M-WOA: Manifold distance-based Whale Optimization Algorithm for clustering in wireless sensor networks

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***Abstract*- Wireless sensor networks (WSNs) rely on limited-energy batteries that cannot be recharged or replaced, making energy efficiency a crucial topic. While previous studies have focused on selecting the head to reduce the energy consumption of the sensor nodes, this paper aims to address another weakness of clustering in WSNs: better cluster formation for each header to minimize energy consumption across the network. To achieve this goal, an advanced algorithm based on a Manifold distance-based Whale Optimization Algorithm (M-WOA) is presented. The idea is to send a packet from a source to the header using intermediate nodes, which may consume less energy than delivering the packet directly. Selecting the interface neighbors based on the remaining energy in each sensor is vital in increasing the lifetime of the entire network. The MATLAB results indicate that the proposed algorithm successfully extends network lifetime, particularly in scenarios with many scattered sensors in space.**

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***Index Terms*-** Wireless sensor networks; Clustering; Energy efficiency; Manifold distance; Whale Optimization Algorithm.

I. INTRODUCTION

The Internet of Things (IoT) is a versatile technology in several areas, including smart grids, network vehicles, and smart homes. Networking experts are developing a practical and achievable architecture for understanding the IoT model. Wireless Sensor Networks (WSNs) play a crucial role in measurement, communication, and processing thanks to their flexibility, independence, and low power consumption. Sensors are the foundation of the measurement component, and their energy

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comes from batteries, making battery replacement a challenge in military surveillance applications and impassable environments.

The efficient functioning of WSNs is essential for reducing power consumption and extending their lifespan. Communication energy is the total energy consumed in transferring and processing data. In a traditional WSN, sensor nodes transmit data to the base station (BS) without intermediaries. However, in the cluster-based model, we divide the network area into clusters to manage network heterogeneity, reduce power consumption, increase lifespan, and decrease latency. This approach is advantageous in WSNs with energy-limited sensors. In cluster-based methods, only the header can exchange information with the BS, and fusion leads to the aggregation of sensor node data, reducing energy resources in WSN. Therefore, this paper aims to enhance the sensor nodes' lifespan while ensuring network connectivity and availability.

Effective and efficient Wireless Sensor Networks (WSN) routing is crucial for smooth communication between sensor nodes and base stations. Various routing challenges, such as node energy consumption, connectivity, coverage, scalability, and security, must be addressed to achieve this. In WSN, sensors can be directly connected to the base station, and the Time Division Multiple Access (TDMA) protocols ensure that sensors remain connected, whether or not they have information to transmit. This paper introduces a new algorithm called M-WOA that leverages this feature to select cluster members, thereby reducing the network's energy consumption and increasing its lifetime [1]. The whale Optimization Algorithm (WOA) is a powerful tool for solving complex engineering optimization problems. Still, it may suffer the same drawbacks as other metaheuristic algorithms, such as slow convergence and getting stuck in local optima [2, 3]. We will decrease this problem and simultaneously focus on the lifetime of wireless sensor networks. One significant problem with previous algorithms that aimed to increase the lifetime of wireless sensor networks is that they only selected neighbors from surrounding areas, irrespective of the manifold structure resulting from the sensors' placement [4]. This approach limits the selection of members to sensors with a shorter direct distance to the cluster, which prevents the examination of the entire graph with a complex distribution placement to find members.

Choosing neighbors based solely on Euclidean distance between sensors is inadequate. To address this challenge, we developed the PHS method, a priority version of the HS method proposed in reference [5], which we utilized in our research. Our approach is to consider the potential energy savings of routing packets from a sensor to a CH using intermediate nodes, compared to direct delivery from the sensor to the CH. As the lifetime of wireless sensor networks depends on the energy available in each sensor, selecting neighbor interfaces with high residual energy is crucial. The proposed method prioritizes paths with interface sensors with high residual energy, as opposed to the direct distance between sensors with low residual energy, to achieve a balance of energy consumption and increase the network's lifetime.

Like LEACH, our proposed method consists of two phases: set-up and steady-state. During the set-up phase, we utilize the M-WOA algorithm, combining manifold-based distance and WOA, to select the CH based on distance, energy, and CH degree. The node with the minimal degree of CH and distance and maximum energy is selected as the CH. In the steady-state phase, sensors transmit their information to the CHs, sending information from the entire network to the base station.

The significant innovation in our research is the M-WOA algorithm. It combines the proposed PHS manifold metric and WOA, and the fitness measure considers factors like distance, energy, and CH degree. The proposed method for enhancing energy efficiency shows great potential and can result in a longer lifetime for networks. It is important to note that our algorithm is particularly effective when dealing with a large number of network nodes, as it can significantly reduce energy consumption. This is because the approach allows nodes to transfer their data to the nearest intermediate node, minimizing unnecessary transmissions and extending the network's longevity.

In this article, we will cover various topics. Firstly, we will discuss our related work in Section 2. Then, in Section 3, we will outline the aims of our proposed method and explain the proposed algorithm. Section 4 will provide details of the implementation and analyze the results. Finally, we will conclude the paper in Section 5.

II. RELATED WORK

Recent research regarding energy efficiency in wireless sensor networks[6] has been checked. Table 1 provides a summary of the previous and related methods. Many research groups seem to have focused on this topic, with one of the top algorithms being the low-energy adaptive hierarchical clustering (LEACH) algorithm [1, 7, 8]. LEACH randomly selects cluster nodes based on the assumption of uniform energy distribution among all sensor nodes, improving the network's overall lifespan. However, this can lead to an imbalance in energy usage among individual sensors. To address this issue, researchers have explored specific aspects of LEACH and developed an advanced version called Centralized LEACH (LEACH-C). LEACH-C achieves optimal cluster node selection by utilizing the benefits of Simulated Annealing (SA) [9].

To address issues in LEACH, such as uneven distribution of cluster heads and disregarding residual energy, ESO_LEACH uses a PSO algorithm for initial sensor node clustering [10]. Enhanced _LEACH [11] extends LEACH by selecting a cluster head based on the shortest distance to the base station, reducing power consumption. Ghosh and Chakraborty combine the Cuckoo-Search algorithm with the LEACH protocol for routing [12]. Wang et al. suggest an energy-efficient clustering technique that employs a genetic algorithm with a new objective function [13]. Yan et al. implement vector quantization to identify active nodes in cooperative communication and analyze overall network performance parameters [14]. Ebrahim Nejad et al. propose a modified artificial bee colony

TABLE I. SUMMARY OF THE PREVIOUS AND RELATED METHODS

Method	**Year**	**Methodology**
LEACH	2000	LEACH randomly chooses cluster nodes assuming equal energy distribution among sensors.
LEACH-C	2007	LEACH-C uses Simulated Annealing (SA) to select the best cluster nodes and achieve optimal results.
ESO_LEACH	2018	ESO_LEACH uses PSO for initial sensor node clustering to fix LEACH's issues with uneven cluster head distribution and residual energy disregard.
Enhanced-LEACH	2019	Enhanced LEACH reduces power consumption by selecting a cluster head based on the shortest distance to the base station.
Ghosh and Chakraborty 's method	2019	Ghosh and Chakraborty have merged the Cuckoo-Search algorithm with the LEACH protocol to improve the efficiency of routing.
Wang's method	2018	Wang et al. propose a clustering technique that uses a genetic algorithm with a new objective function to increase energy efficiency.
Yan's method	2019	Yan et al. utilize vector quantization to detect active nodes in cooperative communication and assess overall network performance parameters.
MABC	2021	MABC proposes a modified artificial bee colony algorithm to solve uncertain SP problems in wireless sensor networks.
Yan' method	2019	authors optimize node location to reduce energy consumption during network communication using PSO.
WOATCA	2020	WOATCA chooses trustworthy cluster heads based on five factors: residual energy, forwarded packets, cluster distance, transmission delay, and node density.

(MABC) algorithm to solve uncertain SP problems in WSNs [15].

In [16], the authors consider the impact of node location on energy consumption during network communication and optimize the position of nodes with the lowest energy consumption using PSO. In [17], the authors propose WOATCA, which focuses on selecting trustworthy cluster heads (CHs) by considering five parameters: node's residual energy, number of forwarded packets, average cluster distance, transmission delay, and node density.

III. PROPOSED METHOD

Improving the quality of clustering is essential since it greatly affects the energy consumption of the sensor network. To achieve this, it's necessary to identify the optimal cluster head and members to form high-quality clusters. Our proposed solution involves using intermediate sensors to send data to CHs and selecting members based on the PHS hierarchical manifold distance. You can find the flowchart of our proposed method in Fig. 1. Our approach consists of two primary phases:

1. Choosing the cluster head: We utilize an optimization algorithm called M-WOA, which builds upon previous research on WOA [3] and Aeini et al. [5], to select the cluster head.

2. Selecting cluster members: Once the cluster head is selected, we use the PHS metric, which is

Fig. 1. The flowchart of the proposed method.

based on a proposed manifold-based approach, to select cluster members.

We use a supervised manifold learning method called SH-NGC [5] to create an unsupervised manifold-based distance metric. The energy model used in this research is based on the radio model [18]. In this model, the energy consumption of a node is proportional to d^2 when the distance (d) is less than the threshold distance dt. Otherwise, it is proportional to d^4, according to equation (1).

$$E_{TX}(l,d) = \begin{cases} l \times E_{elec} + \varepsilon_{fs} \times {d_{PHS}}^2 \;, & if \quad d_{PHS} < d0 \\ l \times E_{elec} + \varepsilon_{mp} \times {d_{PHS}}^4 \;, & if \quad d_{PHS} \geq d0 \end{cases} \tag{1}$$

Where $E_{TX}(l,d)$ is the amount of energy reduction per data bit transfer, E_{elec} is the amount of energy reduced, ε_{fs} is the transfer amplifier parameter based on the Free-space technique, d_{PHS} is the manifold distance between the typical node and the CH, and L is a data packet [18]. Similarly, to receive 1 bit of data, the energy consumed is calculated according to equation (2).

$$E_{RX}(l) = l \times E_{elec} \tag{2}$$

In WSN, all nodes can be connected directly to any other node and the CH. Previous methods for measuring the distance between sensors consider their direct distance in Euclidean space. To explain our idea, see Fig. 2. We want to send a packet from *e* to *CH*. Regarding the Euclidean distance metric, the distance between *e* and *CH* is $d1>dt$. So, the energy consumption is proportional to d^4. However, if we utilize the path connected by shorter edges (i.e., $d2<dt$), the total energy consumption will be smaller than that of the direct path. In other words, the energy consumption of (ed+dc+cb+ba+aCH) is proportional to $5d^2$. So, instead of using the shortest straight line between a sensor and CH, we propose to use the manifold distance between them.

The remaining energy of each sensor plays a crucial role in extending the network's lifespan. Sensors can monitor their energy levels and adjust transmission power and distance accordingly. Instead of selecting members with the most accessible access to the CH, the proposed method prioritizes members based on the shortest PHS metric. This paper aims to prolong the lifespan of wireless sensor networks that utilize SH-NGC by prioritizing nodes in routing. SH-NGC consists of two main phases - the first phase constructs the neighborhood graph using the supervised neighborhood graph method [19], while the second phase optimizes the SNG neighborhood graph using HS [5]. We developed the PHS phase of HS to achieve our goal, and we believe our solution will discover better paths than Euclidean distance due to the more reliable estimation of geodesic distance. The M-WOA algorithm proposal utilizes specific clustering criteria based on several factors. Firstly, each sensor can directly connect with the other sensors and the base station. Secondly, the

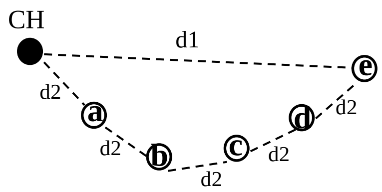

Fig. 1. An example, the Euclidean distance metric is not always the shortest one for WSN.

energy model employed in this research is based on the radio model outlined in [18] and reflects that the energy consumption of a node is proportional to d^2 if the propagation distance (*d*) is below the threshold distance (*dt*).

Otherwise, it is proportional to d^4. Thirdly, the TDMA scheduling for LEACH results in applications paying little attention to whether the sensor has information to transmit. Finally, the inert mode concept is not feasible for sensors due to WSN's requirement that each sensor remains open for connection at all times. Arbitrarily removing or stopping sensor hubs is not practical.

This section provides a detailed explanation of the M-WOA algorithm, which integrates WOA [3] and the proposed PHS manifold distance metric for sensor clustering. Inspired by the hunting behavior of humpback whales and the bubble net strategy, WOA is enhanced by M-WOA through geodesic distance and residual energy considerations. In wireless sensor networks, energy consumption depends on data transmission amount and distance. Unlike most protocols, M-WOA believes that a straight path between two points is not always the quickest, and a suitable distance measure for clustering in WSN does not always serve the triangle inequality of the Euclidean metric [5]. Therefore, sensors with little information to transmit and more residual energy are used as intermediaries to extend the network's life. To ensure the node has little information to transfer, the ratio of residual energy to initial energy is employed, i.e. $\frac{E_{residual}}{E_{initial}}$.

By following the steps presented in Fig. 3, we can improve clustering and energy efficiency in wireless sensor networks. Here are the steps involved in the proposed method for finding k cluster members for CHs by using the PHS method:

i. ***Initialization***: First, the sensors are randomly placed in space, and the primary clusters are formed using the LEACH-C algorithm. We take all the candidate headers as the initial population of whales Ar (r = 1, 2, ..., N) in the search space.

ii. ***Compute fitness function***: Next, we compute the fitness measure as follows. We measure the Euclidean distance between two sensors and sort the distance list in ascending order. Then, we select the first K sensors as the neighbors, where K is the number of sensors in the neighborhood. The list of selected neighbors is indicated by $\mathrm{N}(CH_i)$, and the cluster distance to the candidate neighbor sensors with $dis_{PHS}(CH_i)$, which is arranged in increasing order. The neighborhood list $\mathrm{N}(CH_i)$ is given as input to the PHS algorithm, which is optimized using our proposed priority HS by equation (3).

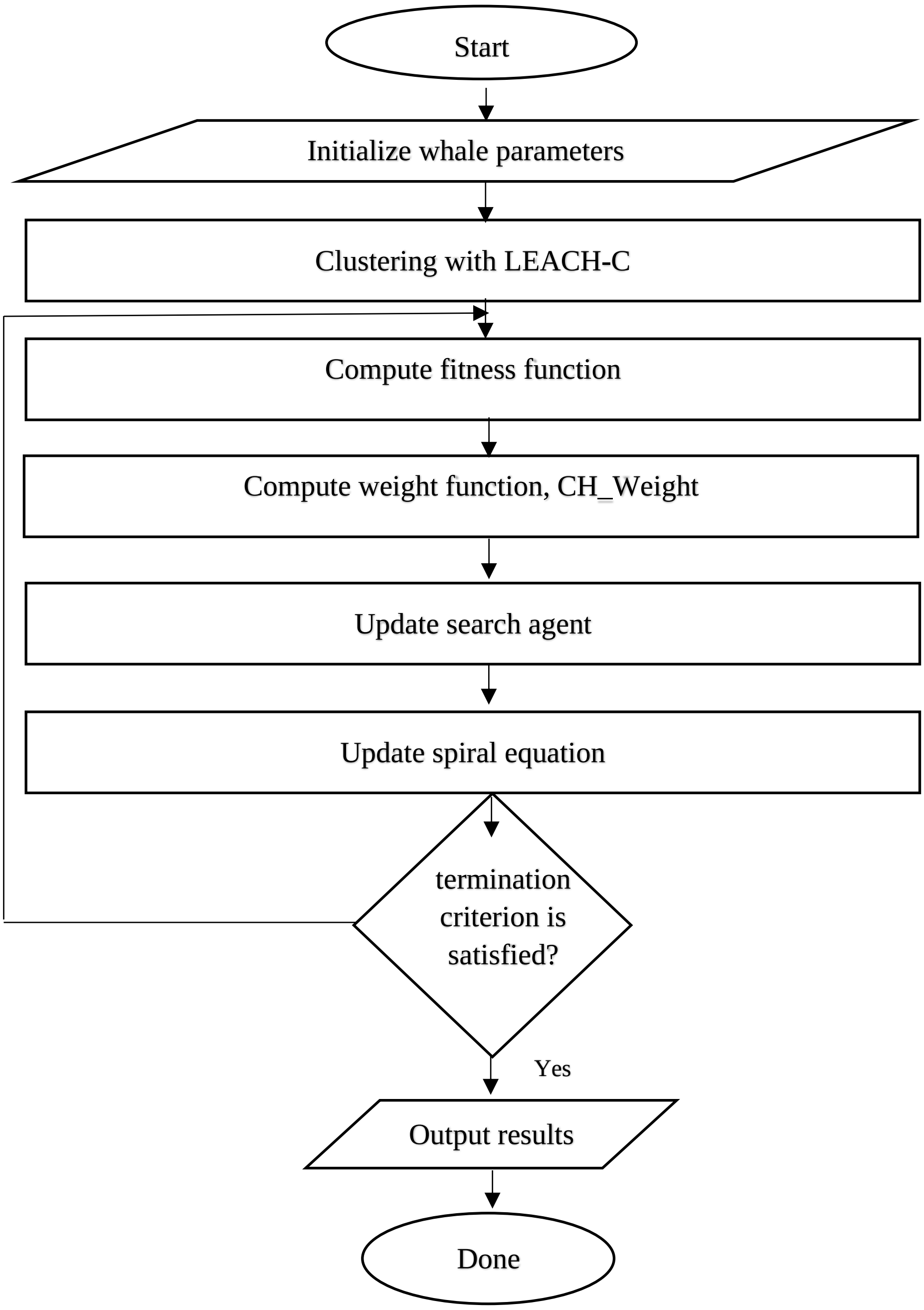

Fig. 3. The flowchart of the proposed M-WOA method

$$D_{PHS}(CH_i : s_k) = \frac{\mathrm{E}_{initial}{}^{CH_k}}{\mathrm{E}_{residual}{}^{CH_k}} D_{HS}(CH_i : s_k) \tag{3}$$

Determine distance: The distance $D_{HS}(CH_i : s_k)$ is determined by the HS distance criterion, as detailed in [5].

Clustering is based on a weight function, CH_Weight. The weight function depends on the following parameters.

1. To minimize power consumption, a sensor node (s_i) should be connected to the nearest cluster head (CH_j). This can be expressed as:

$$CH_{Weight}(s_i, CH_j) \propto \frac{1}{D_{PHS}(s_i, CH_j)} \tag{4}$$

2. Cluster heads are responsible for sending collected data to the base station. To ensure efficient data transfer, sensor nodes should be connected to cluster heads closer to the base station. This can be expressed as:

$$CH\_Weight\ (s_i, CH_j) \propto \frac{1}{D_{PHS}(CH_j, BS)} \tag{5}$$

, where DPHS is the distance between the cluster head and base station.

3. When connecting a sensor node (s_i) to a cluster head (CH_j,), it's important to choose a CH_j, with a lower degree than any other cluster head within the communication range of the sensor node.

$$CH\_Weight\ (s_i, CH_j) \propto \frac{1}{node\ \ degree(CH_j)} \tag{6}$$

4. When the distance between a sensor node (s_i) and the base station is shorter than its distance to the nearest cluster, the data will be sent directly to the base station. This can be calculated using Equations (4), (5), and (6):

$$CH\_Weight(s_i, CH_j) = L \times \frac{E_{residual}(CH_j)}{D_{PHS}(s_i, CH_j) \times D_{PHS}(CH_j, BS) \times node\ \ degree(CH_j)} \tag{7}$$

In this scenario, L remains constant. For the simulation, an L value of 1 was chosen as it did not compromise the quality or performance. To determine the cluster head, each sensor computes its CH_weight using equation (7) and connects to the cluster head with the highest weight.

Here L is fixed. In this work, L = 1 was estimated for simulation without losing quality and influence on performance. Each sensor calculates its CH_Weight using equation (7) and joins the cluster head with the highest weight.

iii. ***Update search agent:*** The whales find the best-known solution as the best whale or the closest to the optimal solution, and the others will modify their positions accordingly as equation (8),

$$\vec{X}(t+1) = \vec{X^*}(t) - \vec{A} \cdot \vec{D} \tag{٨}$$

Where t is the current iteration, $\vec{X^*}(t)$ is the current best-known solution, $\vec{D}$ and $\vec{A}$ are defined by

$$\vec{D} = D_{PHS}(\vec{C} \cdot \vec{X^*}(t), \vec{X}(t)) \tag{٩}$$

$$\vec{C} = 2 \cdot \vec{r} \tag{10}$$

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \tag{١١}$$

$$a = 2 - t\frac{2}{\max} \tag{١٢}$$

equations (9) - (12).

Where $\vec{r}$ is a random vector in the interval of [0,1] and $\vec{a}$ is a vector that starts from 2 and decreases linearly to 0. The decreasing process of $\vec{a}$ is shown by equation (12) where max is the maximum number of iterations.

iv. ***Update spiral equation:*** Modeling the spiral movement is described by equation (13).

$$\vec{X}(t+1) = \overrightarrow{D'} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X^*}(t) \tag{13}$$

where $\overrightarrow{D'}$ is the distance calculated by equation 12 and *b* is a constant that makes the logarithmic spiral movement of whales and *l* is a random number between [-1,1].

$$\overrightarrow{D'} = D_{PHS}(\overrightarrow{X^*}(t) - \vec{X}(t)) \tag{١٤}$$

The exploitation phase of WOA uses a random strategy to select between the shrinking encircling, and spiral movement of whales. Hence, a random number is produced between 0 and 1. If the number is less than 0.5, the shrinking encircling mechanism will be activated. Otherwise, WOA activates the spiral movement of the whales. The selection mechanism of the exploitation phase is formulated by equation (15), in which P is a random number in the interval of [0,1].

$$\vec{X}(t+1) = \begin{cases} \text{Use equation 6} & \text{if } (P < 0 \cdot 5) \\ \text{Use equation 11} & \text{if } (P \geq 0 \cdot 5) \end{cases} \tag{15}$$

v. ***Exploration Step:*** This step employs a random feasible solution to update the rest of the solutions. Using a random solution will increase the searchability of WOA. The process of

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A} \cdot \vec{D} \tag{16}$$

updating solutions based on a random solution is formulated in equation (16).

where $\overrightarrow{X_{rand}}$ is a random solution. Also, the distance which is shown by $\vec{D}$ is calculated by equation (17).

$$\vec{D} = D_{PHS}(\vec{C} \cdot \overrightarrow{X_{rand}} - \vec{X}) \tag{١٧}$$

vi. ***Termination:*** The above steps are repeated until the best solution is obtained in the search space.

In the process, M-WOA determines the cluster heads by having each sensor identify a header with the shortest geodesic distance using the PHS metric and notifying the header that it will be a part of the cluster. This selection process is carried out for all nodes, enabling them to select the appropriate header.

Once the set-up phase is complete, the steady-state phase begins, which is similar to basic LEACH, but with the PHS distance criterion. During this phase, an ordinary node gathers data from its surroundings and transmits it to the header selected during the set-up phase within the designated time frame.

IV. EXPERIMENTAL RESULTS

In this study, we have reviewed four protocols for wireless sensor networks, namely the LEACH protocol [8], the ESO_LEACH protocol [9], WOATCA [17], and the proposed M-WOA method.

The LEACH algorithm selects a closer cluster head without considering the distance from the CH to the base station. In the ESO_LEACH algorithm, the initial clustering of sensor nodes is done using the particle swarm meta-heuristic algorithm. WOATCA examines existing trust-based clustering routing protocols and introduces a new energy-efficient protocol. It selects trustworthy nodes as cluster heads by considering residual energy and transmission delay factors. The M-WOA method clusters sensors using the manifold distance-based Whale Optimization Algorithm. Once the set-up phase is complete, the steady-state phase commences. This phase is comparable to basic LEACH but operates on the PHS distance criterion. During this phase, an ordinary node gathers data from its surroundings and transmits it to the header selected in the set-up step within the allotted timeframe. Our hypotheses regarding the effectiveness of previous and proposed methods are summarized in Table II. These hypotheses were selected based on a simulation similar to the Enhanced-LEACH protocol [8]. All nodes initially have the same energy level of 0.5 joules, which is reduced with each data transmission according to equations (1) and (2). In this network, each node sends its location information to the base station, which then utilizes the previous and proposed M-WOA algorithms to identify clusters. The base station broadcasts the header number of each node to all nodes, and each node sends its information to the specified header. To evaluate the performance of the proposed algorithm, we consider the following criteria:

1. Energy consumption based on the number of nodes: We calculate the total energy consumption for a specific number of nodes [8]. Headers collect and aggregate data, which is then sent to the base station.

2. Energy consumption based on the number of rounds: We calculate the total energy consumption for a specific number of cycles [9].

3. Network lifetime: We examine the number of rounds until the last node dies, which is commonly referred to as LND. The longer the network life, the better the network's performance.

4. Number of received packets: We calculate the total number of data packets received by the base station during the network's life. A higher number of received packets indicates better network performance. In terms of power consumption, Fig. 4 illustrates how well the proposed method performs compared to LEACH, ESO_LEACH, WOATCA, and proposed M-WOA algorithms. Fig. 5 displays the energy consumption at different rounds between LEACH, ESO_LEACH, WOATCA, and the proposed method based on the simulation performed according to the proposed hypothesis. The M-WOA algorithm indicates that the network has passed more rounds than other algorithms, increasing the network life while reducing the total energy consumption of the network nodes in each

TABLE II. Simulation Parameters [11]

Simulation area	100 m× 100 m
Number of nodes	45–85
Packet length (from cluster head to BS)	6400 bits
Packet length (default packet length from normal node to cluster head)	200 bits
Initial energy	0.5 J
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

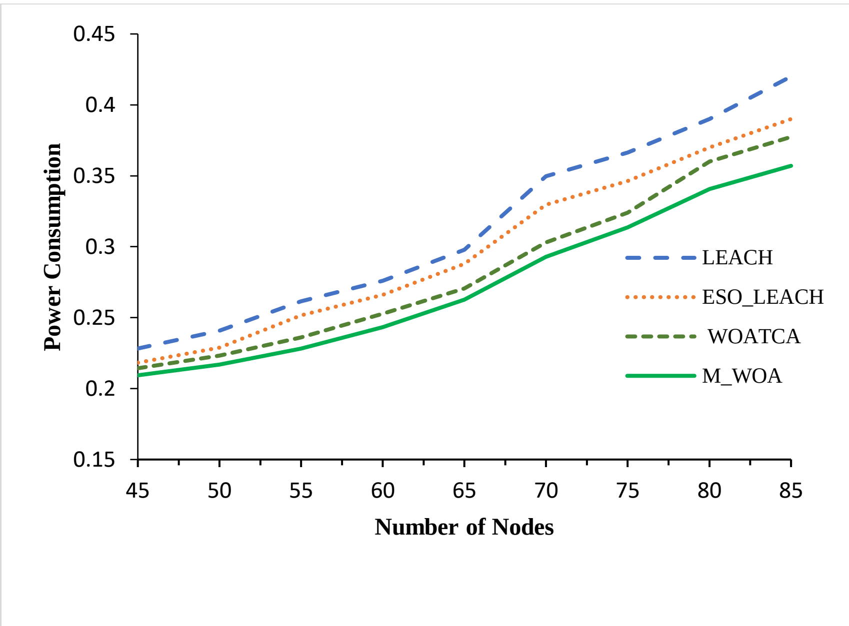

Fig. 4. Power consumption in LEACH, ESO_LEACH, WOATCA, and M_WOA based on different numbers of nodes

round. Additionally, Figs. 6 and 7 depict the number of live nodes per round and the number of packets the base station receives. The diagram highlights the superior performance of the proposed algorithm compared to previous algorithms. The graph depicted in Fig. 6 shows the live node count per round, with the green line indicating a significant increase. Additionally, Fig. 7 showcases the

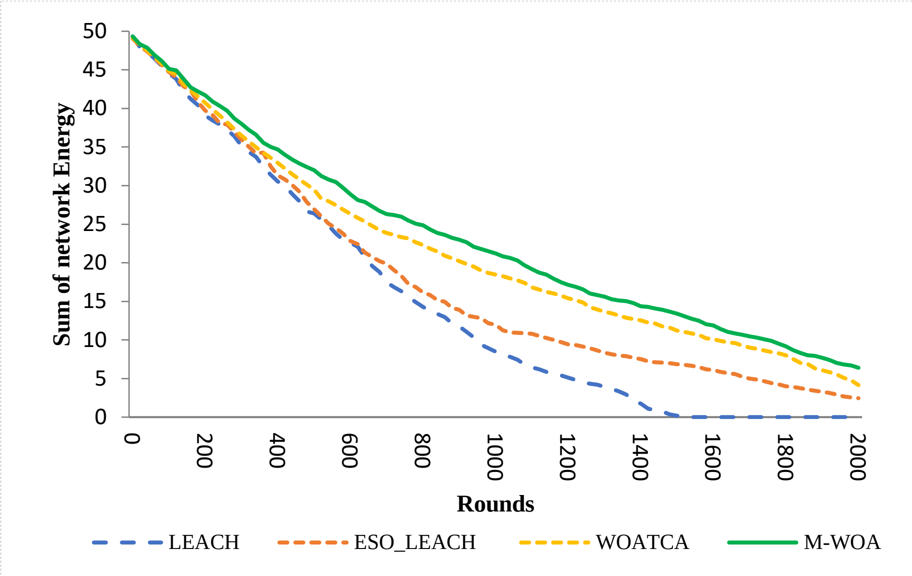

Fig. 5. Sum of network Energy for each round using LEACH, ESO-LEACH, WOATCA and M_WOA.

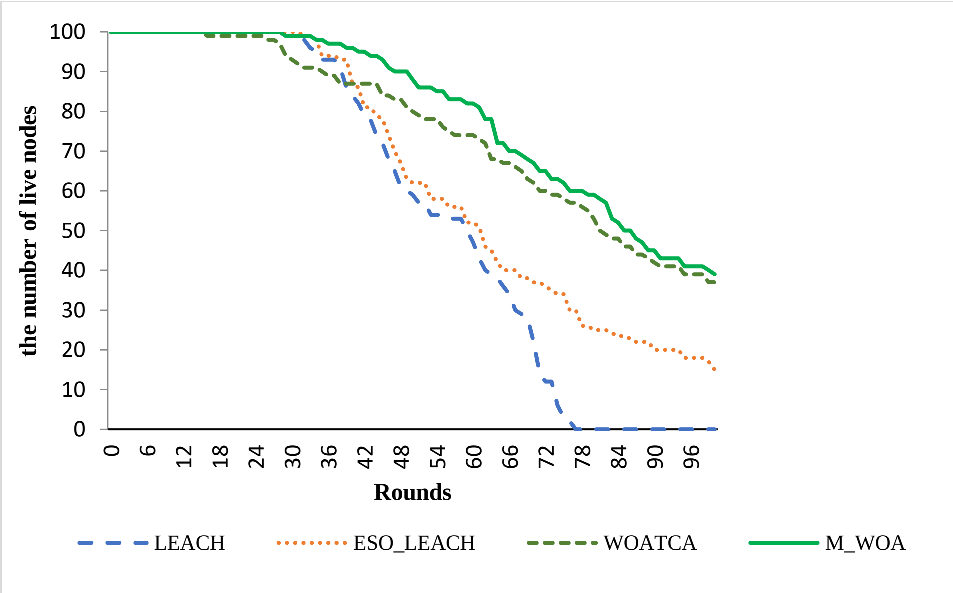

Fig. 6. The number of live nodes for each round using LEACH, ESO-LEACH, WOATCA and M_WOA.

number of packets received by the base station, revealing a noticeable improvement in network performance, as observed in the previous graphs. It is evident that the proposed method has resulted in an improvement in energy consumption, thereby increasing the network life. Notably, when the network nodes are numerous, the proposed algorithm significantly reduces energy consumption. Such improvements are attributed to the fact that, in the proposed approach, nodes can transmit their data to the nearest intermediate node, thereby minimizing extra transfers and prolonging the network's lifespan.

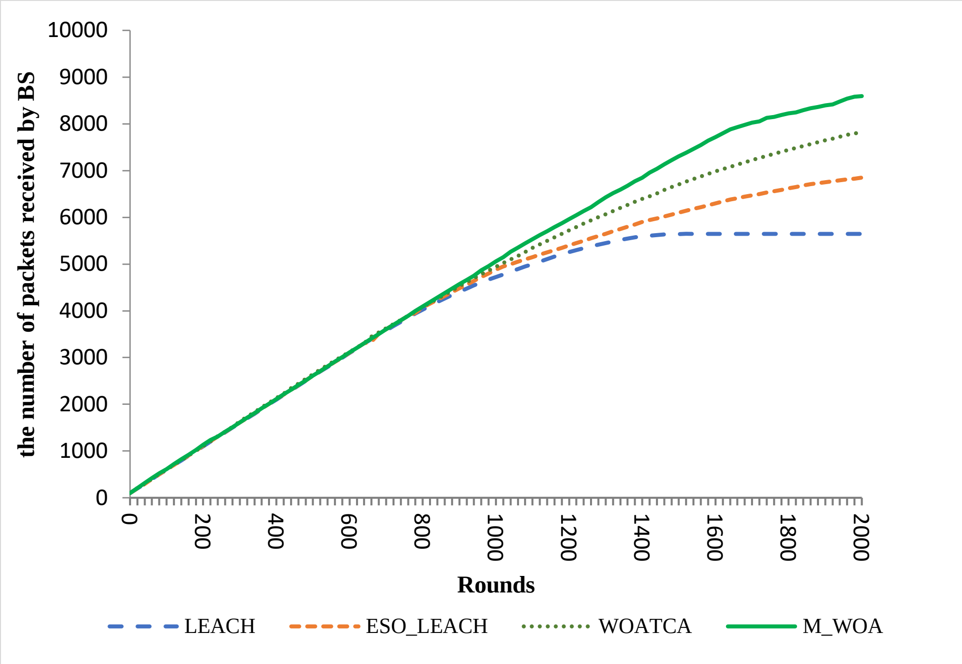

Fig. 7. The number of packets received by the base station for each round using LEACH, ESO-LEACH, WOATCA and M_WOA.

V. CONCLUSION

This research aims to explore how energy efficiency is impacted by the selection of a suitable cluster head by regular nodes. To achieve this, a simulation-based study was conducted, comparing the energy consumption of our proposed method against LEACH and two other recent algorithms that aimed to improve LEACH similarly. Our findings indicate that power consumption decreases, resulting in an extended lifespan for the network. LEACH allows each node to determine its remaining energy, which varies based on the data transfer rate. In this paper, we have endeavored to enhance the performance of the whale algorithm by utilizing the geodesic distance between sensors and prioritizing remaining energy as a clustering criterion. Our proposed solution is a manifold distance-based whale, which utilizes higher residual interface nodes to minimize the total distance between source sensor nodes and the base station. Thus, instead of transferring data directly from a sensor node to a station node, we use nodes that are closer in proximity and have more energy.

Developing a reliable wireless sensor network (WSN) is challenging due to insufficient energy of sensors for growing WSN applications. To save sensor energy, a sleep-wake scheduling scheme can be implemented by assigning tasks to a dominant group of awake sensors while other nodes sleep. However, finding the smallest dominant set in a large graph is time-consuming. We propose using a deep learning-based Graph Neural Network to identify the smallest dominant set and extend the network lifespan, as future work.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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