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A modified grasshopper optimization algorithm based on levy flight for cluster head selection in wireless sensor networks

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Abstract

A wireless sensor network (WSN) is made up of numerous wireless sensors that may be used for a variety of purposes, including security surveillance, terror threat detection, health monitoring, and environmental monitoring. In these applications, thousands of wireless sensors are deployed in remote environments to operate autonomously. The wireless sensor nodes are largely confined by limited energy supply, memory, and bandwidth. Major issues in designing WSNs are energy consumption and maximizing the network lifetime. Low energy adaptive clustering hierarchy (LEACH) is a reliable routing protocol that utilizes the cluster head rotation strategy to uniformly allocate the energy burden among all the available nodes. LEACH maintains the steadiness of the energy consumed by the nodes. However, LEACH protocol does not guarantee the uniform allotment of the cluster heads (CHs), and eventually reduces the network lifetime. A clustering protocol offers a potential solution that guarantees energy saving of nodes and increases the lifetime of the network by organizing nodes into clusters to reduce the transmission distance between sensor nodes and the base station (BS). The traditional grasshopper optimization algorithm (GOA) has a set of shortcomings such as the ease with which it can fall into local optimum and the slow convergence speed. To address these drawbacks, a modified grasshopper optimization algorithm (MGOA) was proposed based on an energy efficient routing protocol in LEACH. It is called as modified grasshopper optimization algorithm, low energy adaptive clustering hierarchy (MGOA-LEACH). It has been proposed to minimize the energy consumption and maximize the network lifetime in WSNs. The levy flight (LF) strategy was used to increase the randomness of the search agent's movement, allowing GOA to have a greater global exploration capability. The evaluation results show that the suggested algorithm provides lower energy consumption and better life time compared to competitive clustering algorithms like LEACH, genetic algorithm (GA), particle swarm optimization (PSO), whale optimization algorithm (WOA), GOA.

Keywords

Wireless sensor network, LEACH, Cluster head, Energy consumption, Grasshopper optimization algorithm.

1.Introduction

In recent years, technological advancements have enabled the use of wireless sensor networks (WSNs) for essential applications such as inventory tracking, health monitoring, remote sensing, seismic event monitoring, military surveillance, industrial monitoring, and automatic target detection and environmental monitoring [1–2]. WSNs consists of thousands of computational nodes distributed in an enormous geographical area, and each sensor node is capable of collecting data from the unattended local environment and sending such information to interested parties [3].

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Hence, the energy utilization by the sensor nodes, which are mostly battery powered devices, has increased by many folds. The energy needed by the sensors to execute different tasks like data acquisition, storage, and data transmission is often supplied by a battery. Generally, the sensor nodes are remotely deployed in unattended environments. Hence, it could be unfeasible to recharge the battery. Therefore, the primary challenge is to design energy-aware algorithms to limit the energy budget in WSNs. Network lifetime is considered to be one of the most imperative metrics for the assessment of WSNs. The network lifetime of single nodes will determine the overall network lifetime of the WSNs. Several research studies have been focused on the development of energy conserving protocols to enlarge the lifetime of the sensors by arranging the nodes into clusters [4]. In the literature, various types of clustering techniques have been proposed to achieve network scalability. Clustering is a procedure in which the original data set is partitioned into different groups or sets called clusters. The data in each cluster has certain common characteristics. Clustering techniques are extensively used for maintaining communication bandwidth and eliminate message redundancy. It is also used for stabilizing the network topology and to reduce communication overhead. Clustering based schemes are broadly classified into two types: heuristic and nature inspired approaches [5]. In recent years, numerous numbers of heuristic strategy-based clustering algorithms are suggested for WSNs [6–8]. Amongst the energy-aware algorithms, low-energy adaptive clustering hierarchy (LEACH) is considered to be one of the popular clustering algorithms [8]. However, it has been seen that LEACH does not ensure a uniform distribution of cluster heads (CHs). Therefore, various improved LEACH protocols were proposed to maximize the efficacy of the traditional LEACH [9–12]. In general, two key types of sensor nodes are considered for these clustered WSNs scenarios. The regular nodes fall into the first group. Whereas, the cluster head (CH) nodes come under the second group. There may also be more than one unique node termed as sink/base station (BS) that is directly connected to the outside world. The selected CHs of each cluster are accountable for collecting and combining the information gathered from other clusters and transmitting the same information to the BS either directly or through multihop communication via their neighbour CHs. The CH selection model in WSN is shown in *Figure 1*.

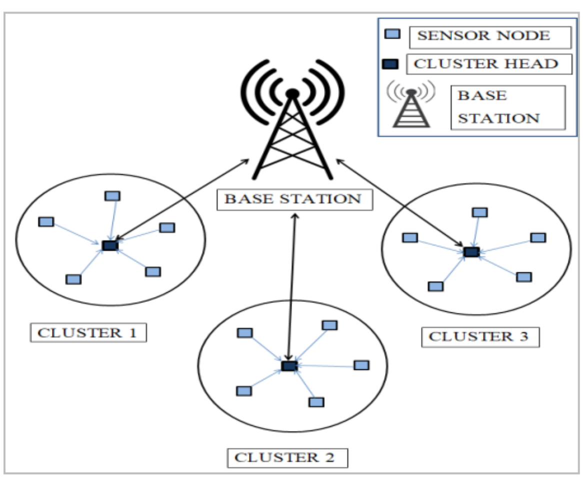

Figure 1 Clustering in WSN

Along with the clustering mechanisms, routing for data transmission plays a significant role in reducing data consumption and, as a result increases the lifespan of the WSN. Therefore, creating routing protocols for WSNs is a complex task because of restrictions on network energy efficiency. To develop a low-energy routing technique, the effective parameters considered for the design are energy consumption, effective deployment of nodes, node capabilities, data aggregation and fault tolerance. Accordingly, several energy efficient protocols have been introduced to ensure the proper use of energy in WSNs. In this work, we only look at homogeneous WSNs, which are made up of static sensor nodes, CHs, and BSs. In this article a modified grasshopper optimization algorithm (MGOA) based energy efficient clustering protocol called MGOA-LEACH is proposed to enhance the lifetime of WSNs. In this proposed approach, we have combined the levy flight (LF) strategy with a grasshopper optimization algorithm (GOA). The movement pattern of LFs fluctuated between frequent short-distance leaps and rare long-distance jumps, allowing them to escape from the local optimal and broaden the search space for the population.

The composition of this article is as follows: Section 2 presents the literature review. In section 3, the theory behind the LEACH clustering protocol, the basic GOA process, the MGOA protocol, the network model and the proposed algorithm are briefly discussed. In section 4, the simulation environment and comparison of obtained results with other standard algorithms are provided. Section 5 contains the comparative study analysis and the overall analysis of the results, as well as the limitations of this study. Section 6 concludes with a summary of the findings and future work.

2.Related works

Because of their excessive workload, CHs quickly exhaust in comparison to the conventional nodes. The failure of the CH node causes the entire cluster to fail, and thus the entire network to fail. Therefore, a substantial number of nature-inspired metaheuristic algorithms-based clustering algorithms have been put forward in the past decade to overcome such situations. Few of them are listed below.

- Differential evolution (DE)
- Chicken swarm optimization (CSO)
- Glowworm swarm optimization (GSO)
- Grey wolf optimization (GWO)
- Genetic algorithm (GA)
- Whale optimization (WO)

- Gravitational search algorithm (GSA)
- Cuckoo search (CS)
- Particle swarm optimization (PSO)
- Firefly algorithm (FA)
- Ant colony optimization (ACO)
- Artificial bee colony (ABC)

A hybrid energy efficient protocol by combing the fuzzy C-means (FCM) and DE was proposed in [13], The FCM was used for cluster creation and DE was utilized to CHs from the pool of nodes. In [14], the authors proposed a hybrid energy efficient protocol called optimized low-energy adaptive clustering hierarchy (O-LEACH) by combining LEACH and GA. The fitness function of the GA was used to find the optimal route. Sridhar and Guruprasad [15] proposed a chaotic whale metaheuristic energy optimized data gathering (CWMEODG) strategy for increasing the network lifetime while reducing the delay. An updated version of the ABC algorithm and an FCM-based energy efficient protocol were developed in order to improve the throughput of the WSN as well as the energy efficiency of the network [16]. The algorithm was created with the goal of balancing energy consumption and increasing energy efficiency when power to sensor nodes was limited. An energy saving protocol to enhance the lifespan of WSN was designed by introducing an improved clustering structure [17]. This protocol is formulated based on modified FCM and a centralized method with an intention to improve the energy spending of WSN. Ajmi et al. [18] proposed a multi weight chicken swarm based genetic algorithm (MWCSGA) to improve the energy efficiency of the WSN. In this protocol, at the initial stage, the combination of CSO and GA determines the CH selection process based on mathematical models to prolong the of network lifespan. Next, multi weight clustering model is used for load balancing in clusters. Subsequently reduces the power consumption. Another hybrid protocol proposed to optimize the CH selection by combing GA and PSO [19]. In this strategy GA is used for clustering and PSO is utilized for routing in WSN. In 2021, Reddy et al. [20] have developed an improved clustering routing protocol by hybridizing ACO and GSO. The presented work aims to find the optimal CH by minimizing the distance between the nodes that have been chosen as CH. In 2022, Raj and Bala [21] developed a hybrid protocol known as energy-efficient centroid-based ant colony optimization (EECAO) to enhance the performance of sensor networks in a WSN-assisted internet of things (IOT) environment. This protocol gathers information of local clusters using a centroid based clustering algorithm. Then, the ACO is used to optimise the path between the CHs and BS. This protocol incorporates clustering elements like energy cost, cognitive sensor throughput and channel consistency for distributed cluster formation design. Pitchaimanickam and Murugaboopathi [22], introduced a hybrid approach to extend the existence of WSN by using FA and PSO. By applying PSO, this strategy improves FA's global search capability. Sekaran et al. [23] have introduced an improved CH selection approach using grey wolf optimization (GWO). To improve the energy efficiency, several parameters including intra-cluster distance, sensor residual energy, and sink distance are taken into account. Inspired by the social behaviour of grasshoppers, the population-based grasshopper GOA was developed in [24]. The GOA algorithm was basically designed to emulate the social behaviour of grasshoppers. Recent years have witnessed the potential use of GOA in the field of science and engineering like multi-objective test problems, image processing, scheduling, machine learning, and motion tracking [25–28]. However, several variants of GOA approaches are suggested to overcome the gaps in GOA [29, 30]. The combination of Bees algorithm (BA) and GOA has been proposed to address the deployment problem in WSN [31]. In [32], a cluster-based routing model using hybrid GA and GOA was proposed to enhance the lifetime of WSN. A Fuzzy logic-based clustering protocol using improved GOA for WSN was proposed in [33]. The proposed protocol outperforms other protocols by achieving enhanced network lifetime. An optimum CH selection protocol by combining multi-objective GOA and harmony search (HS) was introduced in [34]. The proposed hybrid technique has superiority over other existing protocols in terms of energy consumption, packet transmission and data delivery rate. In order to attain energy stability and improve network lifetime a hybrid GOA and DE based protocol was developed in [35]. In Bhat and KV [36] reported a localization and deployment strategy to improve the clustering efficiency and reducing the deployment error. An energy efficient cluster-based routing-based protocol using golden eagle optimization algorithm (GEOA) and improved GOA was introduced in [37] to improve energy stability and network lifetime of WSN by overcoming the challenges in the CH selection process. Whereas, LF is a unique kind of random walk that uses the Levy distribution to determine step lengths and directions [38]. Many research investigations have demonstrated that the foraging pattern and motion pattern of a large group of animals and insects can be described based on LF strategy [39, 40]. Later, the LF has been combined with several nature inspired metaheuristic algorithms to improve their performance [41–43]. An energy-efficient CH selection technique based on the whale optimization algorithm (WOA) named WOA-clustering (WOA-C) is proposed by Jadhav and Shankar in [44]. To reduce the total energy dissipation of the networks, Heinzelman et al. [45] proposed a clustering-based protocol called LEACH, which does this by randomly rotating local CHs. Based on the GWO, Al-Aboody and Al-Raweshidy [46] developed a three-tiered hybrid clustering routing algorithm for WSNs in. In stage 1, it was suggested to use a centralized selection in which the BS plays a significant role in picking CHs. In Stage 2, a GWO routing for data transfer is utilized. In last stage, a cost-based, distributed clustering method is proposed.

This research shows that the aforementioned processes outperform LEACH in terms of energy consumption, node lifetime, number of sent data packets to BS, and number of dead nodes. Nature-inspired algorithms have found widespread use in research and industry because to their effectiveness, ease of implementation, absence of gradients, ability to avoid local optima, and the ability to treat problems as black boxes. Because of this, we also look at how the suggested method might be used to address practical issues.

3.Methods

3.1LEACH clustering protocol

LEACH is widely considered as a dynamic clustering protocol for WSNs [8]. Small clusters of distinct classes of nodes are established in the LEACH network, and one of the nodes is selected as CH. The main objective of the deployed node is to gather the information from the target and broadcast it to its nearest CH. Later, the CH aggregates, compresses, and transmits the information received from all nodes to the BS. In comparison to other nodes, the nodes selected as the CH outlets more energy, since the BS to which the information is to be sent is far away from the point. The LEACH procedure has multiple rounds. The setup phase and steady-state phase of LEACH are discussed in 3.1.1 and 3.1.2.

3.1.1Set-up phase

During the cluster creation phase, each non-CH node chooses to be a CH for the current round based on a set of rules. A node completes the assessment by choosing a random number T_i between the interval of 0 and 1. Furthermore, if the chosen number is less than a certain threshold T(n), then the non-CH node is nominated as CH for the current round. The threshold is calculated using this Equation 1.

$$\mathrm{T(n)} = \frac{\mathrm{p}}{1-\mathrm{p}\times\left(\mathrm{r}\times\mathrm{mod}\frac{1}{\mathrm{p}}\right)}\forall \mathrm{n} \in \mathrm{G} \quad (1)$$

3.1.2Steady-state phase

Every non-CH node begins communicating with their corresponding head node based on their time division multiple access (TDMA) schedule during this phase. All non-CH node radios are turned off until their allotted time for contact is reached thereby reducing energy expenses in those nodes. The receiver of the CH is turned on until all the data is gathered. Once all the information has been gathered, CH compiles theses details and sends them to the sink. In this phase, after a certain period of time the CHs are re-elected.

3.2Modified grasshopper optimization algorithm (MGOA)

The GOA was designed by Saremi et al. [24], is a nature-inspired optimization approach. GAO was developed based on the swarming behavior of grasshoppers. Grasshoppers are insects and are considered to be a pest. They habitually damage crops and agriculture, which leads to being, regarded them as pest. The grasshopper is one of the largest swarms of all species. The swarming behavior of the grasshopper can be viewed in two phases, namely the nymph and adulthood. The nymph grasshopper travels in millions of numbers like a rolling cylinder, and they consume all the plants that come in their way. They create a swarm in the air and move over a vast distance when they mature from nymph to adult. The arithmetic representation used to characterize the behaviour of grasshoppers is specified as per Equation 2.

$$\mathrm{Y_i} = \mathrm{S_i} + \mathrm{G_i} + \mathrm{A_i} \quad (2)$$

Where $\mathrm{Y_i}$ denotes the position of the $\mathrm{i^{th}}$grasshopper during locomotion. $\mathrm{S_i}$ and $\mathrm{G_i}$ represents the social interaction and the force of gravity of the $\mathrm{i^{th}}$ grasshopper respectively. $\mathrm{A_i}$ is the vertical motion in the wind. When the random behaviour is considered, the Equation 2 can be expressed as shown in Equation 3.

$$\mathrm{Y_i} = \mathrm{n_1 S_i} + \mathrm{n_2 G_i} + \mathrm{n_3 A_i} \quad (3)$$

where $\mathrm{n_1}$,$\mathrm{n_2}$ and $\mathrm{n_3}$ are indiscriminate numbers in the interval of [0,1].

The social interaction ($\mathrm{S_i}$) of the $\mathrm{i^{th}}$ grasshopper is given by Equation 4.

$$S_i = \sum_{\substack{j=1 \\ j\neq 1}}^{M} s\left(d_{ij}\right) \hat{d}_{ij} \quad (4)$$

Where $d_{ij} = |y_j - y_i|$, is the distance computed among the i^{th} and j^{th} grasshopper. S represents the strength of the social force. The unit vector from the i^{th} grasshopper to the j^{th} grasshopper is given by the Equation 5.

$$\hat{d}_{ij} = \frac{y_j - y_i}{d_{ij}} \quad (5)$$

The S function given in Equation 2 is determined according to Equation 6.

$$S(n) = f^{\frac{-n}{l}} - e^{-n} \quad (6)$$

Where f and l specify the strength of attraction between the grasshoppers and the attractive length scale respectively.

The component G mentioned in Equation 2 can be computed as

$$G_i = -g_c \hat{e}_e \quad (7)$$

In Equation 7, g_c represents the gravitational constant and $\hat{e}_e$ is a unit vector towards the direction of centre of the earth. The factor $A_i$mentioned in Equation 2 can be computed as

$$A_i = u_c \hat{e}_w \quad (8)$$

where the constant drift is u_c, and $\hat{e}_w$ denotes the unity vector in the direction of wind. Now by placing the values of S, G and A in Equation 2, it can be expanded as shown in Equation 9.

$$Y_i = \sum_{\substack{j=1 \\ j\neq 1}}^{M} s(|y_j - y_i|)\frac{y_j - y_i}{d_{ij}} - g_c \hat{e}_e + u_c \hat{e}_w \quad (9)$$

where the grasshopper's population is denoted by M.

However, in its original form, the mathematical model offered in Equation 9 may not be used to solve a specific problem. Since the grasshoppers attain the comfort zone quickly and the locust groups doesn't converge to a given point. From Equation 9, it can be observed that the swarm simulation prohibits the optimization algorithm from exploring and utilizing the search space around a solution. Equation 10 is an updated version of Equation 9, which is used to fix the problems with optimization.

$$Y_i^d = c\left(\sum_{\substack{j=1 \\ j\neq 1}}^{M} c\frac{ub_d - lb_d}{2} s(|y_j^d - y_i^d|)\frac{y_j - y_i}{d_{ij}}\right) + \hat{T}_d \quad (10)$$

where the upper limit and the lower limit in the D^{th} dimension are ub_d and lb_d respectively. $\hat{T}_d$is the target value (best solution) in the D^{th} dimension. However, while modeling the modified equation the direction of the wind is assumed towards the target $(\hat{T}_d)$ and gravity component (the Gcomponent) is not considered. In Equation 10, the next position of the grasshopper is chosen by considering the current position of the grasshopper, the target position and the relative position of all grasshoppers. The parametric quantity C is utilized to mitigate the attractive and repulsive forces between grasshoppers, and is computed using Equation 11.

$$C = C_{max} - i\frac{C_{max} - C_{min}}{L} \quad (11)$$

where, the utmost estimate of C is C_{max} and the nethermost estimate of C is C_{min}. i is the integer of recent iteration, and L specifies the maximum number of iterations. In traditional GOA, it can be observed that the effect of gravity force while updating the position of the grasshopper is not considered. In [30], the authors introduced a gravity force while updating the position of each grasshopper in the traditional GOA. The following arithmetic model is used to show the updated position of the grasshoppers.

$$Y_i^d = c\left(\sum_{\substack{j=1 \\ j\neq 1}}^{M} c\frac{ub_d - lb_d}{2} s(|y_j^d - y_i^d|)\frac{y_j - y_i}{d_{ij}}\right) - \sum_{\substack{j=1 \\ j\neq 1}}^{M} g\frac{y_j - y_i}{d_{ij}} + \hat{T}_d \quad (12)$$

Further, we employed the LF mechanism to improve the randomness of the movement of search agents and to expand the exploring capacity of the basic GOA [31]. The modified mathematical model is formulated as follows (Equation 13).

$$y_i^{d+1} = y_i^d + \alpha \oplus \text{Levy}(\beta) \quad (13)$$

y_i^{d+1} is the new position of the i^{th} grasshopper. $\propto$ represents the step size. The symbol '$\oplus$'signifies the entry-wise multiplication. Levy distribution can be represented by (Equation 14):

$$\text{Levy}(\beta) \approx t^{-1-\beta}, 0 < \beta \leq 2 \quad (14)$$

Where t is a variable and $\beta$is a stability controlling index. The random step length S of the LF is computed as (Equation 15):

$$s = \frac{U}{|V|^{\frac{1}{\beta}}} \quad (15)$$

Here U, V are drawn from normal distributions. That is $U = N \approx (0, \sigma_u^2)$and with $V = N \approx (0, \sigma_v^2)$

The variance σ_u is given by the Equation 16.

$$\sigma_u = \left\{\frac{\Gamma(1+\beta)\sin\left(\frac{\pi\beta}{2}\right)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}}\right\}^{1/\beta} \quad (16)$$

And the variance σ_v is given by the Equation 16.

$$\sigma_v = 1 \quad (17)$$

where Γ is the standard gamma function.

The GOA's search capability is considerably improved by adopting the LF strategy. This combined technique avoids local minima and improves the GOA's global search capabilities.

3.3Proposed algorithm

The proposed GOA based centralized clustering algorithm, termed as MGOA-LEACH, is designed to use the high energy nodes as CH and create clusters which are evenly distributed throughout the whole sensor map. The MGOA-LEACH algorithm is based on three phases as used in [20]. It consists of (i) the network model, (ii) the energy model, and (iii) the CH selection. Further, the characteristics of the WSN are anticipated as: i) Initially, all sensor nodes are arbitrarily positioned which are motionless, homogenous, and have limited energy in the network, ii) the BS may be established inside or outside the sensing area and stationary in nature, iii) all deployed nodes capable of gathering the data periodically and can forward the data, iii) their own position and the position of other nodes are unknown to the nodes present in the network, iv) after deployment of nodes, the nodes were not monitored. v) Any node can serve as a CH, and vi) The nodes compare the received signal strength to calculate the distance between the BS and other nodes. The application of MGOA for CH selection is provided in section 4.1. Many schemes for low-energy radio networks have been proposed based on various assumptions about radio characteristics. In this work, we have chosen the energy model as provided in [37]. The radio model for transmitting and receiving data from one node to another node is represented as in Equation 18.

$$E_{TY}(i,d) = E_{TY-elec}(i).\,i + E_{TY-amp}(i,d) \quad (18)$$

Further, E_{TY} for transmitting ibit of message at a distance d is expressed using Equation 19.

$$E_{TY}(i,d) = i.\,E_{elec} + i \in_{fs} d^2, \text{if} d < d_o$$
$$= i.\,E_{elec} + i \in_{mp} d^4, \text{if} d \geq d_o \quad (19)$$

The Equation 20 provides a description of the amount of energy that is used by the receiver for receiving i bits of message.

$$E_{RY}(i) = E_{RY-elec}(i) = i.\,E_{elec} \quad (20)$$

Where, $E_{TY-elec}(i)$and $E_{TY-amp}(i,d)$ are the radio electronic dissipation and amplifier dissipation factors respectively. The separation between the transmitter and the receiver is d. E_{elec} , represents the energy dissipation per bit. $\in_{fs}$ and $\in_{mp}$is the amplifier energy in free space and multipath respectively.$d_0$is the threshold value and $E_{RY}(i)$ represents the energy consumed by the receiver. Figure 2 illustrates the optimal CH selection using the proposed MGOA-LEACH algorithm.

3.3.1CH selection

In general, a CH not only forwards the message to the cluster members but also communicates with other CHs and BS. In this process, the CH consumes excessive energy and dies early, which results in reduced network lifetime. High energy preservation is possible by the proper selection of CHs. The suggested algorithm consists of multiple rounds. Every round starts with a set-up phase. All nodes in the network initially communicate with the BS about their current energy and position. The BS computes the mean residual energy from the gathered information and selects the nodes as CH that have a higher residual energy value than the mean energy value. Finally, the MGOA-LEACH algorithm is executed to determine the optimal CHs with the maximum fitness function. Initially, the network is supposed to contains N number of nodes, each of them are represented by CH search agents (grasshoppers). The position of the CH is indicated by CH_j. The optimum CH is found by first locating the best search agent and then using that agent's location relative to the best solution. Figure 3 depicts the suggested MGOA-LEACH algorithm's flowchart. The search agents (nodes) are scattered throughout the field. Next, the fitness values of all the search agents are computed, and the finest one is selected as CH. The parameters of MGOA are restructured in order to place the other search agents with respect to the position of best agent. The fitness function plays a significant role in CH selection. As suggested by Nicolas et al. in [39], the fitness function used in this work is given by Equation 21.

$$f(CH)_j = P_1 \left| N(CH_j) \right. + P_2 \sum CH_{RE} \quad (21)$$

Where, P_1 and P_2 are the parameters, whose values are chosen between 0 and 1. $N(CH_j)$ is the node neighbors around a particularCH_j, the residual energy of the neighbor nodes is denoted by CH_{RE}. The solution with largest fitness function is considered and hence the node with significant number of adjacent neighbors and largest fitness function is selected as the CH.

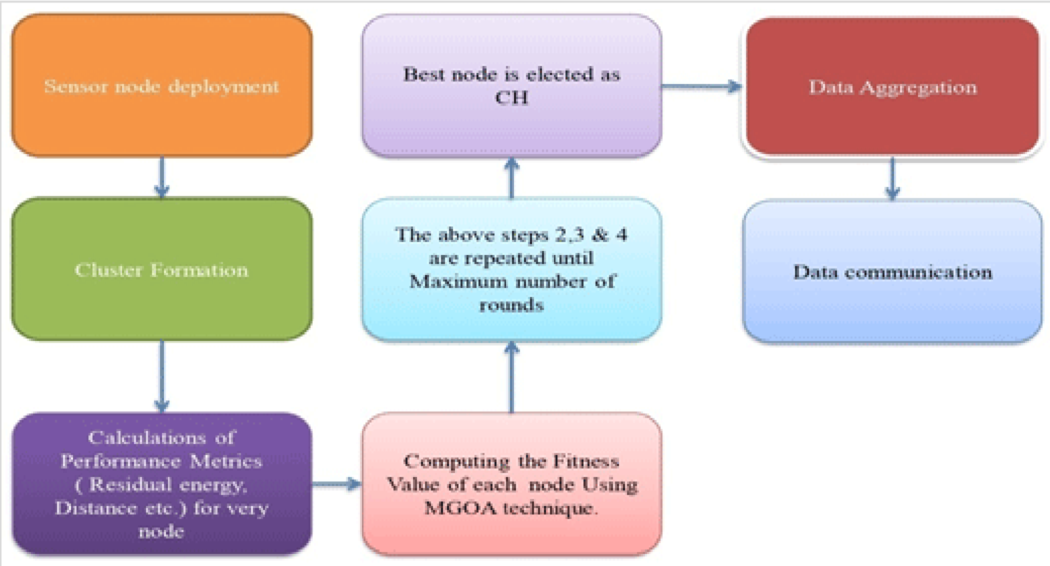

Figure 2 Block diagram of proposed MGOA-LEACH for optimal CH selection

Algorithm: MGOA-LEACH BASED CH SELECTION
1.**Input:** A graph consists of nodes with energies divided into clusters using LEACH.
2. **Output:** (Sink node Location)
3. Initialize the Grasshopper population Y_i, $(i = 1,2 \dots \dots n)$
4. Initialize S_i,G_i,A_i,C maximum iteration Max_T
5. **while**$t \leq$ Max_T
6. **for** all search agent (Grasshopper) CH_j do
7. Obtain the nearest node to CH_j with respect to S_i, G_i & A_i
8. Calculate the fitness value of node according to Equation 21
9. Identify the best node using Equations 2 to 13
10. Update and rank the positions of the search agents (Grasshoppers).
11. Update the finest position (Y^*) if Y is better than Y^*
12. Calculate the fitness function for all search agents
13. **end for**
14. Nearest node to the best position (Y^*) is the CH
15. $t = t + 1$.
16. **end while**
17. Return to Y^*

Figure 3 Algorithm for MGOA based CH selection

4.Results

4.1Experimental platform construction and simulation

In this section, the experimental findings achieved by implementing the proposed GOA-LEACH algorithm as well as the simulation environment used are described. The outcomes of the experiments are then compared to four clustering techniques. They are the LEACH, GA-LEACH, PSO-LEACH and WAO-LEACH protocol. The indicators used for performance evaluation are network life time, total energy consumption, and number of survival nodes over time. The proposed algorithm was evaluated using MATLAB version R2021a. To assess the efficacy of the suggested GOA-LEACH based methodology, we conducted rigorous testing with a variety of nodes ranging from 100 to 500 and a variety of CHs ranging from 10 to 50. In this study, the network simulated area is supposed to be 100 X 100 m2. We run the proposed algorithm 100 times and populations of 25 search agents were considered for our simulation. *Table 1* shows the list of parameters adopted for simulation.

Table 1 WSN network parameters of simulation

S. No.	Parameter	Valuation
1	Field Size	100×100 m^2
2	Number of nodes	100-500
3	BS Location	(50-50), (100-100), (50-200)
4	Number of CHs	10-50
5	Initial energy of node	0.5 J
6	E_{elec}	50 nj/bit
7	$\in_{fs}$	10 pj/bit/m^2
8	$\in_{mp}$	0.0013 pj/bit/m^4
9	Data aggregation energy cost	5 nJ/ bit
10	Packet dimension	4000 bits
11	Message dimension	200 bits
12	d_0	88m
13	Number of agents	25
14	Number of iterations	100
15	P_1	0.7
16	P_2	0.3

4.2Number of dead nodes

The results shown in this section are obtained by considering three scenarios: WSN#1, WSN#2 and WSN#3. 100 nodes and 10 CHs are considered in WSN#1. On the other WSN#2 and WSN#3 are comprised of 300 nodes with 30 CHs and 500 nodes with 50 CHs, respectively. *Figure 4* depicts the number of dead sensor nodes versus the number of rounds for the WSN#1 network at the BS (50, 50). The number of dead sensor nodes versus the number of rounds for WSN#2 and WSN#3 network at BS (100,100) and (50, 200) is shown in *Figure 5* and *Figure 6* respectively. It can be noted from *Figure 4*, *Figure 5* and *Figure 6* that the proposed MGOA-LEACH provides much better lifetime compared to other clustering algorithms. It is clear that the MGOA-LEACH has a lower number of dead nodes compare to other five algorithms in any given time slice.

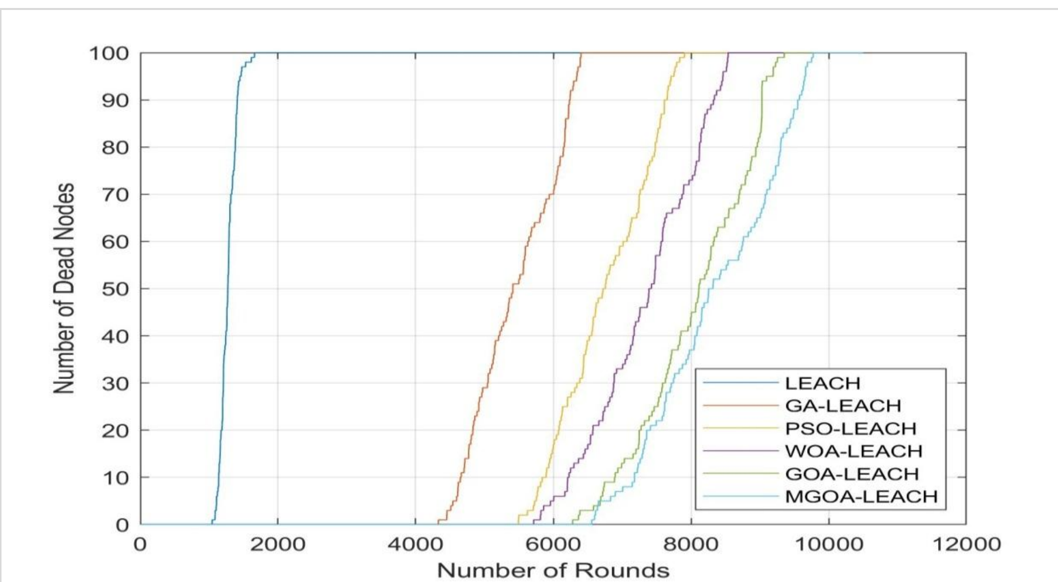

Figure 4 Dead nodes versus rounds in WSN#1 at BS Center (50, 50) by various algorithms

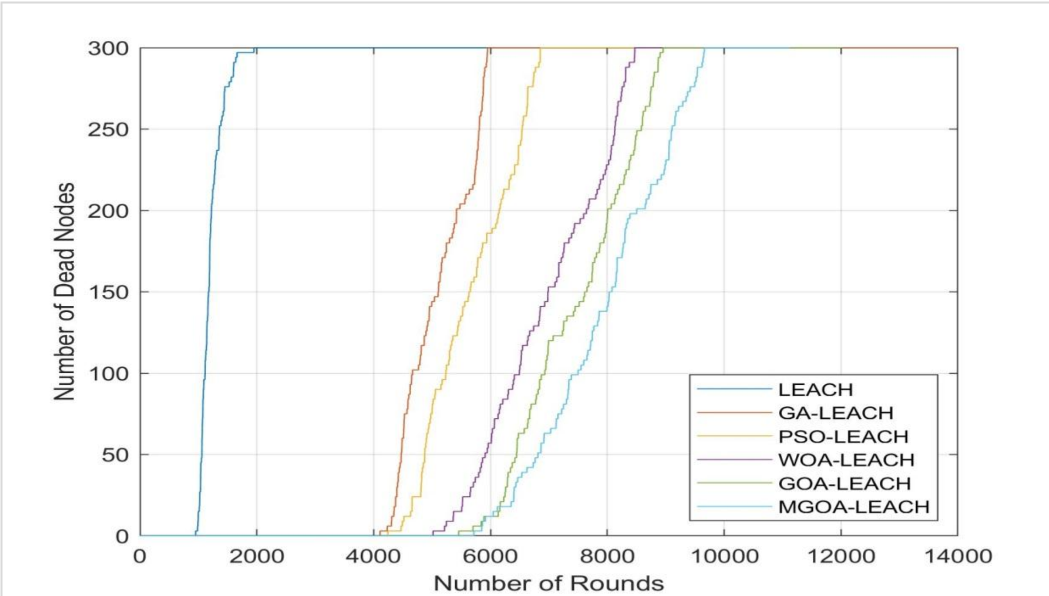

Figure 5 Dead nodes versus rounds in WSN#2 BS Corner (100, 100) by various algorithms

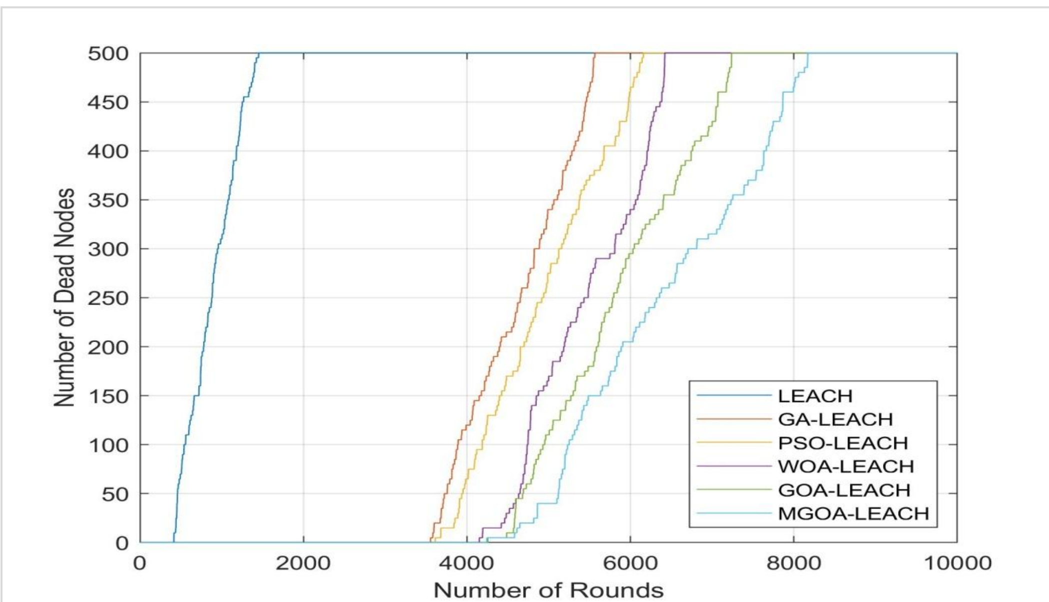

Figure 6 Dead nodes versus rounds in WSN#3 at BS Outfield (50,200) by various algorithms

4.3Total energy consumption

The performance comparison in terms of total energy consumption by various algorithms is provided in *Table 2*, *Table 3* and *Table 4*. It has been found that the MGOA-LEACH expends less energy compared to that of the LEACH, GA-LEACH, PSO-LEACH, WOA-LEACH and GOA- LEACH techniques in all three simulation scenarios. Further, we found that the performance of the MGOA-LEACH algorithm is unaffected by the position of BS. Here, the main objective is not only to minimize the energy consumption of WSN but also to enhance the lifetime. This is accomplished by focusing on the lifetime of CHs, which is critical for extending lifetime.

Table 2 WSN#1's total energy consumption at 6500 iterations with a fluctuating BS position

S. No.	Position of BS (X, Y)	Leach	GA-Leach	PSO-Leach	WOA-Leach	GOA-Leach	MGOA-Leach
1	BS Centre (50, 50)	50.00	50.00	23.07	10.76	2.30	1.15
2	BS Corner (100, 100)	50.00	50.00	50.00	26.92	17.30	8.07
3	BS Outfield (50, 200)	50.00	50.00	50.00	50.00	50.00	45.38

Table 3 WSN#2's total energy consumption at 6500 iterations with a fluctuating BS position

S. No.	Position of BS (X, Y)	Leach	GA-Leach	PSO-Leach	WOA-Leach	GOA-Leach	MGOA-Leach
1	BS Centre (50, 50)	150.00	104.54	37.50	18.18	4.54	1.47
2	BS Corner (100,100)	150.00	150.00	117.04	50.00	30.68	18.18
3	BS Outfield (50, 200)	150.00	150.00	150.00	150.00	131.81	95.45

Table 4 WSN#3's total energy consumption at 6500 iterations with a fluctuating BS position

S. No.	Position of BS (X, Y)	Leach	GA-Leach	PSO-Leach	WOA-Leach	GOA-Leach	MGOA-Leach
1	BS Centre (50, 50)	250.00	161.53	50.00	15.38	7.69	1.92
2	BS Corner (100, 100)	250.00	250.00	157.69	69.23	21.15	22.30
3	BS Outfield (50, 200)	250.00	250.00	250.00	240.38	175.00	134.61

4.4Network lifetime

The performance comparison of different algorithms in terms of network lifetime with varying BS position is shown in *Figure 7*, *Figure 8* and *Figure 9*. In WSN#1 scenario with BS at the center position, The LEACH has a network life time of 1630. The GA-LEACH has a lifetime of 6370 rounds. The PSO-LEACH has 7852. The WOA-LEACH lasts around 8444 rounds. However, the GOA-LEACH and MGOA-LEACH have network lifetime of 9259 and 9704 rounds respectively. The simulation results as shown in *Figure 7*, *Figure 8* and *Figure 9* confirms that the MGOA-LEACH outperforms other algorithms in all three simulation scenarios WSN#1, WSN#2 and WSN#3 respectively.

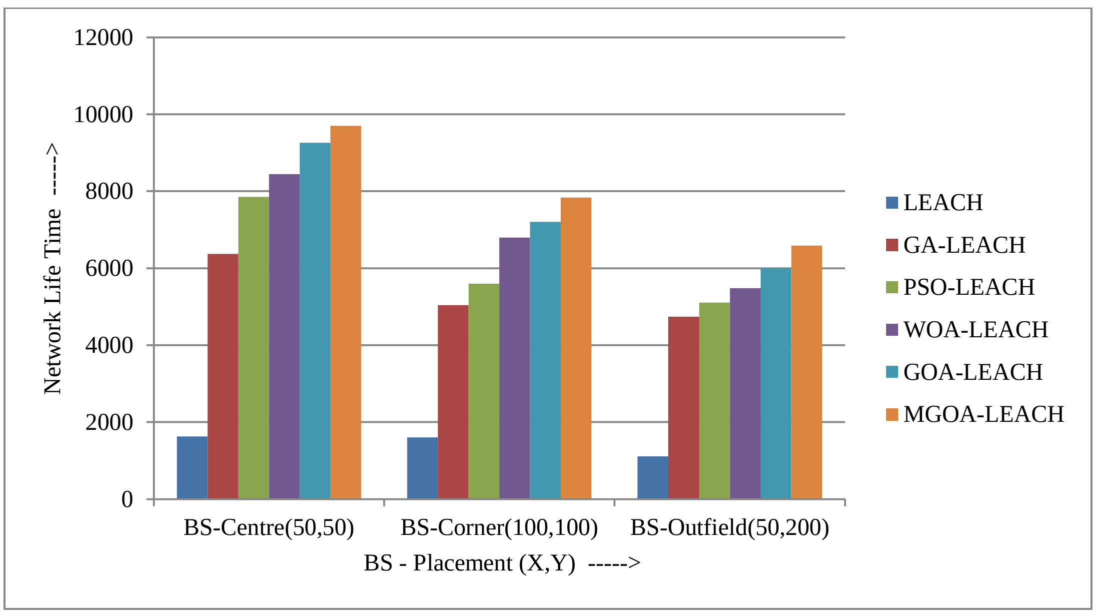

Figure 7 Network lifetime comparison in WSN#1 with varying BS position

4.5Packet delivery ratio

An important parameter computed in our analysis was the packet delivery ratio (PDR), which is the proportion of successfully delivered packets to the BS. The proportion of packets delivered at the base station increases as the network energy distribution improves. We considered three scenarios (WSN#1, WSN#2 and WSN#3) having on the sensing region of 100 m × 100 m with varying positions of BS at the center (50,50), corner (100,100) and outfield (50, 200). The performance comparison in terms of PDR of various algorithms is provided in *Table 5*, *Table 6* and *Table 7*. It is observed that in all three WSN scenarios, the PDR value is higher with the BS located in the middle (50, 50) and lowest with the BS located in the outfield (50, 200), and this value increases with an increment of a number of sensor nodes. The MGOA-LAECH outperforms its competitors regardless of the number of nodes, the number of CHs, and the location of the BSs.

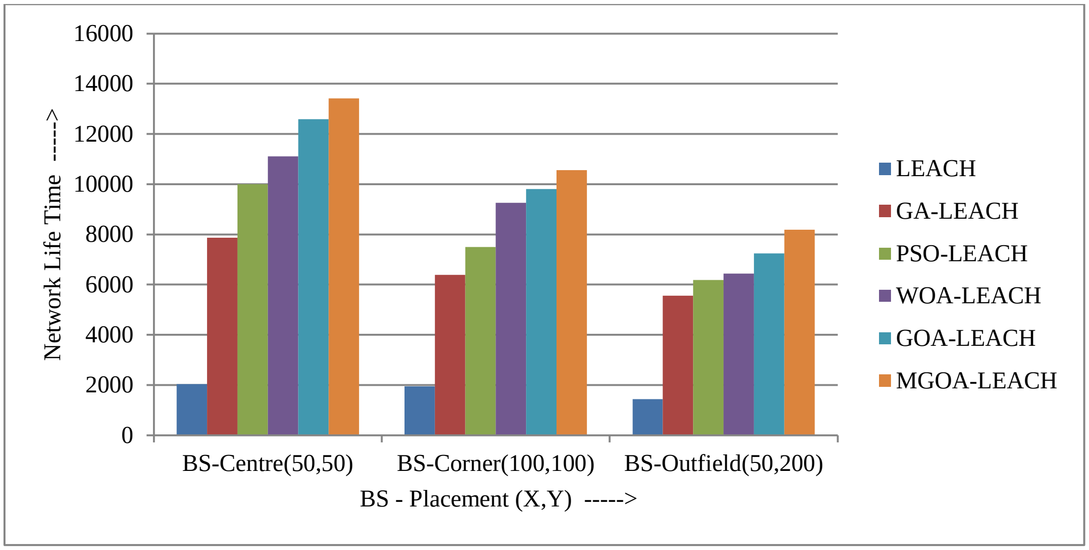

Figure 8 Network lifetime comparison in WSN#2 with varying BS position

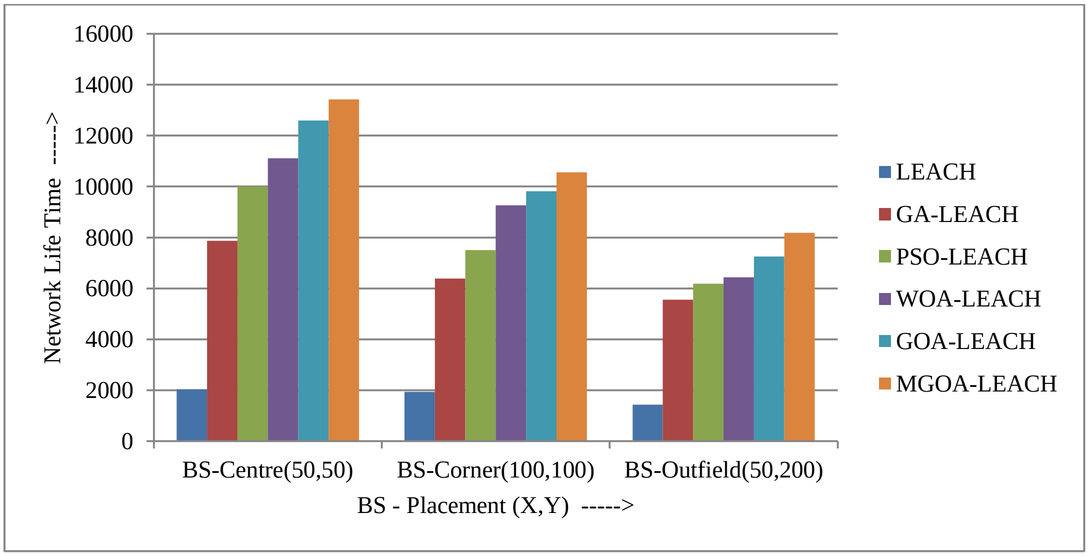

Figure 9 Network lifetime comparison in WSN#3 with varying BS position

Table 5 Ratio of packets received at BS in WSN#1 with varying BS position

S. No.	Position of BS (X, Y)	Leach	GA-Leach	PSO-Leach	WOA-Leach	GOA-Leach	MGOA-Leach
1	BS Centre (50, 50)	0.66919	0.75596	0.83883	0.84763	0.86800	0.914251
2	BS Corner (100,100)	0.64113	0.72634	0.82335	0.83135	0.84040	0.900316
3	BS Outfield (50, 200)	0.63415	0.70945	0.80155	0.81628	0.81356	0.88924

Table 6 Ratio of packets received at BS in WSN#2 with varying BS position

S. No.	Position of BS (X, Y)	Leach	GA-Leach	PSO-Leach	WOA-Leach	GOA-Leach	MGOA-Leach
1	BS Centre (50,50)	0.69145	0.79245	0.86785	0.88272	0.89587	0.94983
2	BS Corner (100,100)	0.66874	0.76984	0.84298	0.86092	0.87032	0.93865
3	BS Outfield (50,200)	0.65875	0.73470	0.83489	0.84982	0.85803	0.92530

Table 7 Ratio of packets received at BS in WSN#3 with varying BS position

S. No.	Position of BS (X, Y)	Leach	GA-Leach	PSO-Leach	WOA-Leach	GOA-Leach	MGOA-Leach
1	BS Centre (50,50)	0.73398	0.83248	0.89854	0.92487	0.92984	0.97765
2	BS Corner (100,100)	0.70624	0.81932	0.87274	0.88749	0.89982	0.95586
3	BS Outfield (50,200)	0.68839	0.77874	0.86982	0.87923	0.88643	0.94872

5.Discussions

In this section, we compare the efficiency based on how many nodes are dead after 6500 rounds, how much energy is used after 6500 rounds, how long the network lasts, and the PDR. Along with the proposed MGOA-LEACH, the LEACH, GA-LEACH, PSO-LEACH, WOA-LEACH, and GOA-LEACH protocols are also considered for performance comparisons.

The following is a comparison discussion of WSN #1 with BS in the centre (50, 50):
The number of dead nodes after 6500 rounds for the methods LEACH, GA-LEACH, PSO-LEACH, WOA-LEACH, and GOA-LEACH, and the proposed method MGOA-LEACH is 100, 100, 40, 35, 4, and 0 respectively.

The amount of energy consumed after 6500 rounds for the methods LEACH, GA-LEACH, PSO-LEACH, WOA-LEACH, and GOA-LEACH, and the proposed method MGOA-LEACH is 50 J, 50 J, 23.07 J, 10.76 J, 2.30 J, and 1.15 J. Similarly, the network lifetime for the methods LEACH, GA-LEACH, PSO-LEACH, WOA-LEACH, and GOA-LEACH, and the proposed method MGOA-LEACH is 1630, 6370, 7852, 8444, 9259, 9704 rounds respectively. The PDR for the methods LEACH, GA-LEACH, PSO-LEACH, WOA-LEACH, and GOA-LEACH, and the proposed method MGOA-LEACH is 66.9%, 75.59%, 83.88%, 84.76%, 86.80%, 91.42%, respectively.

The comparative discussion of WSN#2 with BS positioned at the center (50, 50) are as follows. The number of dead nodes after 6500 rounds for the methods LEACH, GA-LEACH, PSO-LEACH, WOA-LEACH, and GOA-LEACH, and the proposed method MGOA-LEACH is 300, 213, 76, 37, 13, and 0 respectively. Similarly, the amount of energy consumed after 6500 rounds for the methods LEACH, GA-LEACH, PSO-LEACH, WOA-LEACH, and GOA-LEACH, and the proposed method MGOA-LEACH is 150 J, 104.54 J, 37.50 J, 18.18 J, 4.54 J, and 1.47 J. The network life time for the methods LEACH, GA-LEACH, PSO-LEACH, WOA-LEACH, and GOA-LEACH, and the proposed method MGOA-LEACH is 1913, 7216, 9043, 9825, 11042, and 11738 rounds respectively. The PDR for the methods LEACH, GA-LEACH, PSO-LEACH, WOA-LEACH, and GOA-LEACH, and the proposed method MGOA-LEACH is 69.14 %, 79.24%, 86.38%, 88.27%, 89.58%, and 94.98% respectively. The comparative discussion of WSN#3 with BS positioned at the center (50, 50) is as follows.

The number of dead nodes after 6500 rounds for the methods LEACH, GA-LEACH, PSO-LEACH, WOA-LEACH, and GOA-LEACH, and the proposed method MGOA-LEACH is 500, 286, 83, 29, 15, and 0 respectively. Similarly, the amount of energy consumed after 6500 rounds for the methods LEACH, GA-LEACH, PSO-LEACH, WOA-LEACH, and GOA-LEACH, and the proposed method MGOA-LEACH is 250 J, 161.53 J, 50 J, 15.38 J, 7.69 J, and 1.92 J. The network life time for the methods LEACH, GA-LEACH, PSO-LEACH, WOA-LEACH, and GOA-LEACH, and the proposed method MGOA-LEACH is 2036, 7870, 10000, 11111, 12592, and 13425 rounds respectively. The PDR for the methods LEACH, GA-LEACH, PSO-LEACH, WOA-LEACH, and GOA-LEACH, and the proposed method MGOA-LEACH is 73.39 %, 83.24%, 89.85%, 92.48%, 92.98%, and 97.76% respectively.

From the above discussions it is clear that MGOA-LEACH outperforms other protocols in the all the three WSN scenario with BS positioned at the centre (50, 50). The performance of the MGOA-LAECH compared to the other listed algorithms is robust under varying conditions, including changes in the number of nodes, the number of CHs, and the location of the BS.

The consequences for network stability of a broken connection between the BS and CH were not explored in this research. Therefore, in order to lessen the possibility of a disconnection between stations, it is important to define a maintenance strategy for use during transmission between the BS and CH.

A complete list of abbreviations is shown in *Appendix I.*

6.Conclusion and future work

In this paper, we have presented an energy-efficient clustering approach for WSNs called MGOA-

LEACH. The MGOA is designed by introducing the gravity force and exploring the advantages of the LF strategy. The hybrid approach is used for updating the position of the grasshoppers in the traditional GOA. The proposed approach entails choosing energy-aware CHs based on a fitness function that takes into account the nodes residual energy as well as the sum of the energy of adjacent nodes, thereby lowering the overall energy consumption of the sensor network. According to the findings of the experiments the proposed MGOA-LEACH algorithm outperforms the contemporary routing algorithms like LEACH, GA-LEACH, PSO-LEACH, WOA-LEACH, and GOA-LEACH in terms of the number of dead sensor nodes, network lifetime, energy consumption and packet delivery ratio. Therefore, it can be concluded that the proposed MGOA-LEACH based approach increases the system life expectancy. In the future, various security mechanisms can be integrated with the proposed protocol to protect the network from security attacks.

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Conflicts of interest
The authors have no conflicts of interest to declare.

Author's contribution statement
G. Sunil Kumar: Conceptualization, writing original draft, analysis and interpretation of results. **Gupteswar Sahu:** Conceptualization, writing, review and supervision **Mayank Mathur:** Conceptualization, review and supervision.

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Appendix I

S. No.	Abbreviation	Description
1	ABC	Artificial Bee Colony
2	ACO	Ant Colony Optimization
3	BA	Bees Algorithm
4	BS	Base Station
5	CH	Cluster Head
6	CHs	Cluster Heads
7	CS	Cuckoo Search
8	CSO	Chicken Swarm Optimization
9	CWMEODG	Chaotic Whale Metaheuristic Energy Optimized Data Gathering
10	DE	Differential Evolution
11	FA	Firefly Algorithm
12	FCM	Fuzzy C-means
13	GA	Genetic Algorithm
14	GEOA	Golden Eagle Optimization Algorithm
15	GOA	Grasshopper Optimization Algorithm
16	GSA	Gravitational Search Algorithm
17	GSO	Glow-worm Swarm Optimization
18	GWO	Grey Wolf Optimization
19	HS	Harmony Search
20	IOT	Internet of Things
21	LEACH	Low Energy Adaptive Clustering Hierarchy
22	LF	Levy Flight
23	MGOA	Modified Grasshopper Optimization Algorithm
24	MWCSGA	Multi Weight Chicken Swarm Based Genetic Algorithm
25	O-LEACH	Optimized Low-Energy Adaptive Clustering Hierarchy
26	PDR	Packet Delivery Ratio
27	PSO	Particle Swarm Optimization
28	TDMA	Time Division Multiple Access
29	WO	Whale Optimization
30	WOA	Whale Optimization Algorithm
31	WOA-C	Whale Optimization Algorithm Clustering
32	WSN	Wireless Sensor Network