A Cutting-edge Metaheuristic Approach Based on The Manifold Distance for Energy-efficient Clustering in WSN

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Abstract–This paper presents the development of a new algorithm called F-MPSO, which aims to enhance energy efficiency and extend the lifetime of wireless sensor networks. The F-MPSO algorithm aims to optimize the selection of cluster heads, which is a problem that falls under the category of Non-Deterministic Polynomial (NP)-hard problems. To address this challenge, a hybrid metaheuristic approach has been implemented using manifold distance to cluster the sensor nodes. We recommend using a combination of the Firefly approach for local updates and the PSO approach for global updates to create a reliable cluster. Our strategy aims to improve the overall lifespan of the network. We use a metric that takes into account the different routes available and gives preference to paths that go through intermediate sensors with high residual energy, rather than simply selecting the shortest distance between a regular node and cluster heads with low residual energy. Based on the analysis conducted using Matlab, it has been determined that the F-MPSO algorithm proposed is highly efficient regarding energy consumption. Additionally, it has been deemed successful in extending the network lifetime. Results from round 1600 indicate that the proposed method had approximately 78 still operational nodes. On the other hand, Leach's algorithm had no live nodes, while enhanced-LEACH and ESO_LEACH had 25 and 53 live nodes, respectively. Furthermore, the author has compared the results with previous algorithms, and the outcome shows excellent promise.

Keywords:Wireless sensor networks, Energy efficiency, Optimization, Manifold distance, Clustering

1. Introduction

Wireless sensor networks (WSNs) are networks that can organize themselves through the use of many small sensors. These sensors can sense their surroundings and transfer data within their radio coverage. They are also programmed to perceive the physical world and identify it. These wireless sensor nodes are highly valuable due to their small size, affordability, limited computing power, versatility, and ability to communicate within short distances. For WSN applications, the most important requirements are a durable network, dependable data transmission, energy-efficient sensor nodes, and the ability to scale. Wireless Sensor Networks (WSNs) encounter various issues because of the limitations of sensor nodes, such as coverage area, network lifespan, scheduling, and data aggregation. As a result, much research has been carried out to preserve energy in sensor nodes and prolong the network's life [1][2, 3].

The architecture of WSN involves clusters of wireless sensor nodes, which enhances the system's longevity and lowers energy consumption. The cluster head can be selected by either the sensor nodes or the network designer. The primary purpose of this system is to collect data, eliminate duplicate information, and send only the essential data to the base station. Implementing effective routing protocols and clustering algorithms is crucial to extending the network's lifespan, as the routing factor significantly impacts the network's parameters. This paper utilizes a hybrid metaheuristic approach, which incorporates manifold learning routing. This approach is aimed at prolonging the life of a wireless sensor network.

The study delves into a fresh approach to clustering nodes. In order to select the most optimal cluster heads (CHs) from a set of sensor nodes, the Non-Deterministic Polynomial (NP)-hard optimization problem was tackled using Particle Swarm Optimization (PSO). However, the PSO can sometimes become trapped in suboptimal

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solutions, mainly when dealing with medium or large-sized function optimization problems. This article proposes a solution to overcome the limitations of the particle swarm optimization algorithm by combining it with the firefly algorithm. The resulting local search algorithm shows promising results.

TDMA has planned continuous sensor connection, even when no data is transmitted[4]. As per our research, we suggest utilizing sensor nodes with ample residual energy as intermediates to raise the lifespan of wireless sensor networks. This approach can transmit data over shorter distances and reduce energy consumption. Our proposed cluster element selection method prioritizes manifold-based metrics, ensuring that paths with sensors possessing high residual energy are preferred over those with ordinary nodes and low residual energy CH sensors.

Our research suggests enhancing the particle swarm algorithm by incorporating manifold distance and combining it with the firefly algorithm for better energy preservation of transmitted data packets. Our approach focuses on clustering sensors in a network and selecting optimal cluster heads and members. We propose using a metric based on manifolds to measure the geodesic distance between sensors and their energy levels for clustering. We also suggest employing a combination of firefly and manifold-based particle swarm optimization algorithm to determine the optimal cluster heads and associates. Our approach outperforms conventional algorithms regarding energy consumption, network life, and received packets.

The paper's second section delves into related work, while the third section outlines the goals of the proposed method and the study's procedures. Section 4 evaluates the proposed algorithm, and Section 5 illustrates the simulation results. The paper concludes with Section 6.

2. Related works

Researchers have recently conducted significant studies on enhancing energy efficiency in wireless sensor networks. They have developed various algorithms to tackle different aspects of this problem. The LEACH cluster head selection technique is one of the most popular algorithms, as it randomly picks cluster nodes, assuming an even energy spread in the sensor nodes throughout the network[5]. Several energy-based methods have been proposed for initializing CHs in wireless sensor networks. One such method is the particle swarm optimization algorithm suggested by Yadav et al.[6], while another is the firefly algorithm proposed by Sarma et al.[7]. Nigma et al. [1]introduced the ESO-LEACH meta-heuristic particle swarm enhancement, which included advanced nodes and an improved set of rules for CH election to reduce the algorithm's randomness. Salem and Shudifat[8]extended LEACH to enhanced LEACH. Enhanced LEACH protocol selects the cluster head closest to the base station, reducing power usage in the network. Jari and Avokh addressed concerns regarding clustering, multi-sink placement, and load-balanced anycast routing to improve the longevity of the wireless sensor network with multiple sinks[9]. A suggested approach for creating a reliable path is the ACO-PSO method. This method uses the ACO approach for local updates and the PSO approach for global updates[10].

3. Methodology

Our approach focuses on extending the lifespan of the network while minimizing energy usage. We have developed the F-MPSO algorithm by combining the firefly and manifold-based particle swarm optimization algorithms. Unlike traditional wireless sensor network protocols, our approach uses sensors with minimal information as intermediaries to extend the network's lifespan. This method is better because it enables us to divide the shortest direct path between a sensor and CH into shorter line segments. When selecting members for a CH, the energy model based on the radio model must be considered. Our approach aims to optimize network performance while reducing energy consumption by considering the distance between ordinary nodes and CH. Based on the Euclidean distance metric shown in Fig. 1, nodes 2, 3, 4, and 5 should be chosen for CH selection. This will result in a total energy consumption proportional to ($2d^2+2d^4$). However, if a path with intermediate nodes is chosen instead, the energy consumption for nodes (1, 2, 5, 6) will be lower than that of the straight path and proportional to $4d^2$.

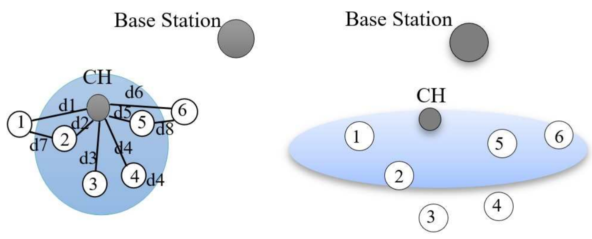

Fig. 1. Compares two types of clustering in wireless sensor networks, showing that the Euclidean distance metric may not always be the best choice.

Therefore, we recommend using the manifold distance between a sensor and CH instead of the shortest straight line for further energy consumption reduction.

We recommend utilizing manifold distance between sensors and CH instead of the shortest straight line to optimize network performance and reduce energy consumption. Our algorithm estimates the distance between two points using a simple manifold distance metric, exploring the shortest path with intermediaries. By selecting definitive sensors as neighbors and calculating the Euclidean distance between them, we can sort the distance list and select the first K sensors as neighbors[11]. The length of a line segment can be expressed as $L(x_i, x_j) = \rho^{\mathrm{dist}(x_i, x_j)} - 1$, where $dist((x_i, x_j))$ refers to the Euclidean distance between$points x_i$ and x_j. Here, ρ represents the flexing factor. The manifold distance betweenx_i and x_j is determined using equation (1)[12, 13].

$$D_M(x_i, x_j) \triangleq \min_{p \epsilon P_{i,j}} \sum_{k=1}^{|p|-1} L(P_k, P_{k+1}) \quad (1)$$

3.Proposed method: F-MPSO

Upon conducting a rigorous investigation, we have discovered that the Particle Swarm Optimization (PSO) algorithm needs to be improved in its ability to solve middle or large-sized optimization problems. In many cases, PSO becomes trapped in suboptimal solutions, which can harm wireless sensor networks. Nonetheless, we have identified a promising solution in the form of a hybrid approach that combines the strengths of PSO with the Firefly Algorithm's local search capabilities. This approach could optimize the placement of sensors and the clustering of nodes, which improves the efficiency and overall performance of wireless sensor networks. Utilizing the F-MPSO technique enables the optimization of residual energy while simultaneously reducing the distance between sensors and the base station.This encourages a more balanced energy consumption among nodes and generally increases the network's lifetime. Our proposed clustering algorithm, which uses residual energy and distance parameters, has demonstrated considerable promise in improving the efficiency and performance of wireless sensor networks. Following the proposed steps shown in Figure 2, we can achieve better clustering and energy efficiency in wireless sensor networks. The approach, which combines the strengths of Particle Swarm Optimization (PSO) with the Firefly Algorithm's local search capabilities, can potentially optimize the placement of sensors and clustering of nodes. This can maximize residual energy and minimize the distance between sensors and the base station, which promotes balanced energy consumption among nodes and increases the network's lifetime. The proposed clustering algorithm, which incorporates residual energy and distance parameters, has shown significant potential in enhancing the efficiency and performance of wireless sensor networks.

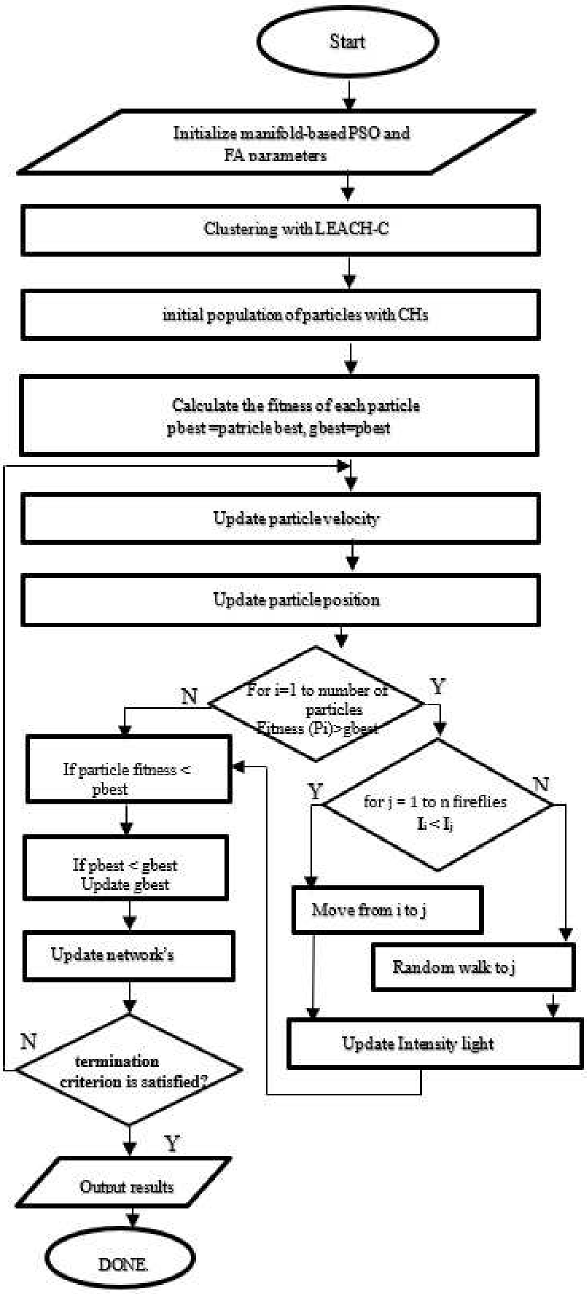

Fig. 2. The flowchart of the proposed F-MPSO method

A method has been proposed to improve the effectiveness of wireless sensor networks by optimizing sensor placement and node clustering. This method utilizes a fitness function that considers three objectives: decreasing the average distance between nodes within a cluster, increasing the remaining energy in each cluster, and minimizing the distance between the base station and all CHs. Equation 2 presents the precise formulation of the fitness function used in the manifold-based PSO approach. By taking these objectives into account, the proposed method has demonstrated the ability to improve significantly the efficiency and performance of wireless sensor networks.

$$\text{Fitness} = \text{minimize} \sum_{j=1}^{m} \frac{1}{l_j}\left(\sum_{i=1}^{l_j} \text{dist}_{PM}(s_i, CH_j) + \text{dist}(CH_j, BS)\right) \quad (2)$$

The variable "$dist$" represents the Euclidean distance. In contrast, "dist_{PM}" calculates the distance between two sensors concurrently using both the geodesic distance and the remaining energy in the sensors. Equation (3) calculates the distance between the two sensors based on the residual energy in the intermediate node, which is deemed important:

$$dist_{PM}(x_i, x_j) = \frac{E_{initial} x_i}{E_{residual} x_i} \times D_M(x_i, x_j) \quad (3)$$

The variable $D_M(x_i, x_j)$ represents the distance between x_i and x_j on the manifold, calculated using equation (1).. We analyzed research findings to determine the best position for the population using *gbest* and for individual particles using *pbest*. Once we assigned these values, we evaluated the improvement in Fitness value using Equation 4. If there was an improvement, we used equations 5 and 6 to calculate the new position and velocity.

$$F(i,t) = \begin{cases} \text{true}, & \text{if } \text{fitness}(\text{paticle}_i^t) < \text{gbest}^{t-1} \\ \text{false}, & \text{if } \text{fitness}(\text{paticle}_i^t) \geq \text{gbest}^{t-1} \end{cases} \quad (4)$$

Vi (t +1) =wVi (t) + c1r1 (pbesti (t) - X i (t)) + c2r2 (gbest(t) - Xi (t)) (5)

X i (t +1) = X i (t) +Vi (t +1) (6)

In this equation, Xi denotes the position of particle i, while Vi represents its velocity. The variable t stands for the current iteration, and $t + 1$ refers to the subsequent iteration in the algorithm. $C1$ and *c2* are collective and cognitive components. $r1$ and $r2$ are random numbers between 0, 1, and *w* is interia weight. We first determined the best position for the population and individual particles to optimize our approach. After assigning these values, we evaluated the Fitness value using Equation 4 and calculated new position and velocity using Equations 5 and 6. If a particle had a higher Fitness value than the global optimum, we performed a local search using the Firefly algorithm. The algorithm is based on nature and randomness. It employs the inverse square rule to compute the light intensity at a certain distance from the light source, as per Equation 7. However, if a particle's Fitness value was not better than the global optimum, we did not change its parameters.

$$I(r) = \frac{l_s}{r^2} \quad (7)$$

Light is absorbed in an environment at a constant absorption coefficient (γ)∈ [0, ∞). Therefore, Equation 8 represents attractiveness.

$$B(r) = B.e^{-\gamma r^2} \quad (8)$$

The attractiveness of the firefly at a certain distance, *r*, can be represented as B(r), while *B0* represents the attractiveness when *r* is equal to zero. To calculate the distance between two fireflies (i and j), their positions (Xi and Xj) are taken into account, and the Euclidean distance formula is applied. The formula is expressed as (9)

$$r_{ij} = \|X_i - X_j\| = \sqrt{(x_i - x_j)^2 - (y_i - y_j)^2} \quad (9)$$

We can calculate the new position of the low-brightness firefly *i* using equation 10, which involves moving towards the more attractive firefly *j*

$$X_i = X_i + B.e^{-\gamma r_{ij}^2}(X_j - X_i) + \alpha\epsilon_i \quad (10)$$

In equation 10, $\epsilon_i$is a vector of random variables, and $(\alpha) \in [0,1]$ is a random parameter [10, 14, 15].

I will modify the light intensity and evaluate the revised solution until the end criteria are satisfied. If the highest overall value remains constant for six consecutive iterations, it might be necessary to set the velocity of the particle to zero. Otherwise, the algorithm will stop once it reaches the predetermined number of iterations. The F-MPSO algorithm will produce the optimal result as its output.

To implement the proposed approach, you need to follow these steps:

Step 1 - The sensors are strategically located in the space based on the requirements of the main issue and initial conditions. Primary clusters are then formed using the basic LEACH-C algorithm.

Step 2 - Select the primary headings of every cluster by considering the highest amount of remaining energy in each sensor.

Step 3 - Using Equation 2, calculate the fitness, gbest, and pbest of each particle and determine their respective values.

Step 4 - To improve fitness, the firefly algorithm must be executed. This involves calculating the light intensity for all firefly populations, moving them according to equation 10, updating the intensity value, and repeating the process for each particle.

Step 5, the pbest and gbest should be updated for each particle in the new population.

Step 6 - Before exiting, make sure to check if the termination criteria have been met. This includes checking if the value of gbest has remained the same for six consecutive rounds or if the final round has been reached. If either of these conditions are met, change the particle velocity to zero and exit.

Step 7 - Choose the best CHs for potential candidacy and group them together using the manifold distance criterion.

Step 8 - Repeat steps 3 to 7 until the final round is reached.

Step 9 - Collect sensor information by CHs.

Step 10 - Transfer information directly from the CHs to the Base Stations.

Step 11 -To determine the residual energy for each sensor, apply equation 11 while considering the number of

$$e_{total} = E_{TX}(l,d) + E_{RX}(l) \tag{11}$$

operational sensors.

where $E_{TX}(l, d_{PM})$ is the reduction of the energy to send l bit of data in manifold space and calculate with equation (12),

$$E_{TX}(l, d_{PM}) = \begin{Bmatrix} l \times E_{elec} + \varepsilon_{fs} \times {d_{PM}}^2 \ , & if \quad d_{PM} < d_t \\ l \times E_{elec} + \varepsilon_{mp} \times {d_{PM}}^4 \ , & if \quad d_{PM} \geq d_t \end{Bmatrix} \tag{12}$$

The energy consumption of a transmitter and receiver circuitis known as Eelec. The free-space technique's transformation parameters are denoted as εfs. The distance between a regular node and a cluster head is labeled as "d," while the packet data is represented by "l". The calculation of energy consumption is based on equation (13).

$$E_{RX}(l) = \alpha \times E_{elec} \tag{13}$$

After identifying the clusters, we proceed with the clustering process using $dist_{PM}$. The geodesic distance between the regular sensors and CHs, along with the remaining energy of each sensor, determines this process.

4. Simulation results

In this section, we will compare the proposed algorithms with four other protocols: LEACH protocol[5], Enhanced-LEACH protocol [8], ESO_LEACH protocol [1], and F-MPSO method. The LEACH algorithm chooses a cluster head based on proximity but does not factor in the distance of the cluster head from the base station. The Enhanced-LEACH algorithm chooses a Cluster Head (CH) based on the shortest distance between the node and the CH and between the CH and the base station. The ESO_LEACH algorithm employs the particle swarm meta-heuristic algorithm to cluster the sensor nodes initially. On the other hand, the F-MPSO algorithm chooses individual CH nodes by utilizing a unique hybrid metaheuristic approach founded on manifold space.

To assess the effectiveness of the suggested algorithm, we will evaluate it based on four criteria: energy consumption per node, energy consumption per round, network longevity, and the quantity of packets received. The first criterion looks at the total energy consumed when a specific count of nodes collects and merges data before transmitting it to the central station. The second criterion measures the total energy consumption over several cycles. The third criterion examines the network's lifespan, or the number of rounds until the last node dies (LND). Finally, the fourth criterion looks at the total number of data packets received by the base station during the network's lifetime. More received packets indicate better network performance. By evaluating the algorithm using these criteria, we can determine how it compares to other protocols and how practical it is in real-world scenarios.

I have compared the F-MPSO algorithm and the LEACH, Enhanced-LEACH, and ESO_LEACH protocols. According to the results, the F-MPSO method outperformed the other methods in energy consumption with respect to the number of nodes, rounds, network lifespan, and received packets. The F-MPSO algorithm uses a combination of manifold learning and metaheuristic methods to choose the best CHs, resulting in improved sensor node clustering and overall network performance.

4.1. Simulation setting

In Table 1, we have presented the hypotheses that we will use to evaluate both the previous methods and our proposed method. To simulate this, we have used a protocol similar to Enhanced-LEACH [8]. We have assumed that all nodes have an initial energy of 0.5 joules and calculated the energy consumption for each data transmission and reception using Equations (13) and (14). The base station in our simulation received coordinate information from all nodes and employed the previous and proposed F-MPSO algorithms to identify clusters. Each node has broadcasted its header number to all nodes and then sent its information to the appropriate header. These hypotheses have been developed to ensure that our comparison between the proposed algorithm and previous methods is fair and takes into account energy consumption, network lifetime, and packet reception rate.

4.2. Results and discussion

Based on the simulations conducted, the F-MPSO algorithm was determined to be more efficient than the LEACH, Enhanced-LEACH, and ESO_LEACH protocols with regard

Table 1. Parameters simulation [8]

Parameter	Value
Simulation area	100 m× 100 m
Number of nodes	45–85
Packet length (from cluster head to BS)	6400
Packet length (default packet length from normal node to cluster head)	200
Initial energy	0.5
Base station coordinates (50, 50)	(50, 50)
Probability to the node to become a CH	0.1
Energy for transferring of each bit	50×0.000000001
Energy for receiving	50×0.000000001
Energy for free space model	10×0.000000000001
Energy for multipath model	0.0013×0.000000000001
Energy for data aggregation	5×0.000000001

to energy consumption, network longevity, and the number of received packets.This algorithm uses manifold learning to select optimal Cluster Heads (CHs), resulting in efficient and effective clustering of sensor nodes and significantly improved network performance. By passing more rounds than other algorithms, the F-MPSO algorithm was able to successfully extend the life of the network. As each round passed, the network nodes' overall energy consumption decreased. The F-MPSO algorithm successfully extended the network life by passing more rounds than other algorithms, and the total energy consumption of the network nodes decreased with each round. The F-MPSO conference had a greater number of active nodes compared to other algorithms, which shows its higher efficiency. Furthermore, it outperformed other algorithms in terms of the quantity of packets received by the base station. These results are significant as they ensure reliable communication between the sensor nodes and the base station, which is crucial in wireless sensor networks. The F-MPSO algorithm has proven to be a promising and effective approach for optimizing wireless sensor networks, providing better network performance, energy efficiency, and lifetime.

After analyzing figures 3-6, it is evident that the proposed algorithms exhibit exceptional performance when compared to other algorithms in terms of energy consumption, network lifespan, and the number of packets received by the base station. In particular, Figure 3 illustrates how the power consumption of the proposed method compares to that of the LEACH, Enhanced-LEACH, and ESO_LEACH algorithms. Based on the proposed hypothesis, Figure 4 illustrates the energy consumption of these algorithms at various rounds during the simulation. It is worth noting that the F-MPSO algorithm has successfully extended the network's lifespan with each round while also reducing the total energy consumption of the network nodes. This is a noteworthy accomplishment.

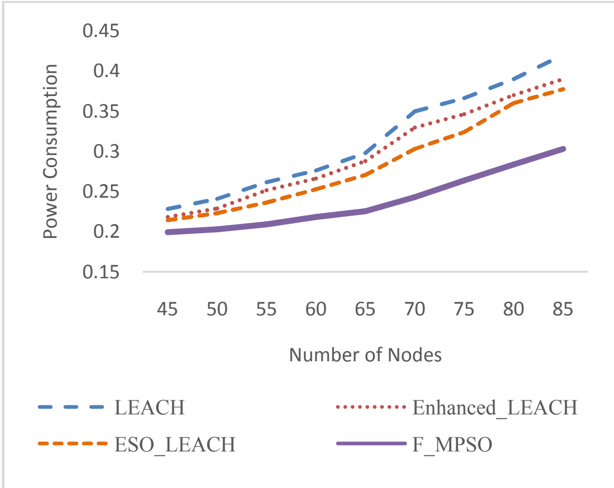

Fig. 3.power consumption in LEACH, ENHANCED_ LEACH, ESO_LEACH, and F-MPSO based on different numbers of nodes

The proposed method has led to a considerable improvement in energy consumption and network lifetime. This is particularly noticeable when dealing with high numbers of network nodes, as the proposed method has been able to reduce energy consumption significantly. The reason for the enhancements from utilizing F-MPSO is that nodes can send information to adjacent nodes with the aid of intermediate nodes positioned at closer distances. As a result, there is no need for any extra transferring, which helps to increase the network's lifetime.

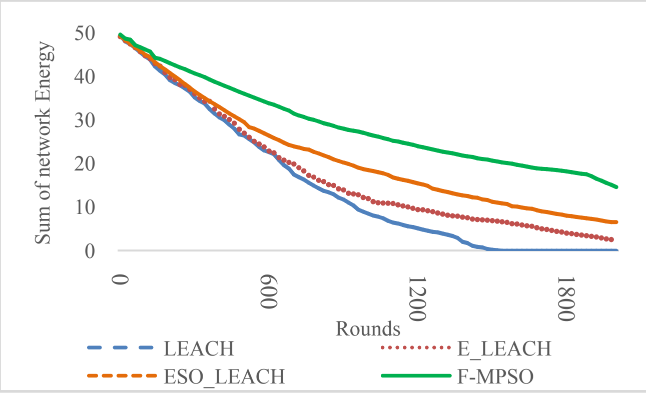

Fig. 4. Sum of network Energy for each round using LEACH, ENHANCED_ LEACH, ESO-LEACH, and F-MPSO.

After analyzing the data, it is evident that Figure 5 shows a considerable increase in the number of alive nodes in the F_MPSO convention as compared to LEACH, Enhanced_LEACH, and ESO_LEACH. This demonstrates the superior performance of the F_MPSO algorithm in terms of network lifespan. It is a promising development that can lead to more efficient and reliable wireless sensor networks.

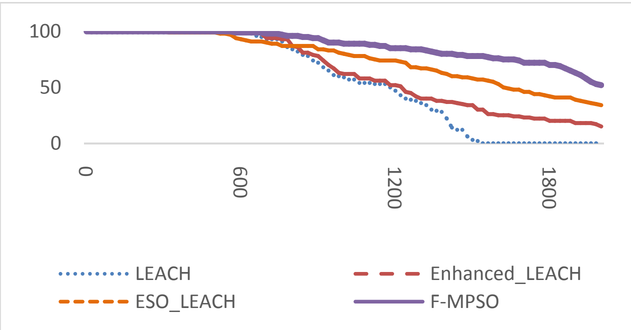

Fig. 5. The number of live nodes for each round using LEACH, ENHANCED_ LEACH, ESO-LEACH, and F-MPSO

After analyzing the data in Figure 6, it is evident that the proposed algorithm surpasses the previous algorithms in terms of the number of packets received by the base station. This is an essential metric in evaluating the efficiency and reliability of wireless sensor networks, and the results suggest that the proposed algorithm is a significant improvement over the previous methods. The diagrams in Figure 5 and Figure 6 demonstrate that the F-MPSO convention outperforms previous algorithms in terms of the number of alive nodes and the number of packets received by the base station. The simulation results indicate that the proposed algorithm significantly extends the network lifetime and provides better vitality efficiency than the conventional LEACH clustering convention. These findings suggest that F-MPSO is a promising approach for reducing energy consumption and increasing network lifetime, especially in scenarios with many network nodes.

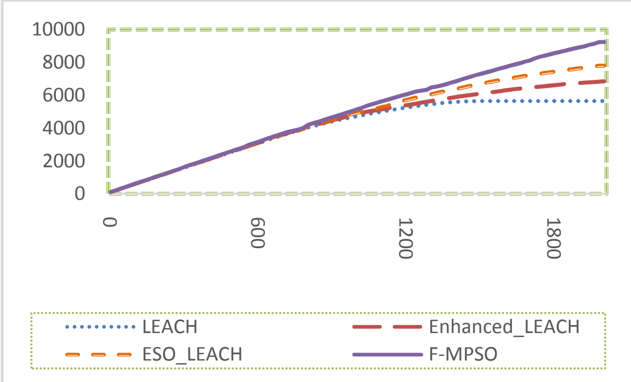

Fig. 6. The number of packets received by the base station for each round using LEACH, ENHANCED_ LEACH, ESO-LEACH, and F-MPSO

In this paper, a clustering approach called F-MPSO is suggested. The findings from the simulation of the F-MPSO algorithm show that almost all central nodes lose their complete power when the network finishes around 1000 rounds. In contrast, for F-MPSO, the first-node dead condition is reached at approximately 580 rounds, but the slope of the curve follows a consistent pattern instead of the sudden drop seen in LEACH, which leads to all nodes dying after about 1600 rounds. Therefore, the network's lifespan is extended with F-MPSO, which provides superior energy efficiency and a longer system lifetime than traditional LEACH.

5. Conclusion

In this paper, a way has been developed to improve wireless sensor networks by optimizing the placement of sensors and clusters. This method uses a fitness function to reduce the distance between clusters, increase energy reserves within each cluster, and minimize the distance between sensors and the base station. By combining the strengths of Particle Swarm Optimization (PSO) with the Firefly Algorithm, we can achieve better clustering and energy efficiency in wireless sensor networks. This approach promotes balanced energy consumption among nodes and increases the network's lifespan. The proposed clustering algorithm has displayed significant potential in enhancing the efficiency and performance of wireless sensor networks, making it a valuable tool for optimizing wireless sensor networks.

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