d_{li}$ , personal best solution is depicted as  $C_p^t$ , the random number  $r$  is ranges from 0 to 1.

### 3.4.4 Rule for routing path update

The intention is to enhance the quality of routes by incorporating information shared by employed agents and updating the routing paths accordingly.

$$P_i^{\text{tH}} = [P_i^t + \bar{\omega} r_2 (P_p^t - P_i^t) + \bar{\omega}_2 r_3 (P_g^t - P_i^t)] \quad (12)$$

### 2.4.5 Re-evaluate the fitness

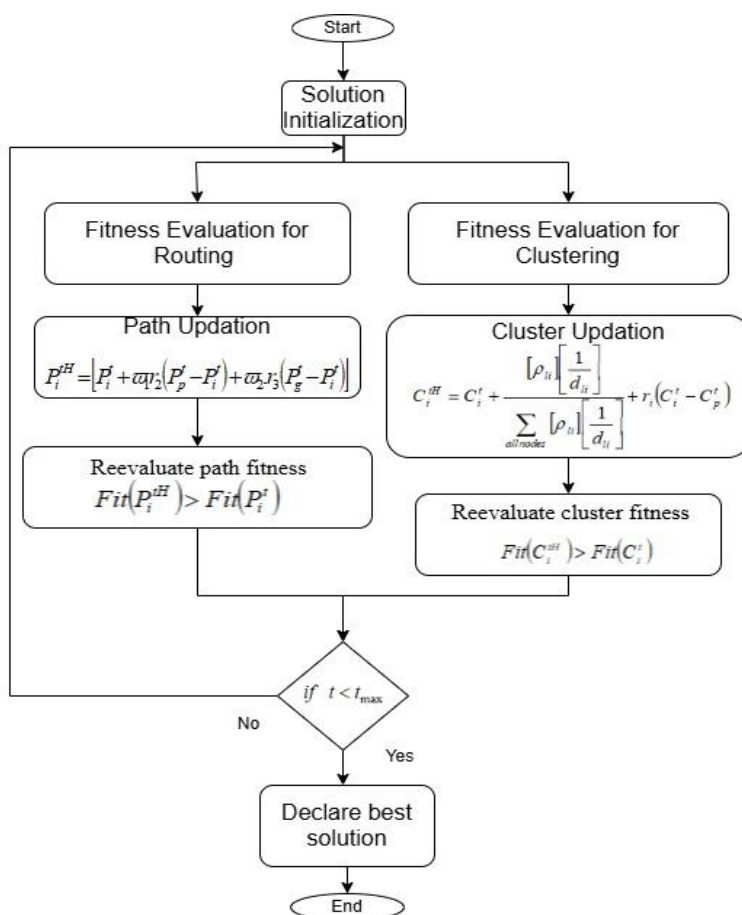
The fitness is re-evaluated for path is based on the following conditions

$$Fit(P_i^{tH}) > Fit(P_i^t) \quad (13)$$

If the above condition satisfied  $P_i^{tH}$  is assigned as best solution otherwise  $P_i^t$  sustained as Pg Same way the fitness is reevaluated for cluster is based on the following condition

$$Fit(C_i^{tH}) > Fit(C_i^t) \quad (14)$$

WSN optimization often involves multiple conflicting objectives, such as energy efficiency, network lifetime, and data delivery. Bee optimization can be extended to handle multi-objective optimization problems, offering a holistic approach to cluster head selection and path determination.



**Figure 3: Flow chart for BA-EAIOR Algorithm**

### 3. Result and Discussion

This section discusses the BA-EAIOR approach's performance results.

#### 3.1 Experimental Setup:

A Windows 10 operating system with 8GB of RAM and PYTHON software were used in the experimental setup. The exact operating system and PYTHON software were carefully selected to

meet the needs of the implementation. The PC used had internal memory of 8GB, guaranteeing there were enough processing resources for carrying out the research.

### 3.2 Performance Evaluation:

The following performance matrices are used to determine how well the suggested method performs.

3.2.1 Throughput (Thr): The amount of data that can be effectively communicated via the network in a specific amount of time is known as throughput, which is a measurement of data transfer rate.

$$\text{Thr} = \frac{\text{total data transmitted}}{\text{Time duration}} \quad (15)$$

3.2.2 Network Lifetime (Li): The duration for which the sensor network remains operational before the first node depletes its energy completely is known as network lifetime.

$$\text{Li} = \frac{\text{Energu Reserve}}{\text{Energy consumption}} \quad (16)$$

3.2.3 Energy consumption: the entire amount of energy used by network nodes for processing, transmission, and reception combined.

### 3.3 Comparative methods

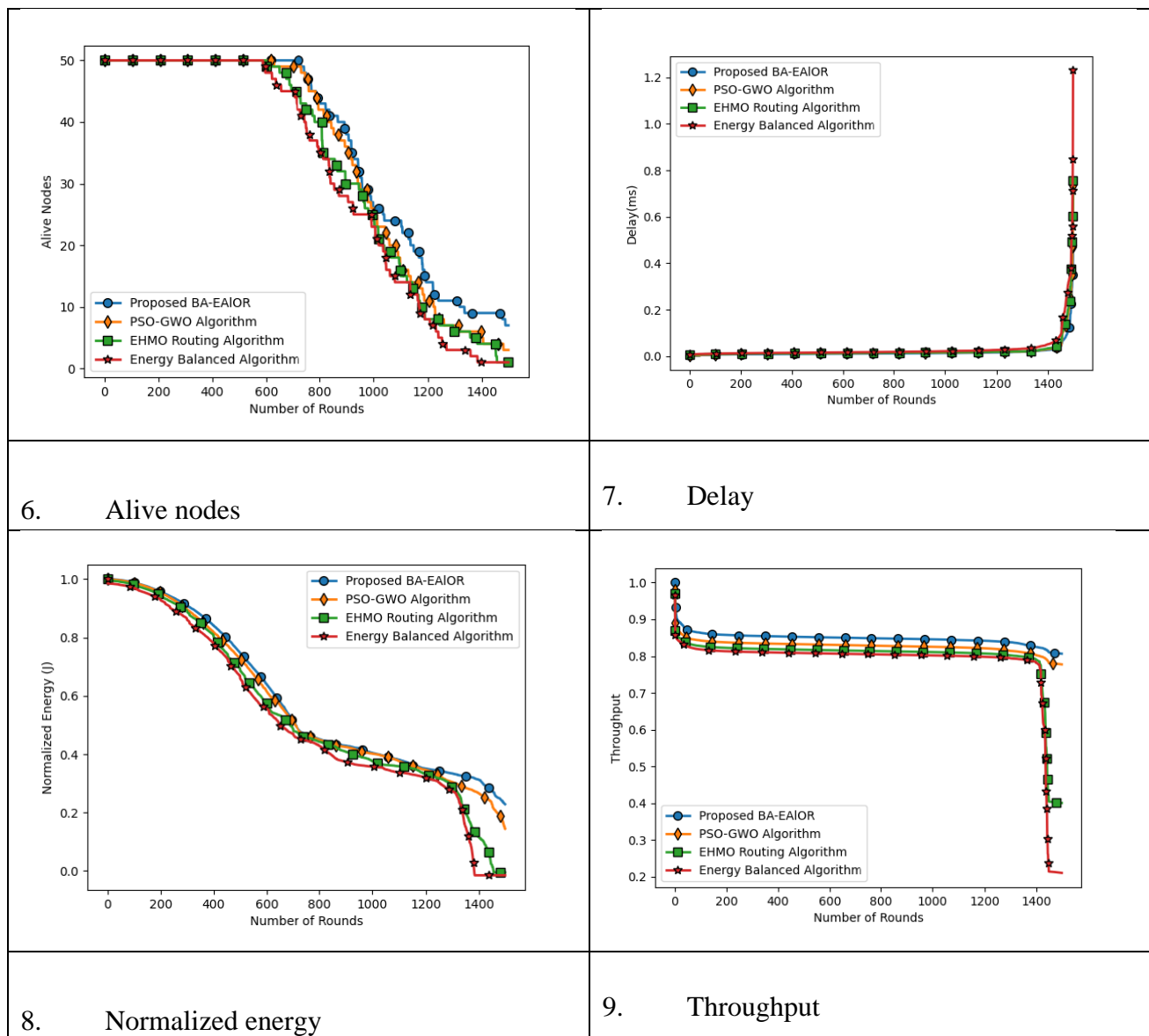
Comparison of the proposed BA-EAIOR with the established methods, including PSA-GWO algorithm (W1) [7], EHMO routing algorithm (W2) [6], Energy balanced routing algorithm (W3) [5] are discussed as follows. Compared with the existing researches proposed BA-EAIOR model enhance the lifetime of the network with low energy consumption.

#### 3.3.1 Comparative analysis for BA-EAIOR

To showcase the effectiveness of the suggested BA-EAIOR model, comparisons using route methods with 50, 100 nodes are evaluated.

##### i) 50 Node Analysis:

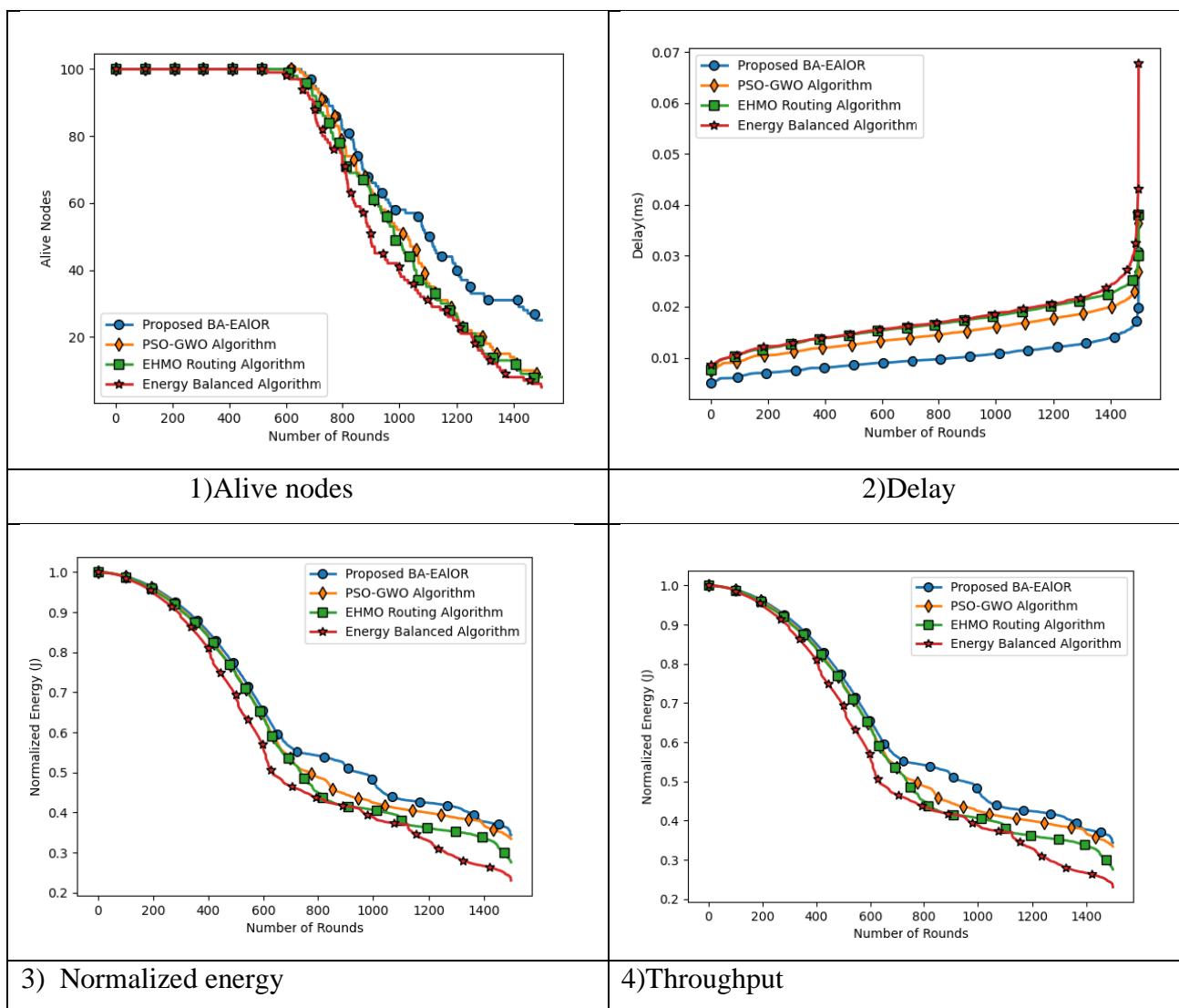
Figure 4 depicts the evaluation of the BA-EAIOR technique with 50 nodes. In contrast to techniques W1 to W3, which demonstrated active node counts of 3, 1, and 1 respectively at 1500 rounds, the developed BA-EAIOR exhibited 7 operational nodes, thereby substantiating the effectiveness of this method (figure 4a). Notably, compared to the W1 to W3 approaches, which produced delays of 0.73, 0.75, and 1.23 respectively, the novel BA-EAIOR dramatically reduced node delay at the 1500-round interval by 0.43 ms (figure 4b). At 1500 rounds, the W1 through W3 approaches obtained values of 0.14, -0.005, and -0.005 for the total energy usage. The proposed BA-EAIOR, on the other hand, measured a cumulative energy consumption of 0.22, exceeding the standards set by the current techniques (figure 4c). The 50 nodes in the W1 to W3 algorithms consistently scored 0.777, 0.400, and 0.210 at 1500 rounds, respectively. A significant throughput of 0.806 was attained by the innovative BA-EAIOR optimization (Figure 4d).



**Figure 4: 50 Node Analysis**

ii) 100 Node Analysis

Figure 5 depicts the evaluation of the BA-EAIOR approach with 100 nodes. In contrast to techniques W1 to W3, which demonstrated active node counts of 8, 8, and 5 respectively at 1500 rounds, the developed BA-EAIOR exhibited 25 operational nodes, thereby substantiating the effectiveness of this method (figure 5a). Notably, compared to the W1 to W3 approaches, which produced delays of 0.0363, 0.038, and 0.0677 correspondingly (figure 5b), the novel BA-EAIOR dramatically reduced node delay at the 1500-round interval by 0.0308 ms. At 1500 rounds, the W1 through W3 methods measured values of 0.33, 0.27, and 0.23 for the total energy consumption. The proposed BA-EAIOR, on the other hand, recorded a cumulative energy consumption of 0.34, exceeding the standards set by the current techniques (figure 5c). The performance of the 100 nodes in the W1 to W3 algorithms consistently achieved scores of 0.527, 0.506, and 0.493, respectively, at 1500 rounds. A significant throughput of 0.566 was attained by the innovative BA-EAIOR optimization (Figure 5d).



**Figure 5: 100 node analysis**

#### 4.4 Comparative Discussion

A comparison is conducted between the proposed BA-EAIOR and the existing measurement methods. The conventional researches such as automata-based mechanisms can increase the complexity of the overall algorithm, making it challenging to implement, debug, and maintain. EHMO routing algorithm has difficulty in finding a feasible solution when a vast infeasible region, formed by a large number of unrealistic solutions, is developed to address these suggested BA-EAIOR. Table 1 provides a comparative examination of the suggested strategy.

**Table 1: The comparative analysis of BA-EAIOR approach**

Method	Alive nodes		Delay		Normalized Energy		Throughput	
	50	100	50	100	50	100	50	100
BA-EAIOR	7	25	0.43	0.0308	0.22	0.34	0.806	0.566

W1 [7]	3	8	0.73	0.0363	0.14	0.33	0.777	0.527
W2 [6]	1	8	0.75	0.038	-0.005	0.27	0.400	0.506
W3 [5]	1	5	1.23	0.0677	-0.005	0.23	0.210	0.493

## 5. Conclusion

In conclusion, this research delved into the critical issue of enhancing the lifetime of sensor networks through the synergistic implementation of optimal path selection, cluster head optimization, and energy-aware routing strategies. The findings highlighted the significance of these approaches in mitigating energy depletion, prolonging network longevity, and sustaining efficient data transmission. Through meticulous experimentation and analysis, it was evident that the proposed methods effectively contributed to energy conservation, promoting an equitable distribution of energy consumption among network nodes. Optimal path selection minimized the distance data needed to travel, while cluster head optimization ensured equitable energy utilization among nodes. The integration of energy-aware routing further refined the process by dynamically adapting to changing network conditions and optimizing energy consumption in real-time. The outcomes of this research have far-reaching implications for the realm of sensor networks and other resource-constrained systems. By significantly extending the operational lifespan of sensor networks, these strategies enable continuous data collection and transmission, supporting various applications such as environmental monitoring, surveillance, and industrial automation. Future research could explore adaptive algorithms that consider varying node capacities and environmental dynamics, as well as investigate potential trade-off between data delivery speed and energy efficiency.

## References

- [1] A. S. Toor and A. K. Jain, “Energy Aware Cluster Based Multi-hop Energy Efficient Routing Protocol using Multiple Mobile Nodes (MEACBM) in Wireless Sensor Networks,” *AEU - International Journal of Electronics and Communications*, vol. 102, pp. 41–53, Apr. 2019, doi: 10.1016/j.aeue.2019.02.006.
- [2] B. Ji, Z. Cai, G. Sun, and K. Yan, “Hydroxyl Changing Mechanism of Cotton Cellulose during Alkaline Treatment Characterized by ATR-FTIR in Combination with Two-Dimensional Correlation Spectroscopy,” *AATCC Journal of Research*, vol. 7, no. 5, pp. 1–8, Sep. 2020, doi: 10.14504/ajr.7.5.1.
- [3] B. Ji, Y. Li, S. Chen, C. Han, C. Li, and H. Wen, “Secrecy Outage Analysis of UAV Assisted Relay and Antenna Selection for Cognitive Network Under Nakagami- $m$  Channel,” *IEEE Trans Cogn Commun Netw*, vol. 6, no. 3, pp. 904–914, Sep. 2020, doi: 10.1109/TCCN.2020.2965945.
- [4] X. Fu and X. He, “Energy-balanced data collection with path-constrained mobile sink in wireless sensor networks,” *AEU - International Journal of Electronics and Communications*, vol. 127, p. 153504, Dec. 2020, doi: 10.1016/j.aeue.2020.153504.

- [5] H. Wang, K. Li, and W. Pedrycz, "An Elite Hybrid Metaheuristic Optimization Algorithm for Maximizing Wireless Sensor Networks Lifetime With a Sink Node," *IEEE Sens J*, vol. 20, no. 10, pp. 5634–5649, May 2020, doi: 10.1109/JSEN.2020.2971035.
- [6] S. Prithi and S. Sumathi, "Automata Based Hybrid PSO–GWO Algorithm for Secured Energy Efficient Optimal Routing in Wireless Sensor Network," *Wirel Pers Commun*, vol. 117, no. 2, pp. 545–559, Mar. 2021, doi: 10.1007/s11277-020-07882-2.
- [7] S. Karthigeyan, S. Bhol, A. Jain, K. Yadav, A. Sinha, and P. P. R, "An Energy Efficient Hybrid Communication Protocol for Large Area Wireless Sensor Networks," *Procedia Comput Sci*, vol. 252, pp. 985–994, 2025, doi: 10.1016/j.procs.2025.01.059.
- [8] K. M. Chowdary and V. Kuppili, "Enhanced Clustering and Intelligent Mobile Sink Path Construction for an Efficient Data Gathering in Wireless Sensor Networks," *Arab J Sci Eng*, vol. 46, no. 9, pp. 8329–8344, Sep. 2021, doi: 10.1007/s13369-021-05415-y.
- [9] V. Sucasas, A. Radwan, H. Marques, J. Rodriguez, S. Vahid, and R. Tafazolli, "A survey on clustering techniques for cooperative wireless networks," *Ad Hoc Networks*, vol. 47, pp. 53–81, Sep. 2016, doi: 10.1016/j.adhoc.2016.04.008.
- [10] R. Yarinezhad and S. N. Hashemi, "Increasing the lifetime of sensor networks by a data dissemination model based on a new approximation algorithm," *Ad Hoc Networks*, vol. 100, p. 102084, Apr. 2020, doi: 10.1016/j.adhoc.2020.102084.
- [11] Y. Cui, W. Hu, and A. Rahmani, "Fractional-order artificial bee colony algorithm with application in robot path planning," *Eur J Oper Res*, vol. 306, no. 1, pp. 47–64, Apr. 2023, doi: 10.1016/j.ejor.2022.11.007.
- [12] G. M. Friesen, T. C. Jannett, M. A. Jadallah, S. L. Yates, S. R. Quint, and H. T. Nagle, "A comparison of the noise sensitivity of nine QRS detection algorithms," *IEEE Trans Biomed Eng*, vol. 37, no. 1, pp. 85–98, 1990, doi: 10.1109/10.43620.
- [13] P. S. Hamilton and W. J. Tompkins, "Compression of the ambulatory ECG by average beat subtraction and residual differencing," *IEEE Trans Biomed Eng*, vol. 38, no. 3, pp. 253–259, Mar. 1991, doi: 10.1109/10.133206.
- [14] M. Achieng and E. Ruhode, "The Adoption and Challenges of Electronic Voting Technologies Within the South African Context," *International Journal of Managing Information Technology*, vol. 5, no. 4, pp. 1–12, Nov. 2013, doi: 10.5121/ijmit.2013.5401.
- [15] Q. Li *et al.*, "An Enhanced Grey Wolf Optimization Based Feature Selection Wrapped Kernel Extreme Learning Machine for Medical Diagnosis," *Comput Math Methods Med*, vol. 2017, pp. 1–15, 2017, doi: 10.1155/2017/9512741.
- [16] W. Pieters, "Acceptance of Voting Technology: Between Confidence and Trust," in *International Conference on Trust Management*, 2006, pp. 283–297. doi: 10.1007/11755593\_21.
- [17] D. Cansell, J. P. Gibson, and D. Méry, "Refinement: A Constructive Approach to Formal Software Design for a Secure e-voting Interface," *Electron Notes Theor Comput Sci*, vol. 183, pp. 39–55, Jul. 2007, doi: 10.1016/j.entcs.2007.01.060.

- [18] M. Hapsara, A. Imran, and T. Turner, "Beyond Organizational Motives of e-Government Adoption: The Case of e-Voting Initiative in Indonesian Villages," *Procedia Comput Sci*, vol. 124, pp. 362–369, 2017, doi: 10.1016/j.procs.2017.12.166.
- [19] M. F.M.Mursi, G. M. R. Assassa, A. Abdelhafez, and K. M. Abo Samra, "On the Development of Electronic Voting: A Survey," *Int J Comput Appl*, vol. 61, no. 16, pp. 1–11, Jan. 2013, doi: 10.5120/10009-4872.
- [20] K. Vassil, M. Solvak, P. Vinkel, A. H. Trechsel, and R. M. Alvarez, "The diffusion of internet voting. Usage patterns of internet voting in Estonia between 2005 and 2015," *Gov Inf Q*, vol. 33, no. 3, pp. 453–459, Jul. 2016, doi: 10.1016/j.giq.2016.06.007.
- [21] F. Zhang and Y. Lian, "QRS Detection Based on Multiscale Mathematical Morphology for Wearable ECG Devices in Body Area Networks," *IEEE Trans Biomed Circuits Syst*, vol. 3, no. 4, pp. 220–228, Aug. 2009, doi: 10.1109/TBCAS.2009.2020093.
- [22] N. Valaei, S. R. Nikhashemi, H. Ha Jin, and M. M. Dent, "Task Technology Fit in Online Transaction Through Apps," in *Optimizing E-Participation Initiatives Through Social Media*, IGI Global, 2018, pp. 236–251. doi: 10.4018/978-1-5225-5326-7.ch010.
- [23] S. S. Sundaram Paulraj and V. Kannabiran, "Neuro-fuzzy-based cluster formation scheme for energy-efficient data routing in IOT-enabled WSN," *International Journal of Communication Systems*, vol. 38, no. 3, Feb. 2025, doi: 10.1002/dac.5984.
- [24] J. Xu, Z. Han, L. Yin, Z. Yan, Y. Yu, and G. Ma, "Multi-strategy-based artificial bee colony algorithm for AUV path planning with angle constraints," *Ocean Engineering*, vol. 312, p. 119155, Nov. 2024, doi: 10.1016/j.oceaneng.2024.119155.
- [25] A. Hoseinpour, M. J. Lahijani, M. Hosseinpour, and J. Kazemitabar, "An Efficient Fitness Function for Clustering of Wireless Sensor Networks," *International Journal of Sensors, Wireless Communications and Control*, vol. 10, no. 3, pp. 318–324, Nov. 2020, doi: 10.2174/2210327909666190408124107.