Improving Lifetime of WSN using Modified Moth Flame Optimization

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Received: 5 March 2023 Revised: 21 June 2023 Accepted: 15 July 2023

ABSTRACT:
The focus is on the longevity and energy efficiency of Wireless Sensor Networks (WSN). WSNs face many obstacles in terms of data transmission. WSNs face difficulties in reducing energy output and shortening life cycles, including node configuration, leader selection, and optimal routing selection. The provisioning of nodes, selection of cluster leaders, and optimal paths have all been recommended using many current methods. However, none of the currently used methods yield sufficient grid energy optimization results. Therefore, this study proposes a modified Moth Flame Optimization Algorithm (MFOOA). Nature passed it on to us. The main inspiration for this optimizer is the lateral flight pattern used by moths in nature. At night, the moth maintains a constant angle to the moon. This is a particularly efficient way to drive long distances in a straight line. Nevertheless, artificial light is everywhere around these amazing creatures, encircling them in a fruitless and deadly spiral. Here, this behavior is theoretically modeled for optimization. The suggested program places the sensor nodes using the flame optimization technique. These sensor nodes might be either dynamic or static depending on the network scenario. The cluster head and the optimum route are chosen using this technique. Within the predetermined search space, it also does phase balancing between the exploration and development phases. In terms of residual energy, sensor node lifetime, used energy, end-to-end latency, and a maximum number of cycles, it differs from current classical and swarm intelligence (SI) techniques. According to the results, MFOOA is superior to its counterpart.

KEYWORDS: Wireless Sensor Networks, Mobile Sink Node, Data Collection, life time, Moth Flame Optimization.

1. INTRODUCTION

A wireless sensor network is made up of tiny sensor nodes that can sense, communicate, and carry out calculations (WSN). Concerns concerning the lifespan and energy efficiency of WSNs are growing. WSNs have the capacity to gather, process, and transmit data from sensor nodes to base stations. When placing sensor nodes in an area, battery life is a crucial factor to take into account. It is challenging to recharge batteries on the field. Energy usage is thus the primary issue [1]. Following elements, including node provisioning, cluster leader selection, cluster formation and best path selection, utilize the network lifecycle. The military and other sectors are increasingly using wireless sensor networks (WSNs), medical services, natural, organic, basic health observations, and government-generated forecasts [2].

A WSN is made up of several little sensor nodes that work together to gather and transmit data from one environment to a user or base station. The computation and communication capabilities of these nodes are limited. A network of several tiny sensor nodes with constrained sensing and information-providing capacities makes up a WSN. Fig. 1 depicts the internal layout of a sensor node.

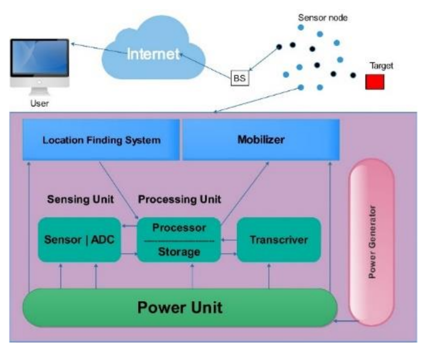

Fig. 1. The internal structure of a sensor in WSN.

A sensor network node has a power supply, a

Paper type: Research paper
DOI: 10.30486/mjee.2023.1978992.1062
How to cite this paper: M. Mahdi Ali and R. Asgarnezhad, **"Improving Lifetime of WSN using Modified Moth Flame Optimization"**, *Majlesi Journal of Electrical Engineering*, Vol. 17, No. 3, pp. 1-7, 2023.

wireless transceiver, a data processing unit and a sensor unit. Depending on the purpose of the node, there may also be other components including propulsion, tracking systems and power generation. Depending on the intended application, a small processor and memory of limited capacity constitute the data processing unit, which receives data from the sensor, processes it minimally and transmits it through the transmitter. The management, coordination and collaboration of other network nodes are done by the processing unit. Nodes are connected to the network through transceiver units. A sensor unit consists of a set of sensors and a device that converts analog data into digital data and transmits it digitally from the sensors to the CPU. A power unit, usually a low-power battery, provides power to all components. One of the biggest hurdles in building a sensor network is power availability. In addition to this part, there may be another component that produces energy, such as a solar cell. The physical location of the nodes is also discovered by the locator. In situations where highly accurate spatial data is required for routing methods and discovery activities, the presence of an intra-node location component is unavoidable. With this in mind, a WSN is a collection of many such sensor nodes that, despite their individual limitations, can form a network of enormous capacity when connected.

The evaluation factors are of concern:

• The data transfer rate in the WSN is measured in bits per second.

• Lost data: The amount of network data that was lost.

• Network latency rate: This figure shows how long it takes for information to travel from the point of reception to the base station in a network.

• Grid life: The amount of time a grid can function completely on the energy it consumes.

• Energy consumption of the network as a whole, including all nodes, branches, and mobile good nodes, is shown in this statistic.

The primary contribution of this study is relevant to:

• Using a modified MFO approach
• Reducing the energy use of WSN nodes
• Extending the network's lifespan

According to the main findings of [3] in a dynamic source routing (DSR) protocol (MANET) for mobile ad hoc networks, BEEDSR uses the artificial bee colony (ABC) algorithm and swarm intelligence to reduce power consumption. Using the ABC method to regulate the optimum route from source to destination, the energy problem can be solved. The BEEDSR algorithm's performance is compared with that of DSR and the bee-inspired protocol. Presentation measures such regular power use, average throughput, average end-to-end delay, routing overhead, and packet delivery rate were used to liken various node speeds and packet sizes.

2. RELATED WORK

Data aggregation in sensor networks has been established using search-based methods. These methods create queries and spread them throughout the network to 90 receivers. As soon as a node responds to a request, it broadcasts the information to its neighbors. Following the completion of the query, 90 sinks receive results. In this scenario, some nodes only execute queries, but others broadcast them and get partial results. They compiled the information and distributed it to 90 sinks [4], [5]. Some of the most significant articles in this field are listed in Table 1.

Table 1. A comparison among some of the existing works.

Ref. / year	Node / Network	Aggregation / Algorithm	Advantage / Disadvantage
2021 [6]	Cluster / Homogeneous	Fixed / Distributed	• Decreasing the redundant data readings • Using symbolic algorithm and adaptive piecewise constant approximation (APCA)
2021 [7]	Cluster / Homogeneous	Fixed / Distributed	• Using a Dynamic Time Warping (DTW) model based on clustering • Combining with Fog Computing
2021 [8]	Cluster / Homogeneous	Fixed / Distributed	• Producing a novel data aggregation method • Using the open-pit mining idea • Dividing the WSN into several clusters in efficient manner
2020 [9]	Cluster / Homogeneous	Fixed / Distributed	• Proposing a systematic data aggregation model (CSDAM) • Using clustering for real-time data processing
2020 [9]	Cluster / Homogeneous	Fixed / Distributed	• Suggestion a novel data aggregation method • Using the open-pit mining idea efficiently.
2020 [10]	Cluster / Homogeneous	Fixed / In Network	• Producing clusters to perform data reduction • Selecting the central values of each cluster
2019 [11]	Cluster / Homogeneous	Fixed / In Network	• Eliminating data redundancy and local outlier data • Enhancing data quality and transmission ratios
2019 [12]	Cluster / Homogeneous	Fixed / Distributed	• Reducing collisions through Multi-channel TDMA scheduling Algorithms • Minimizing the energy consumption and reducing latency using the meta-heuristic algorithm
2019 [12]	Flat / Homogeneous	Fixed / Distributed	• Eliminating data redundancy through the Support Vector Machine (SVM) classifier
2018 [13]	Flat / Homogeneous	Mobile / Distributed	• Using Adaptive Particle Swam Optimization (PSO) for optimum path selection of the mobile node

A Wireless Sensor Network (WSN) is made up of a number of sensor nodes that can gather, transmit, and store data as well as power. By sending aggregated information to base stations instead of redundant transmissions, data aggregation increases power efficiency and increases the lifespan of WSNs with limited power resources. The methods are described in various in-network data aggregating algorithms [14]. A trusted tree-based data aggregation method is suggested in 2021. The sensor nodes are organized in a binary tree using this method. The aggregation procedure begins when the request is confirmed once the aggregate request has been authenticated using the shared key. A dynamic cyclic error-checking code (CRC) generator's polynomial magnitude is also used to detect faults that are added along the way hop by hop. A retransmission request will be sent to the preceding hop in the event of an error. The intermediate node reduces the amount of data that the network transmits by performing aggregation operations like summing and averaging on the received data packets. Given that this method uses less energy and sends fewer packets, the network will last longer. As a result, using this approach with CRC encoding can greatly increase reliability [15].

The features of Gray Models (GM) and kernel-based extreme learning machines are used by the authors to combine data aggregation-based data fusion with effective error detection, enhancing the lifespan and performance of sensor networks (KELM). When recording specific data patterns, GM use data fusion techniques to eliminate redundant inputs from numerous sensor nodes. A well-trained KELM is utilized to effectively detect mistakes and maintain strong network confidentiality. A general WSN dataset gathered from various universities is used to introduce and assess the suggested approach. The outcomes of the simulation demonstrate that the technique can successfully lessen repetitive transmissions and find network flaws. The lifespan of the network is extended by resolving issues with quick and minimal processing time [16].

The writers effectively launch a brand-new data aggregation technique in 2021 that is based on the idea of surface mining. With this approach, WSN is divided into a number of clusters, each of which has a distinct center node around which some hypothetical pits are constructed to gather and send data [8].

3. THE PROPOSED METHOD

Fig. 2 illustrates a diagram of the stages of the proposed algorithm. This figure illustrates the stages of our framework in detail.

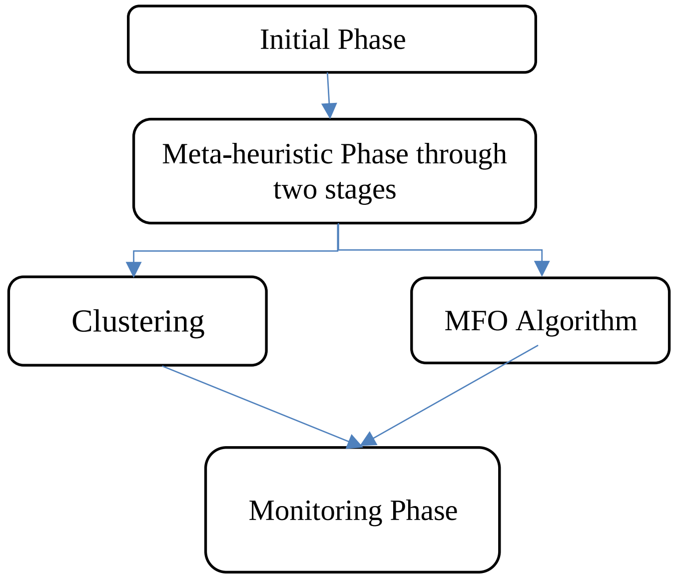

Fig. 2. Three phases of the proposed method.

3.1. Initial phase

The MFO method creates an initial population number (P-Node) during the initial phase, where P stands for the initial population and Node for population size. Sensor nodes are S-Nodes. Only one employed moth searches a single sensor node. As a result, there are the same number of sensor nodes as hired moths.

3.2. Meta-heuristic phase through MFO algorithm

The general framework of our MFO algorithm is defined through:

Algorithm 1: Framework through MFO algorithm

1: ***Begin***
2: *P-Node=I();*
3: ***while*** *T* (*P-Node*) is equal to false ***do***
4: *P-Node =P(P-Node);*
5: ***end while***
6: ***End***

My process is for creating the initial flames and moths as solutions. This function calculates the values of the objective function. The following strategy is explained by:

Algorithm 2: Initial generate

1: ***Begin***
2: ***for*** *i=1 to n* ***do***
3: ***for*** *j=1 to d* ***do***
4: P-Node(i, j)=ublb-rand(i, j);
5: ***end for***
*6****: end for***
7: *OM=FitnessFunction(P-Node);*
8: ***End***

After the initialization task, the P function is repeated until the T function returns true. The P function is mostly used to guide the moths through the search area. The following equation updates the position of each moth with respect to a flame to statistically approximate this behavior:

$$\text{P-Nodei} = \mathrm{S}(\mathrm{P} - \mathrm{Nodei}, \mathrm{Fj}) \tag{1}$$

Where S is the spiral function, Mi is the i-th moth, Fj denotes the j-th flame, and

In light of these considerations, the MFO algorithm's definition of a logarithmic spiral is as follows.:

$$\mathrm{S}(\mathrm{P} - \mathrm{Nodei}, \mathrm{Fj}) = \mathrm{Di}\,.\,e^{bt}\,.\cos(2\pi t) + Fj \tag{2}$$

Where Di is the distance between the i-th moth and the j-th flame, t is a random number between [-1, 1], and b is a constant used to specify the shape of the logarithmic spiral. This equation shows how to predict where a moth will be in respect to a flame in the future. The t parameter of the spiral equation determines how near the flame the moth should be in each of its following places (t = -1 denotes its nearest position and t = 1 denotes its farthest). The following is the D formula:

$$\mathrm{Di} = |\mathrm{Fj} - \mathrm{P} - \mathrm{Nodei}| \tag{3}$$

Where Mi denotes the i-th moth, Fj shows the j-th flame, and Di is the separation between the i-th moth and the j-th flame. Although the presented problem's vertical axis in Fig. 3 only shows one dimension (one variable or parameter), the suggested method can be used to alter any number of the problem's variables.

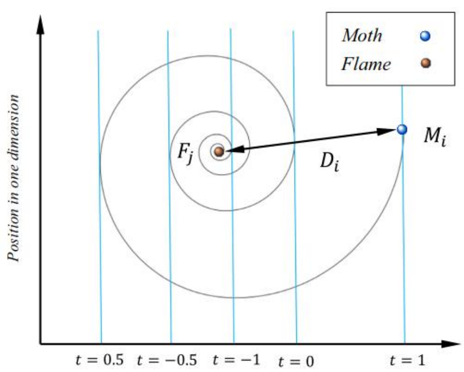

Fig. 3. Logarithmic spiral, space around a flame, and the position with respect to t.

The main component of the suggested tactic is the spiral movement, which regulates how the moths update their positions around fires.

The moths merely alter their positions in relation to the ideal flame during the final cycles. The gradual dwindling of the flames balances the exploration and utilization of the search area. Finally, the general steps of the P function are as follows.

Algorithm 3: The movement Function

```
Begin
OM = FitnessFunction(P-Node);
if iteration == 1
    F = sort(P-Node);
    OF = sort(OM);
else
    F = sort(P-Node t-1, P-Node t);
    OF = sort(P-Node t-1, P-Node t);
end if
for i = 1: n
    for j = 1: d
        Update r and t
        Calculate D with respect to the corresponding moth
        Update P-Node (i,j) with respect to the corresponding moth
    end for
end for
End
```

As was previously said, the P function is employed till the T function returns true. After the P function has finished, the best moth is returned as the closest determined approximation to the optimum.

3.3. Monitoring Phase

Currently, the finished route is still in use. We relate to the lifespan idea put forward by [17]. It claims that the lifetime of the network is equal to the length of the route being disconnected. The route with the most assurance and remaining energy is the best.

4. SIMULATION AND RESULTS

4.1. The Simulation Environment

We need to choose a method that uses the same parameters for comparison and investigation, and simulate our method in the same environment as the other two so that we can compare them [18].

Using C# and MATLAB programming, we simulated the two techniques presented here and our proposed method to test their suitability for the following parameters. The network parameters in our simulations are network area, number of sensor nodes, number of sink nodes and number of headers. Sensor nodes provide information to the header, and then directly collect information related to the sink node and forward it to the sink node [19]. The speed of a sync node is constant. In our simulations, we assume a network size of 2323 meters with 100 sensor nodes, 20 headers and 1 to 20 mobile sink nodes. The detailed information of the simulator is shown in Table 2.

Table 2. Simulator specification.

NO.	Parameter name	Value
1	Network area	312 m^2
2	The number of nodes	100
3	The number of cluster-head	20
4	The number of mobile sink	1-20

The used network has a 312 square meter footprint, 100 nodes, 20 plugs, and somewhere between 1 and 20 mobile sinks. Important modeling factors to consider are data transfer rate and lost data, network delay rate, network longevity, and network energy usage.

4.2. Simulation Environment and Cross Validation Technique

the Network Simulator 2 tool is used to put the proposed metaheuristic into practice. There are 50, 100, 150, 200, 250 and 300 sensor nodes in the wireless sensor network, respectively. 200*200m2 is deployment area for these sensor nodes. It starts at 10,000 J. The sensor nodes range from 20 to 90 m [20]. The proposed technique defines multipath routing between sensor nodes. The performance criteria used to compare the results of the proposed procedure with those of BEEDSR in [3] include residual power, consumed power, device node lifetime, and end-to-end delay.

4.3. The Base Paper

BEEDSR, which was proposed in [3], employs the artificial bee colony (ABC) algorithm and swarm intelligence technique to lower the power consumption of the Dynamic Source Routing (DSR) protocol for mobile ad hoc networks (MANET). Using the ABC method, the best route from source to destination is found in order to solve the energy problem. Differences in node speed and packet size were associated while performance indicators such average power consumption, average amount, average end-to-end delay, routing overhead, and packet delivery rate were used. In terms of power conservation and delay reduction related to node speed and packet size, the BEEDSR algorithm outperforms competing protocols.

4.4. The Obtain Results

The evaluation factors for this job are important:

• Bits per second is used to measure data transfer rates in wireless sensor networks.

• Lost Data: Amount of network data lost.

• Network Latency: This number represents the time it takes for the network to transmit information from the receiving point to the base station.

• Grid lifetime: how long the entire grid can run based on the energy consumed.

• Network Energy Consumption: This figure reflects how much energy is consumed by the entire network, including all nodes, branches, and mobile device nodes.

Fig. 4 shows that compared with BEEDSR, the proposed method gives better results at the same energy level and has the largest remaining energy ratio. Fig. 5 shows that the proposed method outperforms BEEDSR in terms of end-to-end latency. Fig. 6 shows that the proposed method outperforms BEEDSR in terms of network durability. The performance of the proposed method using BEEDSR is shown in Fig. 7. Table 3 shows the parameter values for the algorithms used.

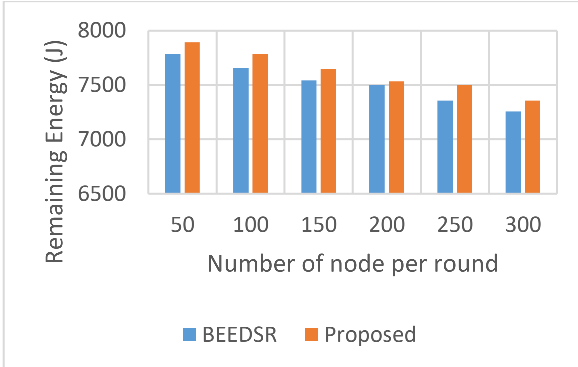

Fig. 4. Remaining energy.

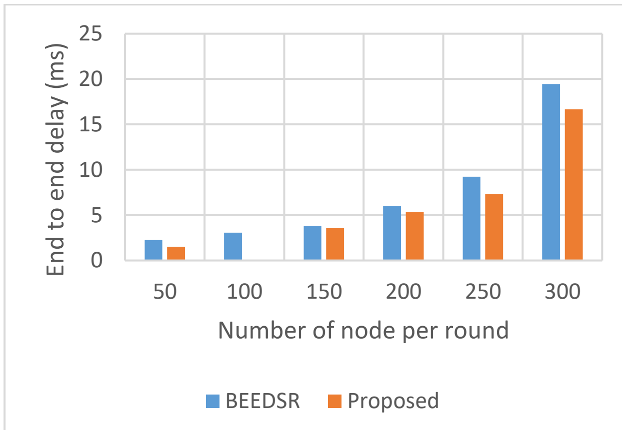

Fig. 5. End to end delay.

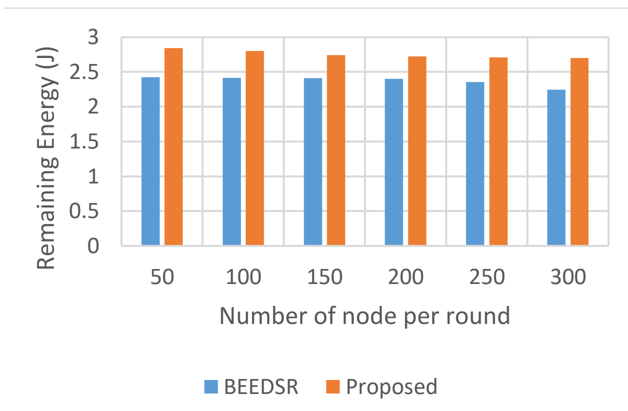

Fig. 6. Lifespan of sensor node on same energy level.

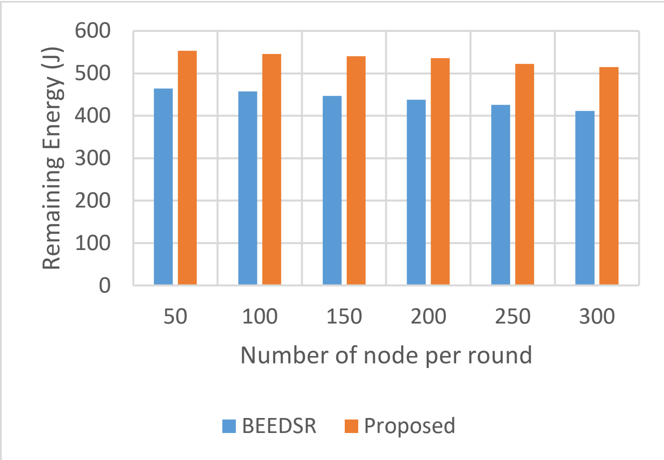

Fig. 7. Network lifespan.

Table 3. The values of the parameters for meta-heuristic algorithms

Parameter	Value
The MFO algorithm	
Number of the initial population of moths	200
Number of generation	300
End condition	Number of generation
The Bee algorithm	
Number of initial bees	200
Number of generation	300
End condition	Number of generation

5. CONCLUSION

Existing classical algorithms in WSN have difficulties in node placement, insufficient remaining energy, and optimal path selection. Using perfect nodes can save more energy during data transmission. Therefore, this paper uses a meta-heuristic procedure to identify optimal paths and execute promising sensor nodes. NS-2 simulator was used for implementation. Previous studies evaluated the effectiveness of the proposed method using benchmark functions and MATLAB. Compared with BEEDSR, the proposed method achieves the best results in terms of consumed energy, residual energy, network lifetime, and end-to-end latency.

For future work, we will develop a combination algorithm to enhance the residual energy and life duration. This algorithm will combine several meta-heuristic techniques.

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