ENHANCEMENT OF WIRELESS SENSOR NETWORKS SURVIVABILITY USING NEURO FUZZY-CLONAL SELECTION OPTIMIZATION

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***Abstract*— Wireless Sensor Networks (WSN) is a kind of wireless network, transmitting data utilizing the multi-hop radio relaying technique, and with no fixed infrastructure. WSN can function as a network host for the transmission and reception of data. The unique characteristics of WSN include distributed routing; frequent path breaks due to mobility, packet switching, and self-organization. The energy restriction is an important aspect to consider while designing a sensor network to increase the network's survivability. Clustering is an essential approach for overcoming energy limits and increasing network longevity. In the LEACH- technique, simulated annealing optimization is employed to generate the optimal cluster construction. This approach consumes more energy to build the best clustering, and the sensor nodes quickly lose energy, reducing the network's survivability. So, Neuro Fuzzy-Clonal Selection Optimization (NF-CSO) model is constructed for minimizing the energy consumption, identifying the optimal position for multi-sink placement, and improving the network survivability. A limiting probability of nodes can be estimated using NF-CSO and the same can be isolated. The algorithms were utilized to determine the best cluster head, resulting in less energy usage and an increase in network survivability. This issue is solved by using NF- CSO to select the optimal position of the multi-sink, which reduces the energy consumption and increases network survivability.**

Keywords — *Wireless Sensor Networks, Survivability, Clonal Selection Optimization, Neuro-Fuzzy, PSO, LEACH.*

I. INTRODUCTION

The term Wireless Sensor Networks (WSN) is a kind of wireless network which is an emerging technology in the latest years for the advanced development of digital electronics methodologies, wireless communications techniques, Micro Electro Mechanical System. The sensor network is liable for sensing, processing of data, and data transmission. The sensor nodes collect data from a group of sensor nodes and transfer it to the base station. Sensor networks are primarily used in medical and healthcare applications, as well as habitat monitoring, military, and civil applications. To understand the important applications of WSNs, efficient communication protocols are required for effective data transmission.

Each sensor node is also confronted with the additional challenge of developing efficient communication protocols based on energy consumption. The communication protocols have been optimized for maximum energy efficiency. The sensor nodes have a limited battery pack. As a result, the protocols' design is primarily focused on power conservation. Deployment of the sensor node is another important issue for designing protocols in the sensor networks. Sensor nodes are indiscriminately installed in unattended areas and the random deployment needs the self-organizing protocols for the communication process. Alternatively, the WSN protocols are used to determine node position and density in the network. WSN utilizes multi-hop radio relaying for the transmission of information. Therefore, effective correlation-based protocols are needed for improving the energy efficiency in WSN. Every sensor node is capable of gathering data from the environment and routing it to a sink or gateway. A sink node is similar to a base station in WSN infrastructure. Information is transmitted to the end-user via sink using multi-hop communication. The sink sends information to the task manager via the internet, geostationary, or any form of the wireless network. Multiple sinks or gateways are also utilized to perform the data communication between the end-users.

The lifetime of the WSN is directly dependent on the battery source. The major task of the sensor node is utilized for detecting the events and performing the data processing. Maximum energy is required only during the data communication. Failure of a few nodes in the network causes topological changes, rerouting the packets, and redeployment of the topology. Hence, the power-aware algorithms and protocols are designed for WSN applications. A particular challenge is required for finding the suitable mechanism in the applications for supporting the lifetime and maintainability requirements [1]. Some of the methodologies are utilized in the WSN applications and also to provide the economically feasible solution.

(i) Multi-hop Wireless Communication: Communication is a significant mechanism for wireless networks. Direct transmission consumes more power for communications over a long distance. Using the intermediate node reduces the total power which requires for the processing.

(ii) Energy-Efficient Operation: The energy-efficient operation is an essential technique to support the long life span of the network. Energy-efficient data can be transmitted between the two nodes. Energy is autoregulated in WSNs. By using the neighbor discovery protocol plays an imperative role in operating the network in an energy-efficient manner. The neighbor discovery performance is evaluated by minimizing the discovery latency.

(iii) Auto-Configuration: WSN is configured by the operational parameters without using external configuration. The sensor node deployment is important in most applications.

The nodes should know the geographical locations by using the other nodes. The network can also tolerate the failures or includes the new nodes in the incremental exploitation after failure.

(iv) Collaboration: A single sensor node is unable for detecting the events for some applications. But several sensors have to collaborate for detecting the event. Many sensors are utilized to collect enough information for data processing. For example, find the highest or average temperature of the particular area and send the report to the base station. This problem is solved by aggregating the readings from the individual sensor node and reducing the amount of data for the data transmission.

(v) Data-Centric: Traditional networks are mainly used for transferring the information between two specific devices and the operation of each device is provided with address-centric. The installation of the sensor nodes can tolerate the node failures and also the particular node provides the irrelevant data. Therefore, the data-centric paradigm is utilized instead of the address-centric paradigm to design the protocol and architectures.

One of the most important considerations when constructing WSN is energy constraints. The sensor nodes serve as a data source for data transmission.

The traffic load is not balanced among the sensor nodes, and the nodes closest to the sink consume more energy. The main goal is to make of the available resources while also extending the network's survivability. A variety of algorithms and methods are used to develop a solution to the problem. The set of sinks is appended to the WSN for topological planning and control. This method reduces the number of hops between sensors and sinks. This technique ensures for exchanging the less number of messages and consuming the minimum energy for the data processing. These solutions are more important for time-sensitive applications. When a large number of sinks are added to the WSN, this difficulty is referred to as a Multi-sink placement problem. It is an NP-hard problem to conclude the optimal number of sinks and its best locations. To determine the optimal position of the sinks, biologically inspired algorithms are proposed to improve the WSN survivability ratio.

II. EXISTING SYSTEM

Akyildiz et al. [2] presented a complete view of current developments and major research issues in WSNs. The sensor network communication architecture, protocol stack, and various design factors of WSNs are also presented. The various routing protocols and the open research issues for different layers for WSNs are explored. Finally, the ongoing research projects associated with WSNs are highlighted. The authors also pointed out the several open research issues like scalability, topology change, cost, power consumption, environment, and fault tolerance which intend to find the solution for the open research issues of the WSN. Lung and Zhou have presented Distributed Hierarchical Agglomerative Clustering (DHAC) for generating the clusters in an efficient way [3]. This method provides the bottom-up approach to join similar nodes together before cluster head selection. With the help of automatic cluster head rotation and rescheduling, DHAC provides uniform energy dissipation and avoids the re-clustering process. Jin et al. [4] presented an Energy Efficient Multi-level Clustering (EEMC) algorithm for achieving the minimum energy utilization. This algorithm is considered as the multi-level scheme to extend the energy efficiency over the single-level scheme. The optimal number of cluster head selections is considered in the EEMC algorithm for reducing the total energy consumption and transmission latency. This algorithm performs better than LEACH and EEMK algorithms to enhance the network survivability, low latency, and moderate overhead of the large-scale network.

Optimization is more important than solving mathematical problems in the engineering field. The main aim is to find the desired solution. This is an active research area and also several methods were utilized for solving the problems [5]. The optimization algorithms can be organized into two categories such as i) Deterministic ii) Stochastic. Certain conventional methods have solved the optimization problems, which require more computational efforts with the increase in problem size. This has been the motivation for using biologically inspired algorithms to find a better solution for optimization problems. Researchers have identified that biologically inspired algorithm is a better alternative to the usage of conventional optimization algorithms. The biologically inspired algorithms have been inspired by nature. They have been utilized to solve complex problems by using simple rules and conditions with no knowledge of search space. The biologically inspired algorithm has a decentralized method that consists of many simple entities that interact locally and give the solution to global processing. Most researchers are trying to develop technological solutions based on natural behavior. Biologically inspired algorithms have become a new era of computing for various applications such as computer networks, control systems, robotics, and biomedical engineering. Classical problem-solving techniques consist of two different methods namely i) Exact methods ii) Heuristic methods. The traditional methods have failed in finding the solution for hard and complex problems. Biologically inspired algorithms are heuristic methods that inspire the behavior of nature for solving problems. The design of the biologically inspired algorithm represents the proper formulation of the problem; evaluate the quality of solution by using the fitness function and generate the new set of solutions by defining the new operators.

From the literature surveyed, the Multiple Sink Placement problems are to locate the optimal placement of the sink to reduce worst-case delay and also to maximize the network survivability. The existing multiple sink placement problem applies various optimization algorithms like PSO and BFO with local search [6]. The PSO with local search is easy to implement and more efficient than LEACH and BFO, and the PSO will not converge fast to obtain the optimal solution in local search. The main aim is to adopt the different human-inspired algorithms in WSNs to prolong the network survivability. Initially, we adapt the NF-CSO methodology in WSNs for evaluating the network performance. The behavior of the Neuro-Fuzzy algorithm is improved with the help of a human-inspired algorithm that evaluates the network survivability and prolongs the network lifetime. The NF-CSO has been identified to perform efficiently for many real-world algorithms in terms of convergence speed and solution accuracy.

The main objectives of this research work are:

1. To develop the energy-efficient technique for wireless sensor networks using Neuro Fuzzy-Clonal Selection Optimization Algorithm to extend the network survivability and to reduce energy consumption.

2. To design the hybrid Clonal Selection Optimization Algorithm with Neuro-Fuzzy algorithm to incorporate energy-efficient routing for prolonging the network survivability. In particular, Neuro-Fuzzy algorithm reduces the energy consumption by using routing-centric parameters for hop selection.

3. To design the CNN-CSO for identifying the optimal multi-sink placement problem in WSN.

III. METHODOLOGY

Real-time problems in the engineering discipline are framed as optimization problems. Certain conventional methods have solved the optimization problems, which require more computational efforts with the increase in problem size [7]. This has been the motivation for utilizing human-inspired algorithms to find a better solution for optimization problems. Researchers have identified that a human-inspired algorithm is a better alternative to the usage of conventional algorithms. The human-inspired algorithm has the decentralized method which consists of many simple entities that interact locally and give the solution to global processing. The adaptation, robustness, and emergent behavior are the important characteristics of the human-inspired algorithm. Among the presence of several optimization algorithms, this section has a keen focus upon the utilization of the CSO Algorithm for providing an effective energy utilization of the wireless sensor network, owing to its convergent property based on local minima.

A. *PROPOSED NEURO FUZZY-CLONAL SELECTION OPTIMIZATION (NF-CSO) ALGORITHM*

Artificial immune systems (AIS) are algorithmic tools that mimic the biological immune system's processes and mechanisms. Because our lives depend on it, the immune system is one of the most important biological mechanisms we have [8]. Clonal selection optimization (CSO) is a significant proportion of immune metaheuristic technique that is inspired by clonal selection theory to generate efficient multi-objective methods. CSO is not just a dynamic parallel approach that relies on clonal selection theory, but it is also an intelligent application of a heuristic search in a large feasible solution space. When a new resource request arises, the system will execute the CSO to optimal multi-sink placement. Before using the CSO to discover the optimum solution, we first convert the mapping relationships between resources and sensor nodes into the binary format as several predefined population A (0). An individual $A_i^G = (a_{i1}^G, a_{i2}^G, \dots . a_{ip}^G)$, where the current generation is defined as G, and p signifies the population size (i.e., number of sensor nodes). Every individual (immune response) represents a candidate solution as a binary sequence of bits. The size of the bit sequence is appropriately chosen by the user to provide a satisfactory solution to the problem. Every gene on the chromosome has a value of 0 or 1. After the first population has been produced, the affinity value of every individual is calculated and retained for further use. The CSO is used in optimal multi-sink placement problems, and the affinity mechanism is designed with energy efficiency as,

$$aff(a) = e^{\min Energy + \min(Ms)} \quad \text{….. (1)}$$

The CSO for resource allocation is explained in the following section: The clonal operator is a random mapping of antibodies produced by affinity. Cloning in the biological immune system refers to the generation of a set of identical cells from a single ancestor, and only antigens with high affinity would be cloned to target invaders. The antibodies are assessed across an affinity function and sorted in order of decreasing affinity. In the beginning, the affinity of every antibody is assessed, and the individuals with the highest affinity are chosen for the next generation. The chosen antibodies then grow into specific copies, and both the copied and original antibodies are duplicated in the present population. Following that, the antibodies inside the population will carry out the mutation procedure. For producing a mutant individual A_i^G, the CSO employs a unique mutation operation. Finally, the strongest antibody A_{best}^G from the clonal repository replaces the weakest antibodies in the antibody colony.

With the assistance of the CSO algorithm, the placement of multi-sink issues was resolved and an energy-efficient routing scheme based on a fuzzy neural network is adopted with CSO to reduce energy consumption while uniformly distributing the energy across sensors, thus enhancing the survivability of the WSN.

We postulate that N sensors will be randomly dispersed around the network environment to monitor the position and physical attributes regularly. Each sensor is surrounded by other sensors, and it sends data to one of them. It can be assumed that the sensors are immobile and have equal starting energy. Each sensor is equipped with the same processing power. Any two neighboring sensors are considered for symmetric radio connections. The sink is located in the network area. Assume that each sensor's maximum transmission is R. The distance among any two surrounding sensors is taken into account while considering reactive transmission. The first-order logic model is explained in analyzing the energy consumption of the suggested routing. Let m denote the packet size in bits. The amount of energy required conveying m bits of the packet over a unit distance d between a sender sensor node and one of its surrounding sensor nodes is represented as,

$$e_{TX}(m,d) = \begin{cases} m*e_{select}+m*\varepsilon*d^2<d \\ m*e_{select}+m*\varepsilon*d^4\geq d \end{cases} \quad \text{….. (2)}$$

The energy requirement for receiving a packet of m bit is determined as,

$$e_{RX}(m) = m * e_{select} \quad \text{….. (3)}$$

The anticipated energy usage for transferring m bits of data from one sensor node to the next hop of the other sensor node can be stated as,

$$e(e_{total}(m,r) = e_{TX}(m,r) + e_{TX}(m) = \left[2e_{select} + e\left(\frac{n_h}{2n_h+1}r\right)^2\right]m \quad \text{….. (4)}$$

Figure 4 depicts the five-layer design of the Neuro-Fuzzy System, which includes a fuzzy layer, a T-norm layer, a normalized layer, a de-fuzzy layer, and an aggregate layer. The linguistic attributes of routing metrics can be defined as follows: residual energy(eR) = {low, good, high} and represented by {e1, e2, e3}, degree of sensor (∞) = {poor, average, dense} which can be written as $\{\infty_1, \infty_2, \infty_3\}$, forward pass ($f_{ij}$) = {adjacent, equidistant, isolated} is represented as {f_1, f_2, f_3} and resultant output metric= {weak, moderate, strong, very strong} as H= (O_1, O_2, O_3, O_4}. The sample fuzzy rules can be denoted as,

Rule 1 = if e_R is e_1, f_{ij} =f_1, and ∞ is ∞_1, then $O_{1=}q_1$ e_R+r_1 f_{ij}+s_1∞+t

Rule 2 = if e_R is e_2, f_{ij} =f_2, and ∞ is ∞_2, then $O_{2=}q_2$ e_R+r_2 f_{ij}+s_2∞+t

Then the fuzzy membership function can be written as,

$$\partial_{e_k}(e_r) = exp\left[-\left(\frac{e_r - z_k}{2x_k}\right)^2\right] \quad \text{….. (5)}$$

The output of the T-norm layer and normalized layer is calculated as,

$$T_k = \partial_{e_k}(e_r) * \partial_{\infty_k}(\infty) * \partial_{f_k}(f_{ij}) \quad \text{….. (6)}$$

$$T_{nk} = \frac{T_k}{\sum T_k} \quad \text{….. (7)}$$

Finally, the output of the aggregate layer is given by,

$$H = \sum T_{nk} H_k = \frac{\sum T_k H_k}{\sum T_k} \quad \text{….. (8)}$$

Neuro Fuzzy-Clonal Selection Optimization (NF-CSO) Algorithm
Input: Population Size, Probability of Mutation p , Max Generation G, e_R,, f_{ij}, degree of sensor ∞
Start
Step 1. Construct an antibody population at randomly AN(0).
Step 2. Determine the affinity of the original population AN(k).
Step 3. Select halves of the antibodies with the highest affinity $AN_l(k)$.
Step 4. Every individual is clonned to develop new population NP(k) and the developed population is directly proportional to its affinity.
Step 5. Perform mutation process from $AN_l(k)$ to create population PP(k).
Step 6. Select operation is selected from population PP(k) and optimal multi-sink placement position is identified.
Step 7. Fuzzy layer determines the anticipated energy usage for every node using,

$$e(e_{total}(m,r) = e_{TX}(m,r) + e_{TX}(m) = \left[2e_{select} + e\left(\frac{n_h}{2n_h+1}r\right)^2\right]m$$

Step 8. Firing Strength is tuned at T-Norm Layer as

$$T_k = \partial_{e_k}(e_r) * \partial_{\infty_k}(\infty) * \partial_{f_k}(f_{ij})$$

Step 9. Calculater the Firing Strength as,

$$T_{nk} = \frac{T_k}{\sum T_k}$$

Step 10. Execute Defuzzification and energy efficient routing is achieved at aggregate layer using,

$$H = \sum T_{nk} H_k = \frac{\sum T_k H_k}{\sum T_k}$$

Output: Improved Survivability of Network Attained by Energy Efficient Routing and Optimal Multi-Sink Placement.

IV. SIMULATION RESULTS

The network simulator is used to implement the existing and proposed techniques. The other version like 6, 10, or 12 has not been supported for implementing the techniques. The trials are repeated 20 times with different topologies. The error graph is constructed using the average readings and a 95% confidence interval. N and round have values of 40 and 100, respectively. Wireless sensor nodes are installed in a 150*150m square area in these experiments. The network's size varies from 20 to 100, with a 20-step increment. The base station is positioned at (50,000), and the initial energy of each sensor node ranges from 1 Joule to 5 Joules. In each round, 5% of the cluster head nodes are counted toward the total number of sensor nodes. Each experiment takes 4600 seconds to simulate. Table 1 details the simulation settings for testing the proposed system.

Table 1. Simulation Settings

Parameters	**Value**
Topology Size	150*150 m^2
Number of Sensor Nodes	100
Base Station Position	50,000
Percentage of Cluster Head	5%
Transmission Range	200m
Size of the Packets	400 Bytes
Sensor Nodes Initial Energy	1-5 Joules
Simulation Time	4600 Seconds

V. PERFORMANCE EVALUATION METRICS

The performance of the proposed NF-CSO algorithm and existing algorithms such as LEACH, Bacterial Forage Optimization (BFO), and Particle Swarm Optimization (PSO) algorithm has been compared using the following performance evaluation metrics.

(i) Number of Alive Nodes: The number of nodes that are active during the simulation's predefined timeframe.

(ii) Energy Consumption: The total quantity of energy utilized during the simulation period.

(iii) Lifetime of the Network (First Dead Node): It denotes the time when the first sensor node in the wireless sensor network neglects to work.

(iv) Lifetime of the Network (Last Dead Node): It denotes the exhaustion of the last node in the simulation process.

(v) Lifetime of the Network (Difference between FDN and LDN): It denotes the time elapsed between the first and last node's expiration.

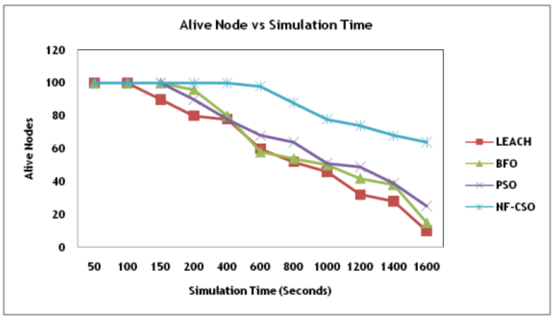

Fig. 1. Comparison of Alive Nodes and Simulation Time

Figure 1 illustrates the number of alive nodes and simulation time. LEACH, BFO, and PSO methods sustain the nodes alive up to 150 seconds, 250 seconds, 360 seconds respectively. NF-CSO method prolongs the alive nodes up to 700 seconds. In LEACH and BFO methodology, the number of alive nodes quickly reaches the dead state after the simulation time around 200s. NF-CSO enhances the network lifetime by 25% from original BFO and PSO, and it improves 40% of the network lifetime compared to LEACH. From Figure 1 it is evident that NF-CSO performs well for increasing the network survivability when compared to other algorithms.

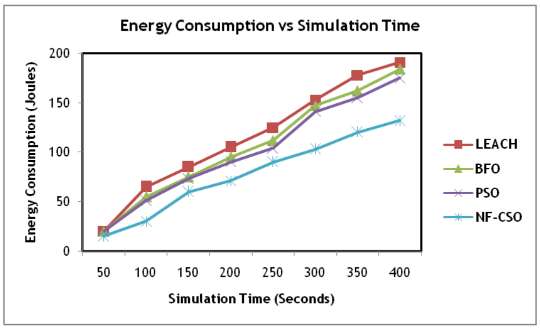

Fig. 2. Comparison of Energy Consumption and Simulation Time

Figure 2 illustrates the energy consumption during the simulation time. LEACH and BFO algorithms have consumed more energy when compared to PSO and NF_CSO. The proposed methodology consumes less amount of energy compared to the existing methods quickly forms clusters that consume a minimum amount of energy. Neuro-fuzzy logic fine-tunes the optimal placement of multi-sink at appropriate positions.

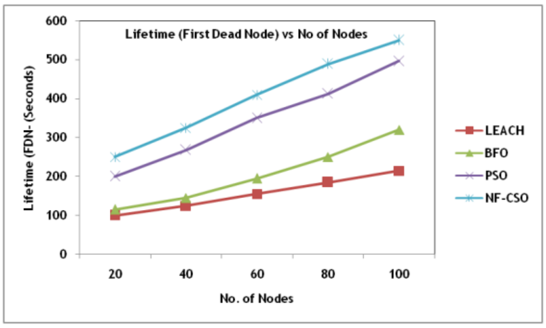

Fig. 3. Comparison of Lifetime (First Dead Node) and Number of Nodes

Figure 3 depicts the comparison of the network lifetime (FDN) with the number of sensor nodes. LEACH algorithm selects the node with the maximum energy level as cluster head. The LEACH algorithm selects cluster heads depending upon the outstanding energy of the node and the average energy level of the nodes. A slight difference occurs for finding the network lifetime between the LEACH and BFO algorithm with considering the number of sensor nodes. NF-CSO gives a better life than LEACH, BFO, and PSO. As the forming of clusters requires a minimum period, it initiates the extension of the lifetime of the network and identifies the optimal position for multi-sink placement.

Figure 4 illustrates the number of sensor nodes versus network lifetime (LDN). The network lifetime of NF-CSO and PSO show better results than LEACH and BFO. NF-CSO presents a better lifetime (LDN) compared to the existing algorithms. NF-CSO method forms the clusters that consume a minimum amount of energy and identifies the optimal position for multi-sink placement. From the experimental results, it has been demonstrated that the NF-CSO method gives better results when compared to LEACH, BFO, and PSO algorithms for the metrics of network lifetime and energy consumption.

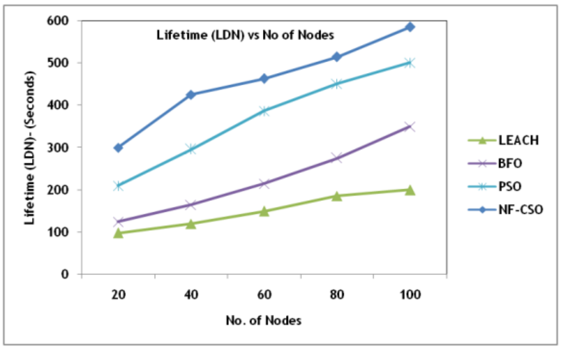

Fig. 4. Comparison of Lifetime (Last Dead Node) and Number of Nodes

VI. CONCLUSION

With the growing demand for time-constraint areas like healthcare, forest fire warning, and intrusion detection, one of the primary difficulties in WSN is ensuring energy limitation. To address energy constraints, topological level solutions are proposed. Finding the optimal number of sinks and their placement is an NP-hard problem. This can be solved by suggesting an effective heuristic strategy based on the Clonal Selection Optimization (CSO) to discover the optimal sink placement placements. The problem is defined using a mathematical description, and all viable sink candidate positions are identified. To merge routing-centric metrics such as forward progress, residual energy, and degree of the sensor, a dynamic Neuro-Fuzzy algorithm was used. The next-hop selection algorithm employs Neuro-Fuzzy to allocate the duty of routing packets to an adjacent sensor node as the next hop. To route the packet from the source sensor to the sink with minimum energy consumption with a primary motive of increasing network survivability, the Neuro-Fuzzy algorithm is incorporated with the CSO algorithm. The experimental results demonstrate that the NF-CSO method gives better results when compared to LEACH, BFO, and PSO algorithms for the metrics of network lifetime and energy consumption. The proposed routing will be explored further in the future using several machine learning algorithms for emerging areas of application.

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