Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7546452

INNOVATIVE EFFICIENT ENERGY MANAGEMENT IN ROUTING PROTOCOLS FOR WIRELESS SENSOR NETWORKS: A COMBINED APPROACH USING ELEPHANT HERDING AND SWARM OPTIMIZATION

G K Abani Kumar Dash[1][0009-0006-0692-8629] and **Chinmaya Kumar Nayak**[2][0000-0002-4089-469X]

[1,2] Faculty of Engineering & Technology (FET), Sri Sri University, Odisha, India
abanidash1982@gmail.com,cknayak85@gmail.com

Abstract: In wireless sensor networks (WSNs), energy consumption and limited sensor node capacity are significant challenges, primarily because sensor nodes cannot easily recharge their batteries. To address this issue, a clustering-routing technique is employed. This approach entails organizing adjacent sensor nodes into separate clusters, with each cluster designating a cluster head. The cluster head's role is to collect data from within the cluster and send it to the base station. The method outlined in this research aims to improve the network's lifespan and energy efficiency by employing cluster-based routing protocols. The study optimizes energy efficiency through a three-step process.Firstly, dolphin swarm optimization (DSO) is applied to form a set of clusters. In the second stage, the Elephant Herding Optimization (EHO) method is utilized to identify the cluster heads within the clusters. Subsequently, the Chicken Swarm Optimization (CSO) algorithm is applied to determine the most efficient routing path for transmitting the collected data to the base station. These algorithms contribute to a more balanced distribution of energy consumption among the network nodes. Empirical evidence indicates that this strategy enhances energy efficiency and prolongs the network's operational lifespan compared to traditional methods.

Keywords: WSN, DSO, EHO, CSO, Energy Efficient

1. Introduction

Wireless sensor networks (WSNs) are built on wireless sensor nodes, which gather and monitor environmental data. These networks are used in various fields such as weather forecasting, disaster management, agriculture, security, and healthcare [1]. Each sensor node includes components like a transceiver, memory, battery, microprocessor, and microsensor, enabling communication within the network [2].

However, WSNs face challenges due to the limited resources of sensor nodes, particularly in terms of energy consumption, which is a critical factor in their deployment. Various algorithms and protocols have been developed to improve energy efficiency and extend the lifespan of sensor nodes [3]. Clustering techniques are used to enhance energy efficiency, with a cluster head (CH) managing communication within a group of nodes. In single-hop communication, the CH sends data directly to the base station (BS), while in multi-hop communication, relay nodes are employed [4]. Hierarchical clustering reduces long-distance communication and energy use, decreases channel interference, improves throughput, enhances scalability, and optimizes data aggregation [5]. However, non-uniform clustering can lead to connectivity issues and increased energy consumption. This work focuses on hierarchical cluster-based routing algorithms to maintain connectivity and optimize energy use in WSNs [6]. Routing in WSNs is challenging due to the need to follow traditional network protocols in remote ad hoc networks

[7][9].

Routing in wireless sensor networks (WSNs) involves using a set number of nodes to ensure successful data transmission to a base station with a high success rate. Challenges include data processing, cross-layer design, bandwidth, quality of service (QoS), compression techniques, and energy consumption [10]. Protecting the WSN infrastructure against attacks and finding optimal configurations for sensor hubs are critical challenges [11]. The goal is to select the best strategy for information routing by optimizing sensor hub selection.

Nature-inspired algorithms, particularly for clustering and routing, have been widely researched to address these issues. These algorithms aim to reduce energy consumption by selecting appropriate cluster heads (CHs) among nodes [12]. The proposed approach clusters sensor nodes using dolphin swarm optimization, and selects CHs using Elephant Herding Optimization (EHO), based on node energy and distance. Finally, routing is optimized with chicken swarm optimization to find the most efficient data path, enhancing network longevity and energy efficiency.

1. A hybrid nature-inspired metaheuristic algorithm, based on dolphin swarm optimization, was developed and implemented for clustering sensor nodes within wireless sensor networks (WSNs).
2. The Elephant Herding Optimization (EHO) algorithm was applied, incorporating a fitness function that could be tailored to meet the specific requirements of the network.
3. When selecting the appropriate Cluster Head (CH) using EHO, factors such as residual energy, intra-cluster distance, inter-cluster distance, and node distance were considered.
4. Chicken Swarm Optimization was introduced as a routing strategy for efficient data transfer to the base station in WSNs.
5. The application of these nature-inspired and bio-inspired algorithms was evaluated in various scenarios to compare their performance with existing protocols, particularly in terms of energy consumption and network lifetime. Section 2 offers a literature review that outlines the workflow of the article, while Section 3 details the preliminary methods used in the proposed approaches. The system model is introduced in Section 4, followed by the proposed protocol in Section 5. An analysis of the experimental results is provided in Section 6.
6. Finally, Section 7 concludes the process.

2. Literature Survey

Wireless Sensor Networks (WSNs) consist of numerous sensor nodes that are strategically deployed to gather data from various environments, including transportation security, military operations, and climatic observation. One of the key challenges in WSNs is managing the limited energy resources of sensor nodes, which directly impacts the network's lifespan. Addressing this challenge, Bhola et al. [13] introduced the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol combined with a Genetic Algorithm (GA) for optimization. LEACH is a hierarchical protocol that selects cluster heads (CHs) to collect data from the nodes and transmit it to the base station. The GA optimizes the route discovery process based on fitness values. However, LEACH’s efficiency diminishes as the network size increases, which limits its scalability.

To enhance network longevity and adaptability in larger networks, Ahmed et al. [14] proposed the Energy-Efficient Scalable Routing Algorithm (EESRA), which employs a three-layer hierarchy to control the cluster head selection and manage the load on CHs. This hierarchical and clustering-based approach effectively extends the network's lifespan even as the network size grows. Hang et al. [15] developed the Clustering Routing with Chaotic Genetic Algorithm (CRCGA), which integrates clustering, routing path prediction, and cluster control. CRCGA uses a chaotic genetic algorithm for optimal CH selection, ensuring that the most efficient routing strategy is used, thus improving network performance.

In a more recent advancement, Nguyen et al. [16] combined the Red Deer Algorithm (RDA) with blockchain technology to create RDAC-BC, a secure and energy-efficient clustering-based data transmission protocol for ubiquitous wireless networks. The RDAC method initializes node clustering, followed by CH selection and secure data transmission using blockchain technology, thereby enhancing both energy efficiency and data security.

Another approach, known as PEGASIS (Power-Efficient GAthering in Sensor Information System), offers an alternative to LEACH by utilizing a chain-based routing protocol. This method organizes sensor nodes into chains using a greedy algorithm, where each chain acts as a leader. The leader chain aggregates and transmits data directly to the sink node, thus reducing energy consumption. However, as noted by Rao et al. [17], the use of a leader chain can reduce overall network energy and lifespan. To address these limitations, Sharma et al. [18] proposed improvements to the PEGASIS protocol by optimizing the clustering of sensor nodes, which further enhances energy efficiency and extends the network's lifespan.

In the PEGASIS protocol, clusters are organized in a chain, a strategy that effectively minimizes energy consumption and reduces delays. Clustering is a well-established method to optimize each hub's energy use and lower traffic and overhead during data transmission. Barzin et al. [19] introduced a multi-objective, nature-inspired approach known as MOSFA, which combines the shuffled frog-leaping algorithm and the firefly algorithm. This method is applied to Wireless Sensor Networks (WSNs) where an adaptive clustering-based multi-hop routing protocol is utilized. MOSFAs are employed to select Cluster Heads (CHs) in various scenarios during each cycle. Additionally, Bhowmik et al. [20] proposed an enhanced gravitational search algorithm (GSA) integrated with particle swarm optimization (PSO) for improving WSN routing and clustering. This clustered protocol ensures a uniform distribution of energy across the network.

Optimizing data transfer routes between cluster heads and the base station is crucial for effective routing in wireless sensor networks (WSNs). Shahbaz et al. [21] address clustering and routing using the firefly algorithm and fuzzy logic, creating primary and backup paths. Kaur et al. [22] propose the Particle Swarm Optimization-based Dual Sink Mobility (PSODSM) technique to reduce sensor node energy consumption, focusing on node degree, initial energy, and centrality.

Despite these improvements, energy consumption remains challenging due to the limitations of traditional algorithms. Bio-inspired and metaheuristic methods often outperform conventional approaches but can lack adaptability to specific applications. To tackle these issues, this study introduces the CSO-EHO algorithm, which combines Dolphin Swarm Optimization (CSO) and Enhanced Harmony Optimization (EHO) for efficient clustering and routing [23].

3. Initial Procedures

In this section, we will explore the algorithms employed in the current study. The Dolphin Swarm Algorithm utilizes the echolocation skills of dolphins to detect and target its prey. In Elephant Herding Optimization, elephants mimic their natural herding behavior, which involves leaving their family groups to search for resources. Similarly, the Chicken Swarm Optimization Algorithm is based on the collective food-searching behavior of chickens.

Figure 1 presents the block diagram of the proposed method.

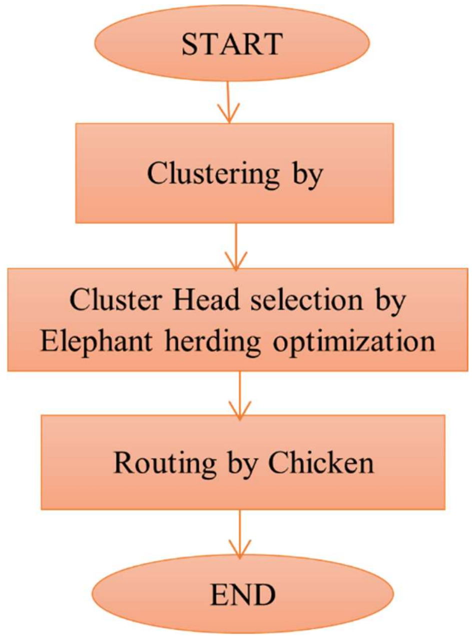


Figure 1. Schematic representation of the proposed method

a) Dolphin Swarms Optimization (DSO)

Tian-qi et al. [24] highlighted the DSO (Dolphin Swarm Optimization) as an effective global research approach for addressing various advancement challenges. The core execution strategy involves emulating the natural traits and behaviors observed in the dolphin's natural habitat. Key aspects of this approach include:

1) **Echolocation in Dolphins:** Despite having excellent vision, dolphins experience slight reductions in visual clarity under low light conditions. To hunt effectively, dolphins rely on echolocation—a remarkable ability that few organisms possess. By emitting high-frequency sounds and analyzing the returning echoes, dolphins can accurately locate prey, gauge its distance, and even estimate its size. This advanced use of echolocation also allows dolphins to make predictions about weather conditions through sound reverberations.
2) **Division of labor and cooperation:** Predatory behavior in dolphins often involves teamwork rather than solitary action. Dolphins typically collaborate and divide tasks to effectively hunt, with one dolphin monitoring the prey while others manage different aspects of the attack. This division of labor ensures a coordinated effort, as a single dolphin alone cannot manage the entire predation process, especially with large prey.
3) **Information Exchange:** Dolphins communicate through a sophisticated system of sounds, using varying frequencies to convey different messages. They coordinate and divide tasks during hunting, calling on others to share information about prey locations. This data exchange enhances their ability to make strategic decisions and improve hunting success.

The DSO algorithm functions through a sequence of three main stages. Initially, dolphins use their echolocation abilities to determine the position of their prey. Following this, they communicate their findings to other dolphins with similar characteristics. Once a dolphin estimates the probable future location of the prey, it seeks help from other dolphins to track or encircle the target effectively. In the final phase, the dolphins execute their predation strategy by capturing the prey to meet their hunger needs.

Method 1: Dolphin Swarm Optimization Algorithm (DSO)

1. **Initialization**:
   - Set parameters (population size, iterations, etc.).
   - Initialize dolphin positions and velocities randomly.
   - Evaluate fitness of each dolphin's position.
2. **Evaluation**:
   - Compute fitness values for each dolphin.
   - Identify the global best (GBest) dolphin.
3. **Update**:
   - Update each dolphin's velocity and position based on:
     - Personal best (PBest)
     - Global best (GBest)
   - Ensure positions stay within the search space.
4. **Iteration**:
   - Repeat evaluation and update steps for a set number of iterations or until convergence.
5. **Termination**:
   - Return the best solution found (GBest).

a) Elephant Herding Optimization (EHO)

The hybrid Elephant Herding Optimization (EHO) algorithm, designed for optimal cluster head selection in Wireless Sensor Networks (WSNs), is discussed in the work by Wang et al. [23]. The EHO algorithm incorporates the social behavior of elephants, which are known for their complex social structures. Elephants, living in family groups with a matriarchal leader, exhibit distinct social behaviors: female elephants remain with their family units, while male elephants often separate from their familial groups and live in different social groups. These behavioral traits are leveraged in the EHO algorithm to enhance its performance in WSN applications.

Considering the EHO algorithm’s basis on elephant behavior, the following key points are assumed:

1. There are several clans within the elephant group, and each clan will include a certain number of elephants.

2. A specific number of male elephants will separate from their families at each generation.

3. Each clan's head matriarch allows the elephants to coexist.

Method 2: Elephant Herding Optimization Algorithm (EHO)

1. **Initialization:**
   - Set parameters (population size, iterations).

- Randomly initialize elephant positions in the search space.

2. **Fitness Evaluation:**
   - Calculate fitness for each elephant.
3. **Update Best Solution:**
   - Identify the best solution based on fitness.
4. **Herding Behavior:**
   - Migrate elephants (update positions) based on migration probability and local search.
5. **Convergence Check:**
   - Check if the algorithm has converged or reached the maximum iterations.
6. **Termination:**
   - Return the best solution found.

b) Chicken Swarm Optimization (CSO)

The recent Swarm Intelligence algorithm known as CSO, introduced by Meng et al., [26], emphasizes a hierarchical approach combined with an effective mechanism for locating food. In this algorithm, the entire population of chickens is categorized into three groups—roosters, hens, and chicks—based on their fitness levels. Roosters are the hens that demonstrate the highest capability in searching for food, while chicks are those that exhibit lower fitness and are less effective in locating food. Thus, hens are defined as chickens that can communicate with one another and find food, or that are physically fit. Furthermore, the mother-child bond is established randomly. This mother-child hierarchical relationship is changed every G times. The logical behavior of the CSO algorithm 3 is the birth behavior of a hen trailing the mate chicken and chicks trailing their mother in quest of nourishment. Similarly, the hens would try to scavenge the food that other rival hens in the group had discovered. It's too simple to cooperate with every chicken. They gather as a multitude and form a group with clear hierarchies that look for food.

Method 3: Chicken Swarm Optimization Algorithm (CSO)

1. **Initialization**:
   - Generate an initial population of chickens.
   - Set algorithm parameters (e.g., number of chickens, iterations).
2. **Evaluate Fitness**:
   - Compute the fitness of each chicken using the objective function.
3. **Update Positions**:
   - Identify the best rooster (leader).
   - Update the position of each hen based on the rooster's position.
4. **Update Roosters**:
   - If a hen has a better fitness than the current rooster, update the rooster.
5. **Check Termination Criteria**:
   - Determine if the maximum number of iterations is reached or if convergence criteria are met.
6. **Output the Best Solution**:
   - Return the best solution found during the algorithm's execution.

4. Proposed protocol

In Wireless Sensor Networks (WSNs), sensor nodes are clustered using Dolphin Swarm Optimization (DSO). The base station then employs a Chicken Swarm

Optimization (CSO) routing algorithm to find the best paths from cluster heads to the base station. During setup, the Enhanced Honeybee Optimization (EHO) algorithm selects cluster heads based on factors like inter-cluster distance, node distances, and residual energy. In the stabilization phase, cluster heads use the CSO-based method to forward data to the base station. This process involves using EHO for optimal cluster head selection and CSO for efficient routing, with the Proposed-LEACH approach balancing residual energy and distances.

Here, we go over the suggested methodology, which is divided into three stages: (1) DSA clustering; (2) EHO cluster head selection; and (3) CSO path selection. The suggested method's flow chart is shown in Figure 3. The sensor centers are initially placed throughout the network. Following a hub energy refresh, the network verifies whether or not cycle 1 is in effect by checking the protocol. In the unlikely event that the criterion is met, CSO is used in the network to handle clustering. In fact, the EHO technique is used to select the next round cluster head if it fails to meet the requirement. The CH then selects the shortest way to transfer data to the sink; this shortest way is selected by using CSO. The network then determines if the hub is alive or dead based on whether the center's energy is greater than the threshold. If not, the node is dead. As of right now the network revives the alive node in the corresponding round. Finally, if the final node dies, no more changes

WILL BE MADE; IF NOT, THE NETWORK WILL CONTINUE TO CYCLE CONTINUOUSLY UNTIL THE NODE DIES.

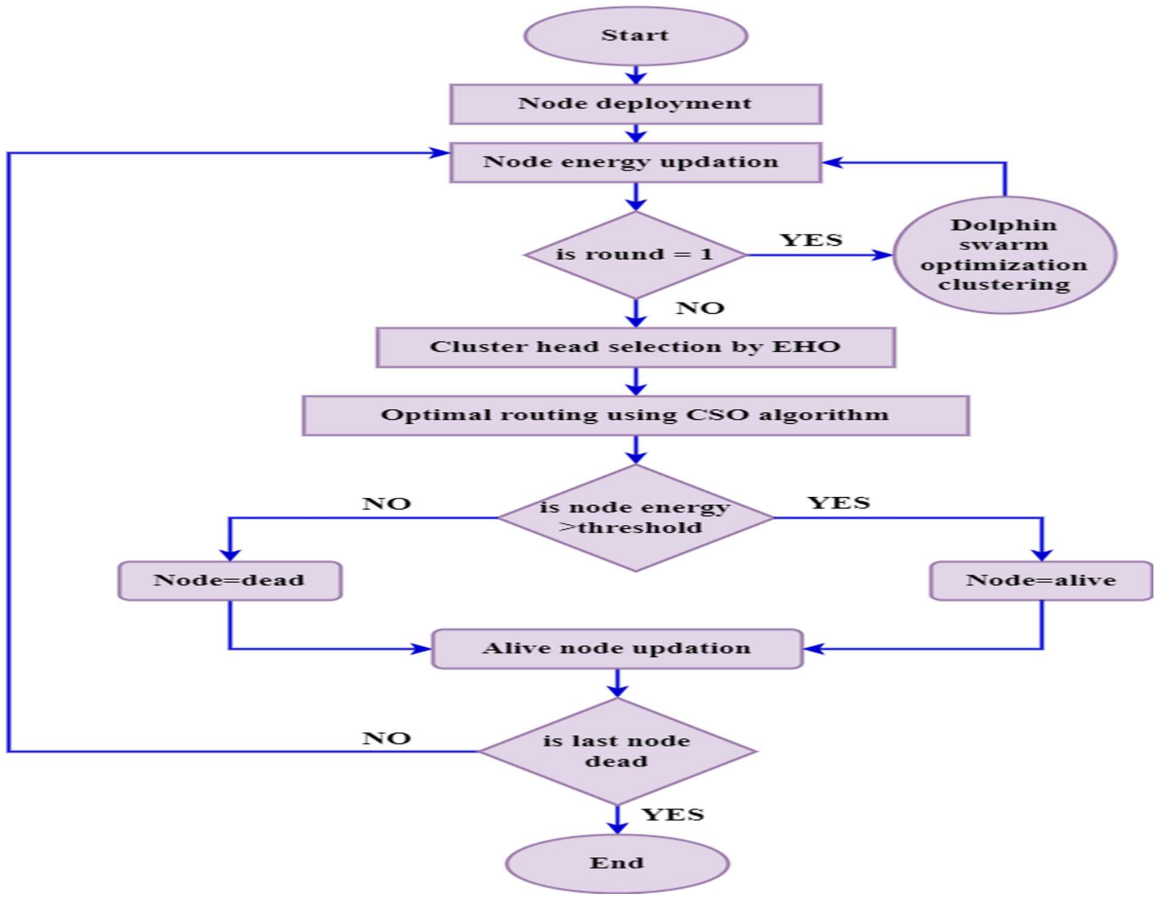


Figure 3. Flowchart of EHO-CSO algorithm.

DSO Clustering Phase

1. Initialization of Clusters:

- Initial Assignment: Assign dolphins to initial clusters randomly or based on some heuristic criteria. This could be based on their initial positions or fitness values.
- Cluster Parameters: Define parameters such as the number of clusters, cluster radius, and criteria for cluster formation.

2. Cluster Formation:
    - Distance Calculation: Calculate distances between dolphins to determine which dolphins should be grouped together. This can be based on Euclidean distance or other metrics relevant to the problem.
    - Cluster Assignment: Assign dolphins to clusters based on proximity or similarity in fitness values. Each dolphin will belong to the cluster whose center or leader is nearest.
3. Leader Selection:
    - Identify Leaders: Within each cluster, identify the leader dolphin. This is often the dolphin with the best fitness (i.e., the one that represents the best solution found so far).
    - Leader Role: Leaders guide the dolphins within their cluster by sharing information about the best solutions and influencing the movement of other dolphins in the cluster.
4. Cluster Optimization:
    - Local Search: Perform a local search within each cluster to refine the solutions. Dolphins in a cluster will update their positions based on the leader's position and fitness.
    - Update Positions: Adjust the positions of dolphins in each cluster to improve their fitness. This involves moving dolphins towards the leader and exploring new positions within the cluster.
5. Cluster Reformation:
    - Re-evaluation: Periodically re-evaluate clusters based on updated fitness values and positions. Dolphins may be reassigned to different clusters if their fitness improves or deteriorates significantly.
    - Re-clustering: If necessary, reform clusters to ensure they are still optimal for the current state of the search space. This helps in adapting to changes and maintaining effective clustering.
6. Convergence Check:
    - Evaluate Cluster Performance: Assess the performance of clusters based on their fitness values and the overall optimization goal. Ensure that clusters are converging towards optimal solutions.
    - Terminate or Continue: Decide whether to terminate the clustering phase based on convergence criteria or continue with further iterations to improve solutions.

Key Considerations:

- Cluster Size and Number: The number of clusters and their size can significantly impact the performance of the algorithm. Too few clusters may miss local optima, while too many may lead to excessive computational overhead.
- Dynamic Adaptation: Adapt clusters dynamically to changes in the search space or problem characteristics to maintain effective clustering throughout the optimization process.
- Communication: Ensure effective communication between dolphins within each cluster and between leaders and their clusters to facilitate information sharing and convergence.

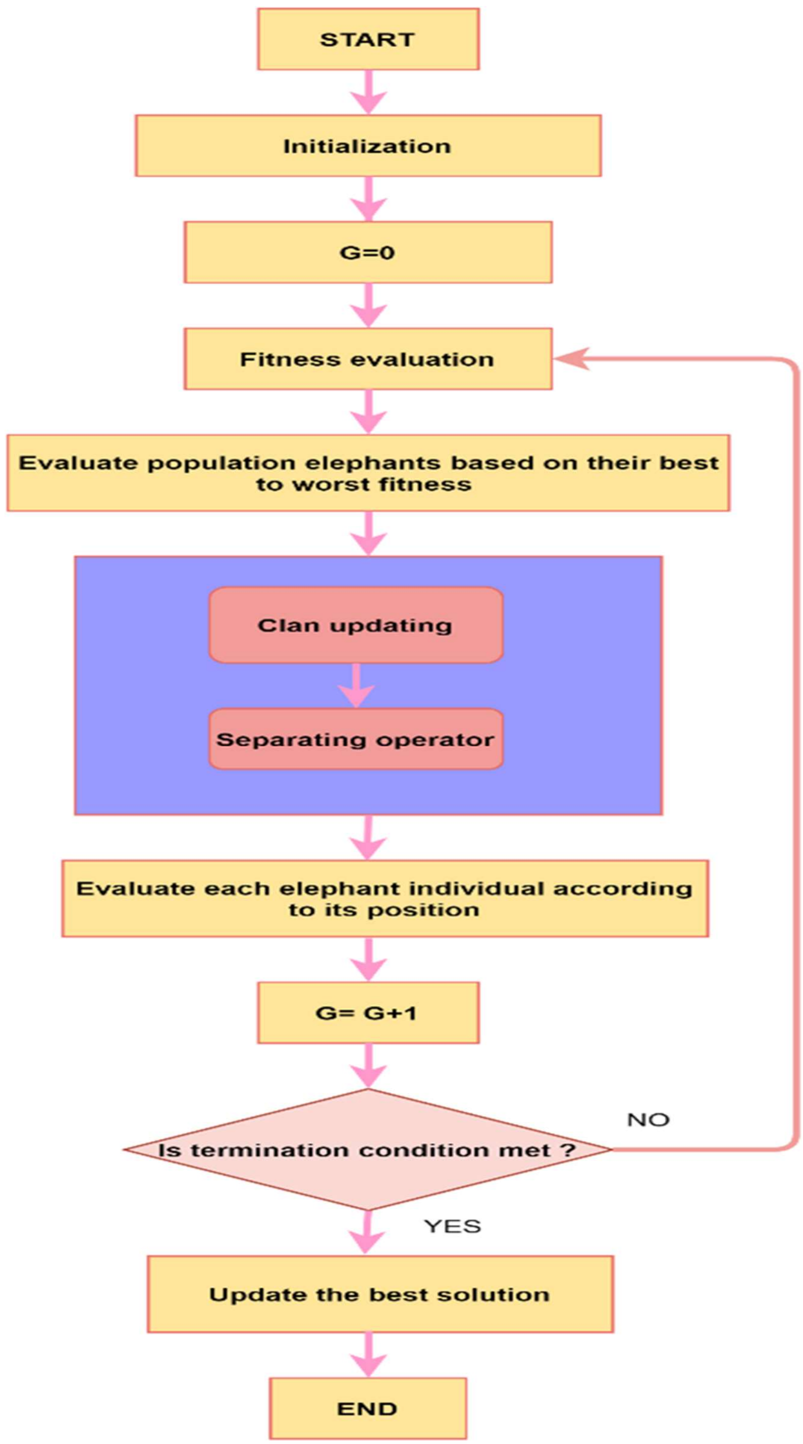


Figure 4. Flowchart of EHO.

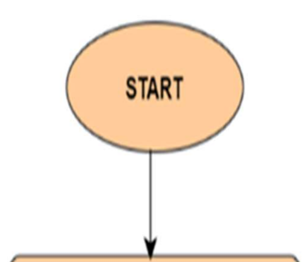


Figure 5. Flowchart of CSO.

Table 1. Simulation parameters of the whole network

Algorithm	Parameter	Values
Simulation parameters		Area 500m*500m
	Initial energy node	2J
	E_{elec}	50nJ/bit
	εfs	10pJ/bit/m^2
	ε_{mp}	0.0013pJ/bit/m^4
	Packet size	5000 bits
	Sink location	(250,500)
	Number of clusters	5
DSA	Maximum search time (t_1)	3
	Maximum transmission time (t_2)	1000
	Speed	0.1
	Node density	50-500
	Number of dolphin (n)	20
	Acceleration (a)	5
	No. of sounds (m)	2
EHO	Elitism	2
	Population size	No. of nodes in each cluster
	Dimension	No. of variables in each population
	Alpha	0.5
	Beta	0.1
CSO	Number of Generation	10
	Population size of Roosters	0.15
	Population size of Hens	0.7
	Population size of Mother hens	0.5
	Maximum iterations	100

5. Results and discussion

The Comprehensive simulations are used to estimate the implementation of the suggested nature-inspired algorithms for cluster-based routing protocol in WSNs. By extending the network lifetime while using least energy, the suggested algorithm's efficiency is calculated. This has been contrasted with the network's current LEACH and fuzzy logic methods. According on the simulation findings, the suggested approach has outperformed the current techniques. This work has been carried out with the simulation program MATLAB 2020a.

Simulation Parameters

The nodes in this proposed work have been placed over a 500 m by 500 m area, with a packet size of 5000 bits. With 500 sensor nodes, the sink has been positioned on the axis of (250,500). Furthermore, the experiment employed the mobility model of random waypoints, taking into account a range of 100 to 500 nodes for the simulation process. Mobility also ranges in speed, ranging from 0 to 20 m/s. There have been 2,250 rounds of trials conducted. The network's simulation parameters are displayed in Table 1.

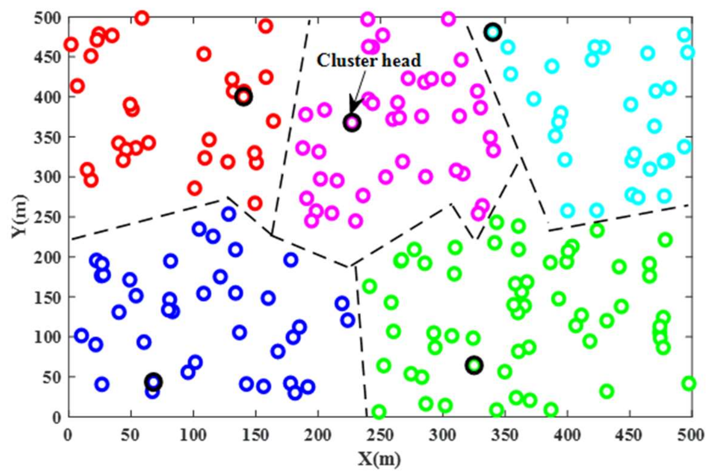


Figure 6. Network portioning by proposed method.

i. Performance measures

1. Residual Energy: Residual energy is a key performance metric for node categorization. Nodes with lower residual energy are assigned as communication nodes, while those with higher energy are categorized as Cluster Heads (CHs). This approach helps reduce packet loss by using low-energy nodes for communication and reserving high-energy nodes for CH roles.
2. Energy Efficiency: The performance metric of energy efficiency is employed to illustrate the extent of improvement in energy management within the proposed LEACH routing protocol when compared to the original LEACH protocol.
3. QoS parameters: To enhance network performance and avoid malicious nodes, optimize key QoS parameters like throughput, Packet Delivery Ratio (PDR), delay, and energy consumption. Lower QoS values in nodes may signal malicious activity, so improving these parameters helps in identifying and mitigating such issues..

b. Simulation Results

Figure 6 illustrates the outcomes of clustering for a network with 500 nodes. The analysis reveals that the network exhibits effective partitioning, with Cluster Heads (CHs) being evenly distributed across the network and centrally located within each cluster. In contrast, traditional protocols such as LEACH and Fuzzy tend to position the CHs unevenly within the sensor field. The proposed Dolphin algorithm, leveraging the natural traits of the swarm intelligence approach, demonstrates superior clustering performance.

c. Residual Energy

The residual energy of nodes over a range of 250 to 1000 rounds is analyzed to evaluate cluster-based routing protocols. Figure 7 illustrates the difference in residual energy between the proposed method and existing techniques. It is evident that the proposed algorithm maintains a higher level of residual energy compared to both the LEACH and Fuzzy methods. This improvement is attributed to the implementation of cluster-based routing protocols in this study, which effectively reduces the number of packets transmitted to the base station (BS). Consequently, this leads to a reduction in overall energy consumption.

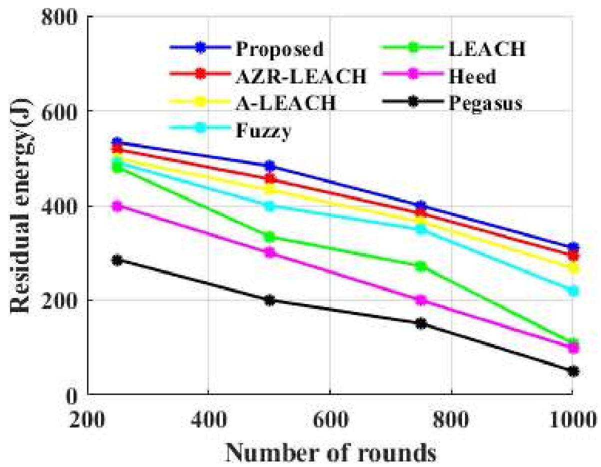


Figure 7. Residual energy vs rounds.

d. Energy Efficiency

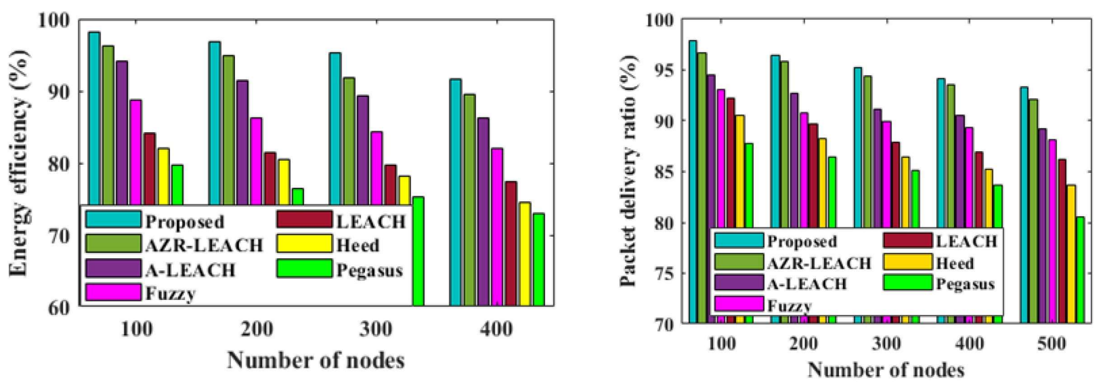
Figure 8(a) compares the energy efficiency of the proposed method with that of existing techniques, such as LEACH and the fuzzy method. The proposed approach demonstrates superior energy efficiency, achieving 98% efficiency. For a network with 100 nodes, the fuzzy method attains 89% efficiency, while LEACH reaches 84%. As the number of nodes increases to 500, the proposed method maintains a high energy efficiency of 90%. This enhanced performance is attributed to the EHO's optimal selection of the best Cluster Head (CH), which contributes to improved energy efficiency. Additionally, by selecting nearby nodes for data transmission, the CH extends the network’s operational lifetime.

e. Packet Delivery Ratio (PDR)

Packet Delivery Ratio (PDR) refers to the proportion of packets successfully transmitted by the sender compared to those successfully received at the sink node. Figure 8(b) illustrates the scalability of the proposed cluster-based routing system. Typically, as the number of nodes in a network grows, there is a decline in packet delivery, accompanied by increased delays and higher energy consumption of nodes. However, the proposed algorithm in this study demonstrates superior performance compared to two other existing algorithms. Notably, the packet delivery ratio improves more rapidly with an increasing number of nodes than with traditional protocols. This enhancement is attributed to the Cluster Head (CH) selection process, which optimizes data transmission by considering factors such as distance and remaining energy. In comparison to conventional methods, the proposed approach achieves a higher packet delivery ratio. Additionally, the EHO (Enhanced Hybrid Optimization) cluster head selection and CSO (Centralized Swarm Optimization) routing protocol effectively reduce packet delivery delays by facilitating uninterrupted transmission to the base station.

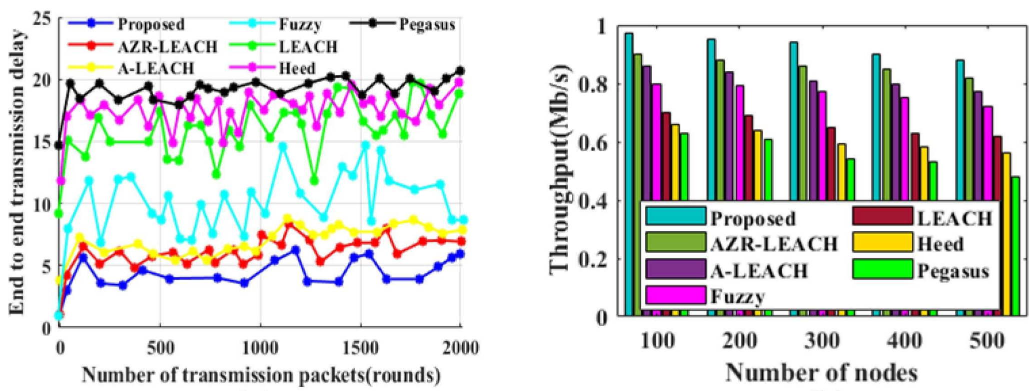
f. End to end transmission delay

The routing protocol designed for the CSO algorithm focuses on reducing delay by optimizing the pathways for data transmission from the source to the base station. By carefully choosing the most efficient routes, this protocol minimizes network congestion and speeds up packet delivery. When compared to current methods, this approach demonstrates a significant reduction in delay. Additionally, the protocol prioritizes cluster head nodes with higher energy levels during the routing process, which contributes to improved overall performance.



(a) (b)

Figure 8. (a) Energy efficiency. (b)Packet delivery ratio.



(a) (b)

Figure 9. (a) End to end delay Vs Rounds. (b) throughput Vs Number of nodes.

node. Through this process, the delay gets a decrease in this proposed method as in Figure 9(a) end to end delay transmission.

g. Throughput

The amount of data units the network can process for a given number of nodes in a given amount of time is known as throughput. Compared to the current technologies, the proposed method offers a higher throughput for more efficient data transmission. The throughput is higher than the fuzzy and LEACH approaches at node=100, reaching a value of 0.98 mbps, and higher yet at node=500, reaching a value of 0.9 mbps. This is the result of the suggested method's constant selection of the most practical data transmission path. A precise path with a shorter distance to the sink or one with more energy than other routes is used to choose the routing path. By using these parameters, the path that sends the data with the least amount of packet drop is chosen. Analyses reveal that as the number of nodes increases, there is a corresponding decline in throughput. Specifically, in the case of Fuzzy, throughput decreases from 0.8 Mbps to 0.74 Mbps as node density rises from 100 to 500 nodes. Similarly, with LEACH, throughput drops from 0.7 Mbps to 0.62 Mbps over the same range of node densities. This relationship between throughput and the number of nodes is illustrated in Figure 9(b).

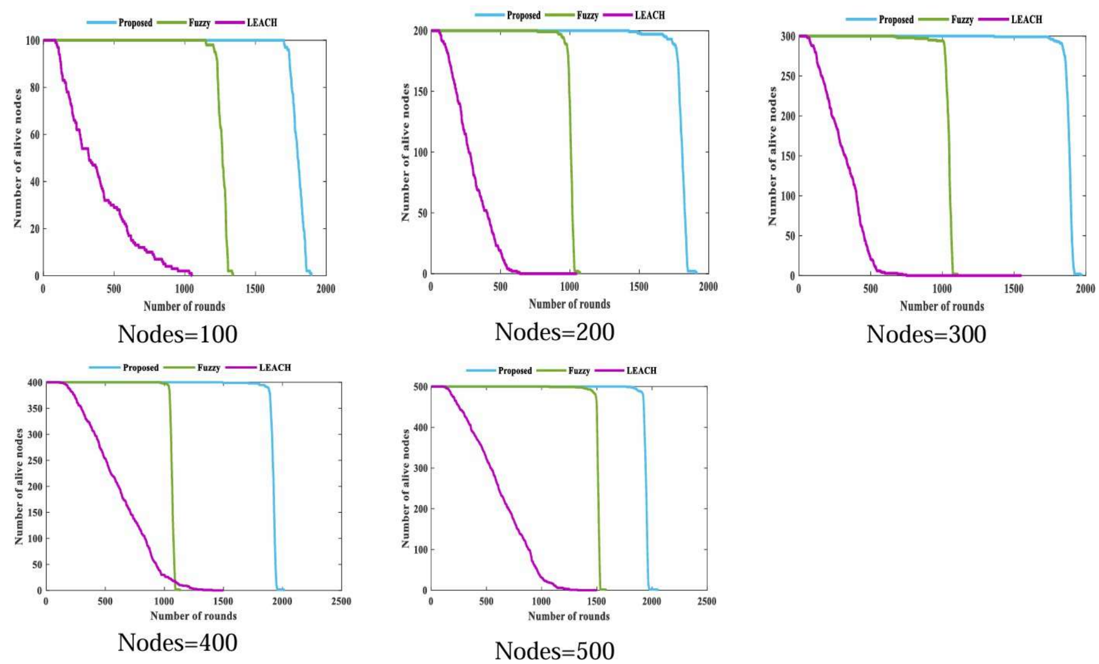


Figure 10. Number of alive nodes.

h. Number of Alive nodes

Figure 10 illustrates the number of active nodes for the proposed method compared to the existing fuzzy and LEACH methods, simulated for 100 to 500 nodes. This parameter helps evaluate the protocol's stability and the longevity of sensor nodes. The proposed method demonstrates a greater number of active nodes across the maximum number of rounds, attributed to its cluster conservation strategy and optimal routing paths. Specifically, the network maintains cluster integrity up to 1701 rounds for 100 nodes and 1848 rounds for 500 nodes. In the proposed method, nodes remain active until 2054 rounds, whereas the Fuzzy and LEACH methods see node activity until 1580 and 1493 rounds, respectively. By employing a balanced energy consumption technique, the proposed method ensures more nodes stay active longer. Consequently, the approach's selection of the shortest routing path results in a more balanced energy use for data transmission.

i. Network Lifetime

The values of the first node dead (FND), half node dead (HND), and final node dead

(LND) are given in Table 2 for the purpose of evaluating the network's lifetime. It is made abundantly evident that, in comparison to the current techniques, the number of active nodes in the network created by utilizing the suggested routing algorithm has a higher number of FND, HND, and LND nodes. The findings indicate that nodes in the immediate vicinity will have the same data rate, meaning that the loss of the network's first node won't stop it from working, but the nodes' quality will decline. The quality of the data decreases when half of the nodes die, but the network shuts down if the last node dies. Unlike the current methods, the first node in this suggested work dies from lack of energy only after a longer period of time. This is made possible by CH's energy balancing mechanism, which uses the EHO algorithm to choose the optimal node among the clusters. The sensor nodes with higher energy levels join the cluster during cluster creation to enable effective data transfer over an extended lifetime.

Table 2. Comparison of proposed & existing model(FND, HND, and END)

	No. of nodes	Proposed	AZR-LEACH	A-LEACH	Fuzzy	LEACH	Heed	Pegasus
FND	Nodes=100	1701	1483	1213	1147	85	68	22
	Nodes=200	1445	1326	1169	930	66	53	16
	Nodes=300	1761	1579	1404	689	73	50	11
	Nodes=400	1838	1635	1028	982	171	96	51
	Nodes=500	1848	1742	1489	1382	156	112	95
HND	Nodes=100	948	816	746	671	525	453	383
	Nodes=200	957	759	647	536	526	438	388
	Nodes=300	986	826	734	554	776	612	485
	Nodes=400	1007	833	749	568	751	614	480
	Nodes=500	1027	876	803	790	747	634	545
END	Nodes=100	1896	1323	1211	1341	1050	501	426
	Nodes=200	1914	1289	1175	1073	1051	504	409
	Nodes=300	1972	1614	1256	1107	1551	734	587
	Nodes=400	2015	1238	1023	1136	1501	725	578
	Nodes=500	2054	1699	1334	1580	1493	756	599

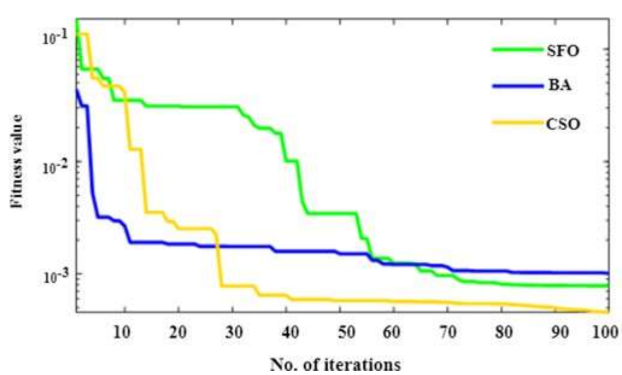


Figure 11. Number of alive nodes.

j. Fitness Function

Figure 11 displays the cost function comparison between the proposed CSO method and existing techniques. It shows that the CSO algorithm converges more rapidly compared to the Sailfish Optimizer (SFO) and Bat Algorithm (BA). The CSO approach demonstrates superior energy efficiency as indicated by the fitness function.

6. CONCLUSIONS

Reducing energy usage and extending network longevity are the primary goals of this endeavor. In WSNs, choosing a CH and creating routing are regarded as difficult jobs. Thus, this research implements an energy-efficient clustered routing technique. It goes through three network operating stages here. The DSO algorithm is used to cluster the sensor nodes in the first step, and the EHO algorithm is used to pick the CH. The CSO algorithm finally finds an effective routing path for data transmission. The sensor nodes are clustered and routed for data transfer using an effective energy balancing mechanism in this algorithm inspired by nature. The suggested approach and current cluster-based routing protocols for optimization have been compared. However, compared to conventional procedures, the suggested technique's sensor nodes survived for approximately 2054 rounds per node 500. The quality-of-service metrics, such as the number of live nodes, energy efficiency, throughput, FND, HND, LND, residual energy, end-to-end delay, and packet delivery ratio, all show improvements with the suggested algorithm. In order to increase energy efficiency, multi-hop routing between cluster head nodes will be implemented in the future. In the future, comparisons with more evolutionary optimization techniques can also be made..

REFERENCES

[1] Abid, M.S., Apon, H.S., Ahmed, A., Morshed, K.A.. Chaotic slime mould optimization algorithm for optimal load-shedding in distribution system. Ain Shams Eng. J. 13.2022.

[2] M. Selvi, S. V. N. Santhosh Kumar, S. Ganapathy, A. Ayyanar, H. K. Nehemiah, and A. Kannan. An Energy Efficient Clustered Gravitational and Fuzzy Based Routing Algorithm in WSNs - Wireless Personal Communications. https://link.springer.com/article/10.1007/s11277-020-07705-4, aug 7 2020.

[3] Xianbing Meng, Yu Liu, Xiaozhi Gao, and Hengzhen Zhang. A new bio-inspired algorithm: Chicken swarm optimization. In Ying Tan, Yuhui Shi, and Carlos A. Coello Coello, editors, *Advances in Swarm Intelligence*, pages 86–94, Cham, 2014. Springer International Publishing.

[4] C. K. Nayak, S. Das, "Minimization of Energy Holes with Lively Bonding and the Division of Coverage", International Journal of e-collaboration (IJeC), IGI Global, Volume 18, Issue-2, Article 5, 2021.

[5] N. Mazumdar and H. Om. Distributed fuzzy approach to unequal clustering and routing algorithm for wireless sensor networks. *International Journal of Communication Systems*, 31(12), may 28 2018.

[6] C. K. Nayak, S. Das, "Energy Efficient Routes Protocols to Minimize Holes in Wireless Sensor Networks using Probability Enhancement Algorithm", International Journal of e- collaboration (IJeC), IGI Global, Volume 17, Issue-4, Article 2, 2021.

[7] S. Prahadeeshwaran and G. Maria Priscilla. A hybrid elephant optimization algorithm-based cluster head selection to extend network lifetime in wireless sensor networks (wsns). *EAI Endorsed Transactions on Energy Web*, 8(31), 7 2020.

[8] C. K. Nayak, S. Das, "Minimization of Energy-Holes in Wireless Sensor Network (WSN) Using Hierarchical Routing Protocols", Journal of Computational and Theoretical Nanoscience, volume. 16, numbers5-6, pp.2357-2361(5),2019

[9] S. P. Singh and S. Sharma. A Survey on Cluster Based Routing Protocols in Wireless Sensor Networks. *Procedia Computer Science*, 45:687–695, 2015.

[10] S. Khan, A. S. K. Pathan, and N. A. Alrajeh. Wireless Sensor Networks. apr 21 2016.

[11] C. K. Nayak, S. Das, "Energy Competent Clustering Algorithm for Minimization of Holes in Heterogeneous Wireless Sensor Networks", International Journal of Systems of Systems Engineering (IJSSE), Vol. 14, No. 3, 2024

[12] P. S. Mann and S. Singh. Energy-Efficient Hierarchical Routing for Wireless Sensor Networks: A Swarm Intelligence Approach. *Wireless Personal Communications*, 92(2):785–805, aug 8 2016.

[13] S. M. Mahdi H. Daneshvar, Pardis Alikhah Ahari Mohajer, and Sayyed Majid Mazinani. Energy-efficient routing in wsn: A centralized cluster-based approach via grey wolf optimizer. *IEEE Access*, 7:170019–170031, 2019.

[14] B. Jan, H. Farman, H. Javed, B. Montrucchio, M. Khan, and S. Ali. Energy Efficient Hierarchical Clustering Approaches in Wireless Sensor Networks: A Survey. *Wireless Communications and Mobile Computing*, 2017:1–14, 2017.

[15] A. K. Das, R. Chaki, and K. N. Dey. Cluster-based energy-aware routing scheme (CBEARS) for wireless sensor network.
International Journal of Sensor Networks, 21(4):262, 2016.

[16] H. Saidi, D. Gretete, and A. Adnane. Opportunistic routing in wireless sensors networks. *Proceedings of the 2nd International Conference on Computing and Wireless Communication Systems*, nov 14 2017.

[17] D. Liu, M. Hou, Z. Cao, J. Wang, Y. He, and Y. Liu. Duplicate Detectable Opportunistic Forwarding in Duty-Cycled Wireless Sensor Networks. *IEEE/ACM Transactions on Networking*, 24(2):662–673, 4 2016.

[18] Y. Liu, M. Dong, K. Ota, and A. Liu. Activetrust: Secure and Trustable Routing in Wireless Sensor Networks. *IEEE Transactions on Information Forensics and Security*, 11(9):2013–2027, 9 2016.

[19] D. Sinha, R. Kumari, and S. Tripathi. Semisupervised Classification Based Clustering Approach in WSN for Forest Fire Detection. *Wireless Personal Communications*, 109(4):2561–2605, aug 23 2019.

[20] P. A. Patil, R. S. Deshpande, and P. B. Mane. Trust and Opportunity Based Routing Framework in Wireless Sensor Network Using Hybrid Optimization Algorithm. *Wireless Personal Communications*, 115(1):415–437, jun 20 2020.

[21] Abba, S.I., Najashi, B.G., Rotimi, A., Musa, B., Yimen, N., Kawu, S.J., Lawan, S.M., Dagbasi, M.,Emerging Harris Hawks optimization based load demand forecasting and optimal sizing of stand-alone hybrid renewable energy systems– a case study of Kano and Abuja, Nigeria. Results Eng. 12.2021.

[22] Abdel-Mawgoud, H., Kamel, S., Yu, J., Jurado, F., Hybrid salp swarm algorithm for integrating renewable distributed energy resources in distribution systems considering annual load growth. J. King Saud Univ. Comput. Inform. Sci. 34 (1), 1381–1393.2022.

[23] Abdelsalam, M., Diab, H.Y., El-Bary, A.A.. A metaheuristic Harris Hawk optimization approach for coordinated control of energy management in distributed generation based microgrids. Appl. Sci. 11.2021.

[24] Abualigah, L., Elaziz, M.A., Sumari, P., Geem, Z., Gandomi, A.. Reptile search algorithm (RSA): A nature-inspired meta-heuristic optimizer. Expert Syst. Appl. 191.2022.

[25] Agrawal, S., Samantaray, L., Panda, R., Dora, L.. A new hybrid adaptive cuckoo search-squirrel search algorithm for brain MR image analysis. Hybrid Mach. Intell. Med. Image Anal. 841.2020