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# Energy-efficient clustering protocol for underwater wireless sensor networks using optimized glowworm swarm optimization

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In the past few decades, cutting-edge information and communication technology has been used in several ways to keep an eye on the marine environment. Underwater wireless sensor networks (UWSNs) can measure the amount of water and soil conditions, such as soil salinity, moisture, and movements, to predict landslides. UWSNs are made up of many wireless underwater sensor nodes (WSNs) that are spread out across the thalassic environment. These networks have several uses, including data collection, navigation, resource analysis, surveillance, disaster prediction, etc. Nowadays, energy efficiency becomes a complex issue to handle in the design of the UWSN due to the limited battery capacity and the challenges associated with changing or charging the integrated batteries. According to previous research, clustering and routing have already been effective methods of improving energy efficiency in the UWSN, as unreplaceable batteries and long-distance communication delays are particularly vulnerable. As a result, one of the UWSN's critical issues is determining how to extend the network's lifespan while balancing its energy consumption and shortening transmission distances. In UWSN clustering, the most important considerations are acquiring a suitable count of clusters, constituting the clusters, and picking the most satisfactory cluster head (CH) for each cluster. Based on several factors, such as residual energy, total energy consumption, and other considerations, our proposed approach picks CHs and arranges them into clusters. Also, the proposed SS-GSO method constructs a fitness function by including various sources of information, like total energy, residual energy, and luciferin value. Several simulation runs were executed to test how much better the SS-GSO approach worked. The comparison results showed that while evaluating clustering time, our proposed SS-GSO technique performs 22.91%, 50.03%, 42.42%, 58.06% better, in case of Total energy consumption 27.02%, 14%, 33.76%, 41.97% more energy efficient, in Cluster lifetime 9.2%, 19.88%, 35.91%, 40.54% less and in Packet delivery rate 8.29%, 14.05%, 17.67%, 23.97% better as compared with other heuristic techniques, such as ACO, GWO, MFO and LEACH.

## KEYWORDS

UWSN, energy, GSO, routing, clustering, bio-inspired

## 1 Introduction

The oceans encompass more than three-quarters of the planet's surface and have focused on human concerns. The oceans are home to many animals and other living things, and humans rely on them for their primary sources of food, transportation, and other resources (Khan et al., 2019). The Internet of Things (IoT) has recently gained widespread acceptance as a viable paradigm that can revolutionize our culture and economy. As a result, it is possible to network together a wide variety of sensors, identifiers, processors, communicators, actuators, and networks. It is a network of dispersed sensors for physical and environmental monitoring that communicate wirelessly with one another.

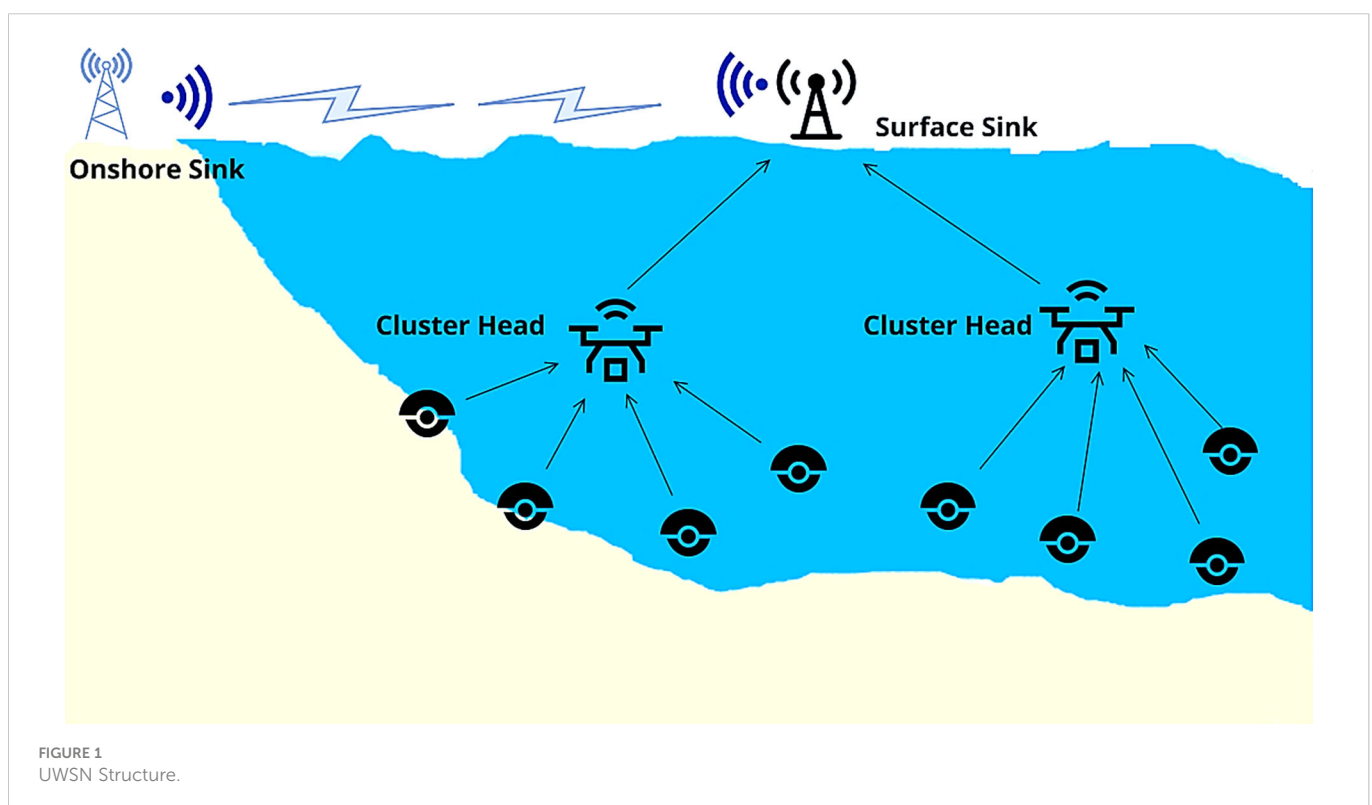
On the other hand, big data is a new technology that has spawned a flurry of academic interest in data mining, machine learning, databases, and distributed computing. Smart homes, smart buildings, smart transportation, intelligent industrial automation, innovative healthcare, smart grids, and smart cities are examples of how IoT-assisted WSNs have been used in the past several decades. The monitoring and defense of marine ecosystems is another natural domain for IoT-based WSNs. As our civilization and economy have progressed, so has the marine environment become a focal point of study for academics and scientists. It will be more expensive when it comes to traditional monitoring of the maritime environment, including oceanographic and hydrographic research vessels. The data they collect and analyze could be better quality, and the processes involved take too much time. With UWSN, data processing is far more potent than within WSNs, allowing for more intelligent object control. Water temperature, pressure, wind direction, speed, salinity, turbidity, pH, oxygen density, and chlorophyll levels are just a few of the physical and chemical parameters that can be measured by sensors employed in

an Internet of Things-based marine environment monitoring system. Depending on the level of sophistication, an IoT-based marine environment monitoring and protection system may be able to manipulate special equipment or devices in the marine ecosystem. The health of the oceans and the marine environment has gained more and more attention as it is a rich source of food and essential transportation.

Since the turn of the twentieth century, WSNs have become more prevalent in this research field (Bharany et al., 2021; Khan et al., 2021). Initially, wireless sensor networks (WSNs) were exclusively employed in terrestrial situations. Nevertheless, as shown in Figure 1, improvements in marine communication technology have made it possible for wireless sensor networks to work underwater. Compared to land-based situations, the implementation and maintenance of underwater wireless sensor networks are more complicated due to the environment (Khan et al., 2019; Bharany et al., 2021). Monitoring and communicating with an underwater environment are critical for various reasons like vast areas, salty water, and high-water pressure. The extent of these applications is broad and includes everything from temperature monitoring, undersea environments, marine ecology, natural disasters, and navigation to the investigation, surveillance, etc. In recent years, WSNs have been seen as an alternative way to study marine environments because they are easy to find, can be tracked quickly, and do not cost too much (Bharany et al., 2021).

### 1.1 Background

UWSNs were divided into sensor nodes (SNs) and data collection stations (collectively referred to as sinks) (Awan et al., 2019; Bharany



et al., 2021; Khan et al., 2021). Sensor nodes are small devices that track and demonstrate physical characteristics and transmit the information to a base station using wireless communication protocols. Radiofrequency waves are not suggested in underwater sensor networks because their signal attenuation is excessive and limited in distance range (Awan et al., 2019; Khan et al., 2021; Nguyen et al., 2021). Due to the limited capacity and frequency of the UW channel, its bandwidth is significantly smaller than that of a conventional radio channel. Due to the high absorption, attenuation, and propagation, UWSNs have a restricted bandwidth, which piqued researchers' curiosity. Another important consideration is the failure of SNs, which might be due to environmental conditions or some other. Energy conservation is another major limitation of UWSNs that significantly impacts network longevity. There is no way to replace or recharge network nodes in the harsh environment of the UWSN, which means the network will run out of nodes (Bharany et al., 2021) with time. Tsunami predictions, offshore exploration, tactical surveillance, oil and gas spill monitoring, aided navigation, pollution monitoring, and several commercial uses are all possible with UWSNs, which are further visualized to enable a wide range of applications (Nguyen et al., 2021). Underwater devices need to communicate with each other optimally for these applications to work efficiently (Bharany et al., 2021). Differentiating from the terrestrial environment, the marine environment is far more complicated and variable, making ocean monitoring more challenging. A UWSN is an *ad-hoc* network designed for underwater communication and data transmission in which several surface stations are required for better communication (Awan et al., 2019; Bharany et al., 2021; Khan et al., 2021; Nguyen et al., 2021) so that Sensor nodes can easily transmit and receive data between a source and a destination.

Sensor nodes are responsible for three primary functions: data monitoring, processing, and reception of data. Each node is designed to sense and monitor a particular physical or chemical characteristic underwater and transmit the information gathered to a central point (Heinzelman et al., 2002). The following are some of the most significant issues related to undersea applications:

- First, there is a substantially longer propagation delay than in the terrestrial environment.
- Because of the multi-path fading issue, the channel has a dynamic character.
- Since channel characteristics change constantly, dynamic channel characteristics allow for high bit error rates and short disconnections.
- Batteries have a certain amount of power, and most are not rechargeable.
- Pollution and rust can cause underwater sensors to malfunction.

Electronic Magnetic waves at high frequencies suffer from considerable attenuation due to the water's saltiness. They cannot be used underwater because of their high frequency (Reddy and Khare, 2017). Several obstacles still make underwater communication more difficult, even after considering the mentioned challenges (Wan et al., 2018). One such issue is a need for more available bandwidth combined with significant energy usage. It has an immediate impact

on the transmission rate of a network. UWSNs use energy quickly due to the current in the water and the many sources of noise present. Because of these issues, clustering in UWSNs has become problematic and expensive (Zhang et al., 2017). Developing an effective clustering procedure to handle the issues outlined above is necessary. The unique characteristics of UWSNs have attracted the attention of researchers interested in exploring their designs and networking protocols. Grounded on this interest, we developed an energy-efficient technique for clustering UWSNs that outperformed LEACH and other bio-inspired clustering algorithms (Heinzelman et al., 2002; Singh and Lobiyal, 2012; Rao et al., 2017; Alhazmi et al., 2018; Wan et al., 2018). Among the most well-known and energy-efficient clustering algorithms, those employed in terrestrial wireless sensor networks cannot deploy in the UWSN network. We also try to figure out why the WSN clustering protocols do not work well in the UWSN (Heinzelman et al., 2002).

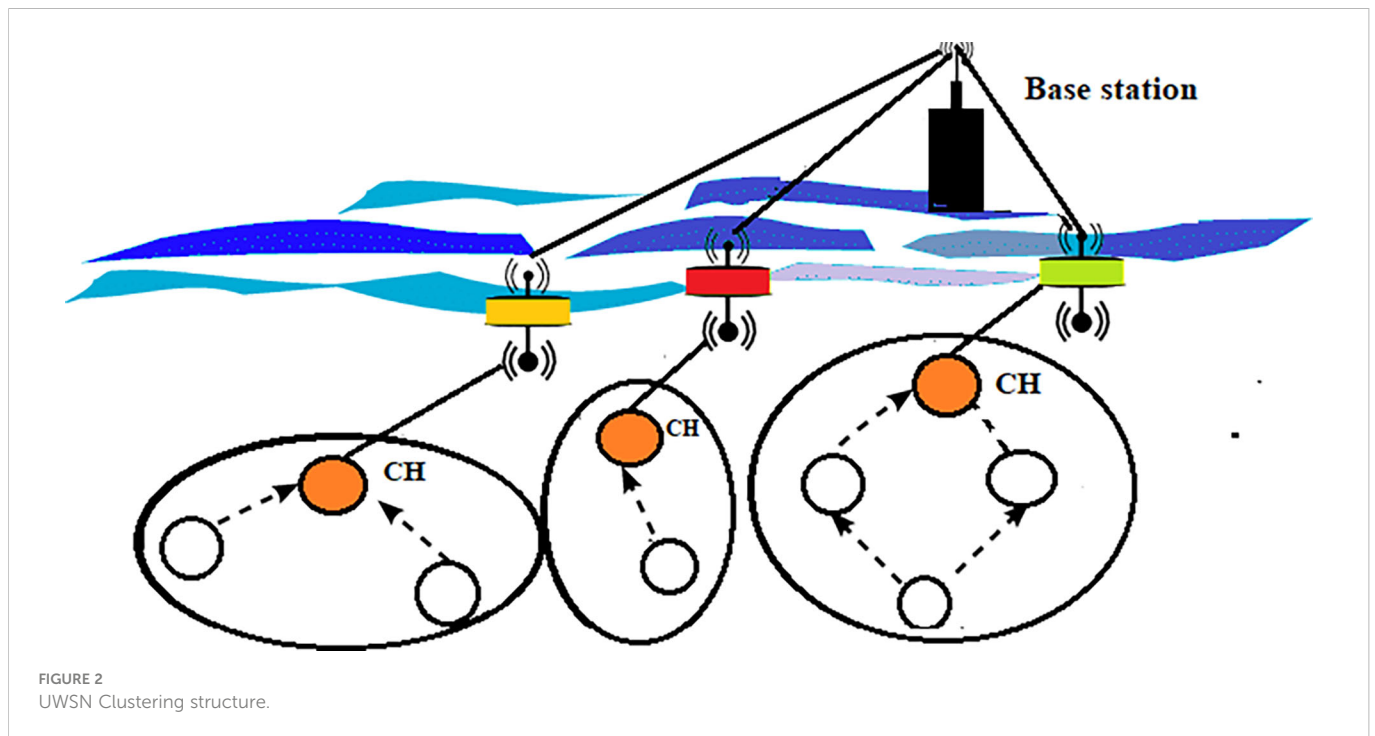
According to the proposed technique, UWSN nodes will be separated into clusters using a dynamic cluster head selection process, as seen in Figure 2. In sensor network design, clustering organizes sensor nodes into logical groups called a cluster. Several nodes assemble information and transfer it to the central station as the Base station. Only one node in the relay is designated as the cluster head, while the leftover nodes are referred to as member nodes (Nguyen et al., 2021). The cluster head's responsibility is to ensure that all inter- and intra-cluster communication is appropriately coordinated. When choosing the cluster head for each node, the amount of energy left and other parameters of the nodes will be considered. Additionally, the distance between CH and BS may be considered in this decision. The cluster size and the cluster heads' election are already important parameters for decision-making (Kazmi et al., 2019).

Additionally, the correct number of clusters in UWSNs impacts the universal energy performance of the network. It will be necessary to select a new CH when the energy of the cluster head is less than a particular threshold value. Optimizing the glowworm swarm optimization (GSO) algorithm (Javadpour et al., 2018; Reddy and Khare, 2017; Rajakumar et al., 2017; Potthuri et al., 2018) is the basis for developing the proposed protocol. An evolutionary-based optimizer ensures enough clusters to keep the network running for a long time, resulting in fewer hops and lower energy usage.

## 1.2 Our contribution

The following are the most significant contributions made by this research:

- Improved communication in the underwater environment by developing an energy-efficient clustering technique for sensor nodes.
- UWSN's clustering can be optimized by using an evolutionary algorithm. These algorithms are built upon various insects' and animals' behavioral patterns to find the most efficient solution. These algorithms also give optimum clustering solutions. They have been utilized effectively in MANET, VANET, and FANET but not in the underwater environment. This study applies the optimized glowworm swarm



optimization approach, which includes various addition to the algorithm to survive in a new environment for clustering optimization to improve UWSN communication efficiency.

- This article compares the results of our proposed algorithm with other popular evolutionary algorithms based on various parameters. which shows that the proposed research is better than the other state-of-art.
- In the proposed method, we use a method to determine the correct number of clusters, choose the best cluster head, and use an aggregation method to get the best information to the base station with least redundancy.
- We build a new fitness function that considers luciferin value while considering residual energy and the entire network's energy usage. Afterward, the fitness function is used to choose cluster Heads.
- Experimental and statistical graphs demonstrate the suggested technique's effectiveness in cluster count consistency, energy consumption, packet transmission, and network lifetime.
- In the proposed algorithm, we utilize the TDMA table for the priority of allotting a slot to transfer data from CH to the base station, which is determined by the UAV's neighbor range, residual energy, and location, that will lead to reducing overhead for load balancing and congestion management purposes.

### 1.3 Related work

Underwater sensor networks have emerged as a new area of interest for academics looking for new and novel approaches. Several

researchers have discovered their distinguishing characteristics for optimal network communication and have handled the setup challenges that arise (Javadpour et al., 2018). Compared to wireless sensor networks, the underwater medium presents an exceptionally high degree of unpredictability and difficulty. The most significant distinctions that make UWSN different from WSN are as follows: (1) amount of energy consumption; (2) propagation delay; (3) a low bandwidth; (4) dynamic topology operation; (5) propagation speed; (6) efficiency; (7) data transmission rate; and (8) noise interference. Several academics have developed a new energy-efficient clustering methodology for UWSNs (Nguyen et al., 2021). Because of the specific constraints of the environment of the underwater scene, the clustering technique developed for terrestrial networks cannot be easily used for UWSNs. Conserving energy is a critical goal for UWSNs. The clustering method is a well-known technology that has been successfully applied to cut down the energy usage of UWSNs (Bharany et al., 2021). A considerable amount of research has been done on clustering and the election of cluster heads to lower the energy consumption of the UWSN. However, there needs to be more research carried out on UWSN. This part addresses some of the research findings in even more detail.

The research in (Heinzelman et al., 2000) proposed a Low-Energy Adaptive Clustering Hierarchy as a low-energy replacement for traditional clustering techniques. Selecting cluster leaders randomly and cycling between them is a common tactic in hierarchical networks to ensure fair energy distribution. LEACH considers the nodes' available data, including their residual energy, communication energy usage, and the number of neighboring nodes, to select the most energy-efficient CH nodes. The LEACH-C algorithm is a significant improvement over its forerunner. Sending information about the sensor nodes' locations and remaining battery life to the base station can increase the system's overall efficiency. Centralized deployment of LEACH-C lowers the network's total energy

consumption and each node's energy consumption. However, LEACH-C also has some problems. If we take the LEACH-C network as an example, every node has an equal opportunity to become a CH. If the network runs out of power, the least powerful nodes will have to act as CHs, reducing the network's overall efficiency and placing an undue burden on the system. To create an energy-conscious CH selection approach, Singh et al. (Singh and Lobiyal, 2012) employed PSO for clustering the nodes. The fitness function is derived by multiplying the fitness metric by the sum of the residual energy, the distance, and the node density. This approach requires consideration of inefficient cluster formation, which drains the network's resources. In order to solve the issue brought up in (Heinzelman et al., 2002; Singh and Lobiyal, 2012), Rao et al. (2017) presented a PSO-based energy-efficient cluster head selection (PSOECHS) that includes journey time to the base station (BS) in its fitness function.

PSOECHS also affects the CH selection mechanism by changing the total number of nodes in each cluster, which extends the network's lifespan. Contrarily, computing and selecting CHs at each node consumes much more power than that. Known as UMOD-LEACH (Alhazmi et al., 2018), it is a highly-improved variant of the Leach protocol. When applied to water, this technique outperforms LEACH by 30%. It uses localization and time-division multiple-access (TDMA). According to (Wan et al., 2018), the Adaptive Clustering Underwater Network (ACUN) for underwater networks was a successor to the aforementioned adaptive clustering routing system. The amount of remaining energy at the CH node and the distance between the CH node and the sending node are the two primary factors in multipath routing.

Zhang et al. (2017) developed a clustering scheme for a medium-sized UWSN using discrete PSO and a genetic algorithm (GA) to increase the network's durability. However, the methodology is not advised because of its low stability, and the clustering model needs to be more precise to use UWSN. Pengwei Li et al. (2017) created an improved particle swarm optimization technique for clustering UWSNs that considers individual nodes' transmission power needs. However, fixing the issues from the previous study and having the network last even longer is challenging because particle coding is much more complex for sensor nodes. The Energy Center Searching model employing PSO (EC-PSO) was proposed in the literature (Wang et al., 2019) to prevent these energy gaps and to search for energy centers for CHs selection. Extra measures were taken to ensure that no two CHs would ever be close to one another. A safeguard with a threshold value was implemented to prevent low-energy nodes from delivering data. However, because the distance between nodes, CHs, and the sink node is not considered while making the fitness function, it affects how much energy the system uses.

The fuzzy enable clustering strategy was used to improve the routing method. In the literature (Alia, 2014), it has been suggested that decentralized fuzzy C-means are used as part of an energy-efficient routing protocol to reduce the total amount of energy a network uses while also making it last longer. CHs are chosen iterative through each cluster one at a time. Bhatti et al. (2016) developed the fuzzy c-means clustering and energy-efficient CH selection mechanism. The FCM method makes clusters, and CHs are chosen based on the SNs' location, signal-to-noise ratio, and residual energy.

On the other hand, the sensor network can only be built in a two-dimensional space in terms of its topology. Researchers who worked with wireless sensor networks came up with a clustered routing method called BECR that used energy in a balanced way (Zhao et al., 2018). The first cluster head chosen was the node closest to the group's center. When the energy level of a cluster head fell below 20%, the FCM was used to choose a new cluster head for that cluster. A fresh round of cluster head elections was performed if the energy level of each cluster head declined by 10%; otherwise, no elections for cluster heads were performed. The randomness feature makes it difficult to avoid falling into the trap of local optimality while employing this technique. So far, a variety of researchers have used the hybrid strategy, which has the advantage of resolving the weaknesses of one methodology while simultaneously incorporating the benefits of another. To generate clusters, the literature (Sharma et al., 2019) utilized FCM and selected the best node to act as a CH. It used a fuzzy inference technique to determine how well each node performed. This technique was used in conjunction with an evolutionary method to choose the CH to make better decisions. The literature (Shokouhifar and Jalali, 2017) reported using an artificial bee colony approach to update the fuzzy rules of LEACH-SF, which was subsequently corrected. It was made to double the network's lifetime by following the rules, and the algorithm's fitness function makes this happen.

We have widely deployed sophisticated algorithms to ensure efficient data routing in WSNs (such as the PSO, GWO, and MFO). However, now we are considering these techniques for UWSNs. In (Javadpour et al., [[NoYear]]), fuzzy clustering was used to connect sensors in a network, and the initial value of the cluster heads was estimated using the PSO technique. It started by clustering using the fuzzy technique and then selected the best cluster head by applying the PSO algorithm to the fuzzy table created by the fuzzy approach. The algorithm had a considerable influence on reducing the amount of energy consumed. Afterward, various clustering methods were proposed by taking this as a base, including differential evolution and simulated annealing (Potthuri et al., 2018), fuzzy c-means, and the Genetic algorithm (Reddy and Khare, 2017). An optimization approach known as the Grey Wolf Optimization Method (GWO) is also used in many UWSNs to optimize clustering as an optimization methodology. GWO-LPWSN (Rajakumar et al., 2017) employs the grey wolf optimization technique to find nodes and fix placement faults. For wireless sensor networks (WSNs), the proposed method (Kazmi et al., 2019) offers a GWO-based transmission rate management mechanism. The grey wolf optimizer is used to fine-tune the support vector machine's (SVM) transmission rate, which controls the rate data is sent between nodes. In particular, a cluster head is chosen by the sink node, and the optimum path for data transmission is determined by the nodes using GWO (Al-Aboudy and Al-Raweshidy, 2016).

Similarly, optimal grouping is achieved with the help of grey wolf optimization and evolutionary algorithms (Lipare et al., 2020). The moth flame optimizer is only one of several innovative algorithms that can be used to solve optimization problems. Taking cues from moths in the wild can help find optimal solutions to NP-complete problems. Optimal clustering is the goal of a method proposed in (Mittal, 2018) that uses the MFO algorithm. Moth-flame and genetic algorithms are

used for efficient and effective clustering (Sharma et al., 2020). Due to its high-quality results, it can also be implemented in UWSNs (Bharany et al., 2022). Another routing protocol designed for innovative ocean applications is SOSNET (Durrani et al., 2019). The moth flame optimizer (MFO) is employed to efficiently perform optimal clustering at a low cost (Patel et al., 2020; Bharany et al., 2022). Similarly, the technique proposed in (Kumari et al., 2019) addresses the problem of fault-tolerant routing by employing MFO, which determines the optimal data transmission path (Namasudra and Roy,

2018; Fattah et al., 2020; Bharany et al., 2022). A comparison of algorithms in Table 1 shows how they deal with different problems and have different goals.

## 2 Methods

While using research into the collective optimization behavior of glowworm swarms, this section suggests a self-organizational approach to clustering. Using this strategy, UWSNs can manage

TABLE 1 Comparison of various algorithms.

Protocol	Category	Objective	Issues
LEACH (Heinzelman et al., 2000)	probabilistic	reducing energy usage	When selecting CHs, it does not take into account the information about the node, resulting in network energy imbalance.
LEACH-C (Heinzelman et al., 2002)	probabilistic	increasing the lifespan of a network	Inefficient in energy consumption and uneven energy load for equal possibility to select the CHs
EACHS-PSO (Singh and Lobiya, 2012)	Heuristic	Selecting an energy-efficient CH to increase the network's lifespan	No cluster formation process is involved
PSOECHS (Rao et al., 2017)	Heuristic	Energy efficient Cluster formation and elects the CHs for energy efficiency	energy dissipation increases while CH selection process
UMOD-LEACH (Alhazmi et al., 2018).	probabilistic	Less energy usage	Clustering is not so much optimal
ACUN (Wan et al., 2018)	Heuristic	To reduce the energy usage of the network	Complex processor for clustering
RCA-UASN (Zhang et al., 2017)	Heuristic	Process of clustering in energy-efficient way for medium-sized scale UWSNs	Lack of stability of algorithm and not fits into the environment of UWSN
IPSOC-UASN[13	Heuristic	Optimizing the network lifespan using improved version of PSO	Highly complex particle coding for SNs
EC-PSO (Wang et al., 2019)	Heuristic	for selecting and searching energy efficient CHs and avoiding energy holes	fitness function ignores the distance between SNs, CHs and sink which leads to lack of efficiency
DFCMER (Alia, 2014)	Non-deterministic	Increase of network lifetime using FCM protocol	No optimization techniques involved and Ch selection process is executed locally
FCM-EECHS (Bhatti et al., 2016)	Non-deterministic	Energy efficient clustering	Suitable for only 2-D space
BECR (Zhao et al., 2018)	Non-deterministic	Make an even balance between energy consumption and network longevity	Easily slips to local optimality issue
EEFCM-DE (Sharma et al., 2019)	Hybrid	Energy efficient clustering and better throughput	Consumption of energy increase is we apply to all SNs
OFC (Shokouhifar and Jalali, 2017)	Hybrid	Balance clustering technique and increase network lifetime	Only for static environment not suitable for dynamic
CFC-PSO (Javadpour et al., 2018)	Hybrid	Optimal CHs selection in energy efficient way	Initial CH is selected randomly and cluster count is fixed
DESA (Potthuri et al., 2018)	Hybrid	Efficient clustering process	No distance between nodes is consider for fitness function
GWO-LPWSN (Rajakumar et al., 2017)	Heuristic	spot the correct position of unknown nodes	Suitable for static and fixed number of SNs
GWO-SVM (Kazmi et al., 2019)	Hybrid	control the congestion	Complex in execution
MLHP-GWO (Al-Aboody and Al-Raweshidy, 2016)	Heuristic	Improve efficiency, lifetime, and stability period.	High energy consumption
TECP-MFO (Mittal, 2018)	Heuristic	load balancing	Not efficient for UWSN
SOSNET (Durrani et al., 2019)	Heuristic	To find optimal number of clusters required for routing	In some case results does not perform in an optimal way
FCM-PSO (Krishnaswamy and Manvi, 2019)	Hybrid	To avoid the early dying of CH node	While selecting CH convergence speed is very low

their networks better and have more reliable communications. GSO analyses the area around the glowworm to calculate its luciferin value. The fundamental justification for using GSO for an underwater WSN (Bharany et al., 2022) is its ability to provide an appropriate optimization solution in the face of a glowworm’s variable luciferin value. This GSO feature could be helpful for a UWSN built on a cluster architecture. After that, we pick the shortest path between the Sensor nodes and the BS. Each node’s residual energy and the average residual energy are determined as the first steps in our suggested algorithm. A node is not considered for CH selection if its residual energy is lower than the mean residual energy. Afterward, the fitness function is determined with the help of methodical equations, which will be detailed in the following section and used in selecting CHs. After then, information travels from CH to BS via a TDMA slot. The XOR operation is used during an aggregation process to eliminate duplicate information. Figure 3 depicts the sequence of

events before data is transmitted to BS. Therefore, our method is divided into three parts.

### 2.1 Overview of mathematical representation of GSO

The GSO algorithm assigns a luciferin value to each glowworm and a neighborhood range for making decisions locally. The objective function and its position establish the luciferin value of a glowworm. Compared to other glowworms, a higher luciferin value indicates that the glowworm is located in an exceedingly bright area. You can see the entire SS-GSO process in Figure 3, which is the algorithm.

The following equation is used to keep track of the glowworm’s Luciferin value:

$$Luci_i(t + 1) = (1 - \rho)Li(t) + \gamma F (pi(t)) \quad (1)$$

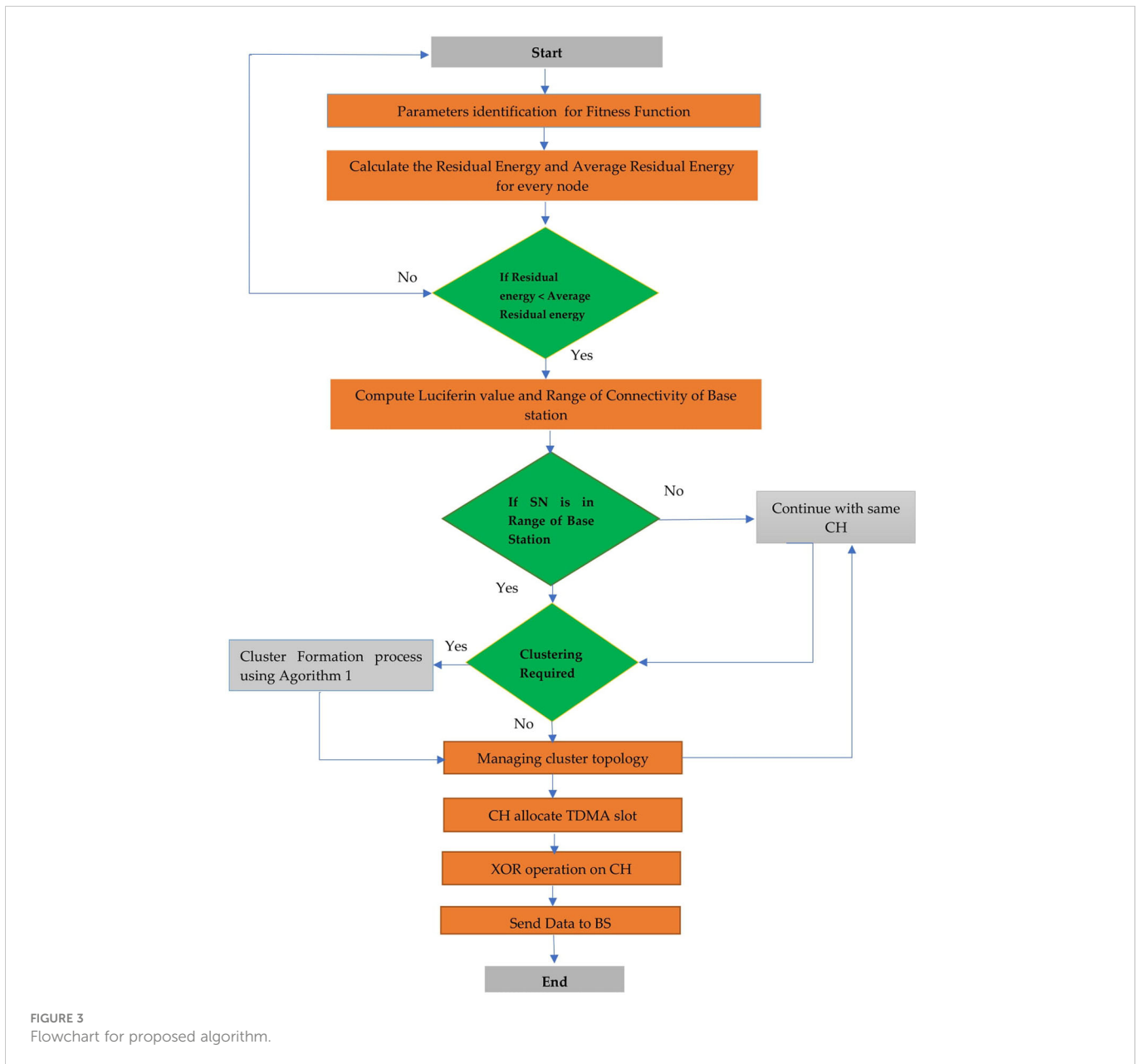


FIGURE 3 Flowchart for proposed algorithm.

With respect to each individual glowworm  $i$ ,  $Luci_i(t)$  symbolizes the luciferin value of that glowworm. In addition, the luciferin decay constant, announced by  $\rho$  which ranges from zero to one, the luciferin enhancement fraction, which is acted by  $\gamma$  and  $F(p_i(t))$  which represents the objective function, given for current position  $p_i$  of glowworm  $i$ .

Then, using the following rule, each glowworm  $i$  investigates its immediate surroundings in search of the neighbour with the greatest luciferin value:

$$z \in Ni(t) \text{ if } f_{Dist_{iz}} < rang_i(t) \text{ and} \tag{2}$$

$$Luci_z(t) > Luci_i(t)$$

$Ni(t)$  is the group of glowworms surrounded by glowworm  $i$ , while  $z$  is  $i$ 's nearest neighbor. Glowworm  $i$ 's local decision range is denoted by  $rangi(t)$ , and the luciferin concentrations of glowworm  $z$  and  $i$  is represented by  $Luci_z(t)$  and  $Luci_i(t)$ , respectively. Using the probabilities of each neighboring glowworm, as shown in Equation 3, a best-neighbor glowworm is selected.

$$Prob_{iz} = \frac{Luci_i(t) - Luci_z(t)}{\sum_{x \in Ni(t)} L_x(t) - L_i(t)} \tag{3}$$

The location of the glowworm is updated in accordance with the best position of an adjacent glowworm that has been identified and computed as follows:

$$p_i(t+1) = p_i(t) + s \frac{p_z(t) - p_i(t)}{Dist_{iz}} \tag{4}$$

where  $s > 0$  denotes the distance travelled by a glowworm in order to reach another glowworm. The decision range  $randec_i(t)$  is computed by the following equation:

$$randec_i(t+1) = \min\{rads, \max[0, randec_i(t) + \beta(nt - |Ni(t)|)]\} \tag{5}$$

Where  $rads$  is the constant representing the radial sensor range,  $\beta$  represents the model constant, and  $n_t$  controls the maximum allowed number of neighbors.

## 2.2 CH selection and cluster establishment

In our proposed clustering strategy the selection of CH is considered based on connectivity with the base station and fitness function. Fitness function is contingent the luciferin value, total energy consumption, and residual energy value of the UWSN to ensure effective communication and data transfer (Khan et al., 2019).

The fitness functions are represented by the following equation:

$$\text{Fitness function} = w_1 \times f_1 + w_2 \times f_2 + f_3 \times w_3 \tag{6}$$

where  $w_1, w_2, w_3 = 0.5$

First of all, we calculate the residual energy of the every UWSN node by:

$$ReSE_i = (initialE_i - CurrentE_i) \tag{7}$$

The residual energy is represented by  $ReSE_i$ , the starting energy of the  $i$ th UWSN is represented by  $initialE_i$ , and the current energy level of the  $i$ th UWSN is represented by  $CurrentE_i$ . After calculating residual energy of every node, we make an average of all nodes residual energy and then compare the residual energy of a node with average energy of all nodes. If current energy of a node is less than the average energy then this node is being skipped for the current round of CH selection.

Total amount of transmission and reception energy of a node is calculated by:

$$f_1 = Total_{Econ_i} = TranB_i \times Engy_{Tran} + RecB_i \times Engy_{Rec} \tag{8}$$

The number of transmitted bits and received bits in node  $i$  are denoted by the  $TranB_i$  and  $RecB_i$ , respectively.  $Engy_{Tran}$  and  $Engy_{Rec}$  are characterized as transmission energy and reception energy correspondingly are calculated as:

$$Engy_{Tran} = \text{Energy for radio signal transmitter} + E_A * Dist^2 \tag{9}$$

$ET_{radio}$  and  $ER_{radio}$  are the energy needed for radio transmission by the transmitter and the receiver, respectively.  $E_A$  is the energy needed to boost (amplify) a signal, and  $Dist$  [Khan et al., 2019; Bharany et al., 2021] is the distance between two nodes,  $m$  and  $n$ .

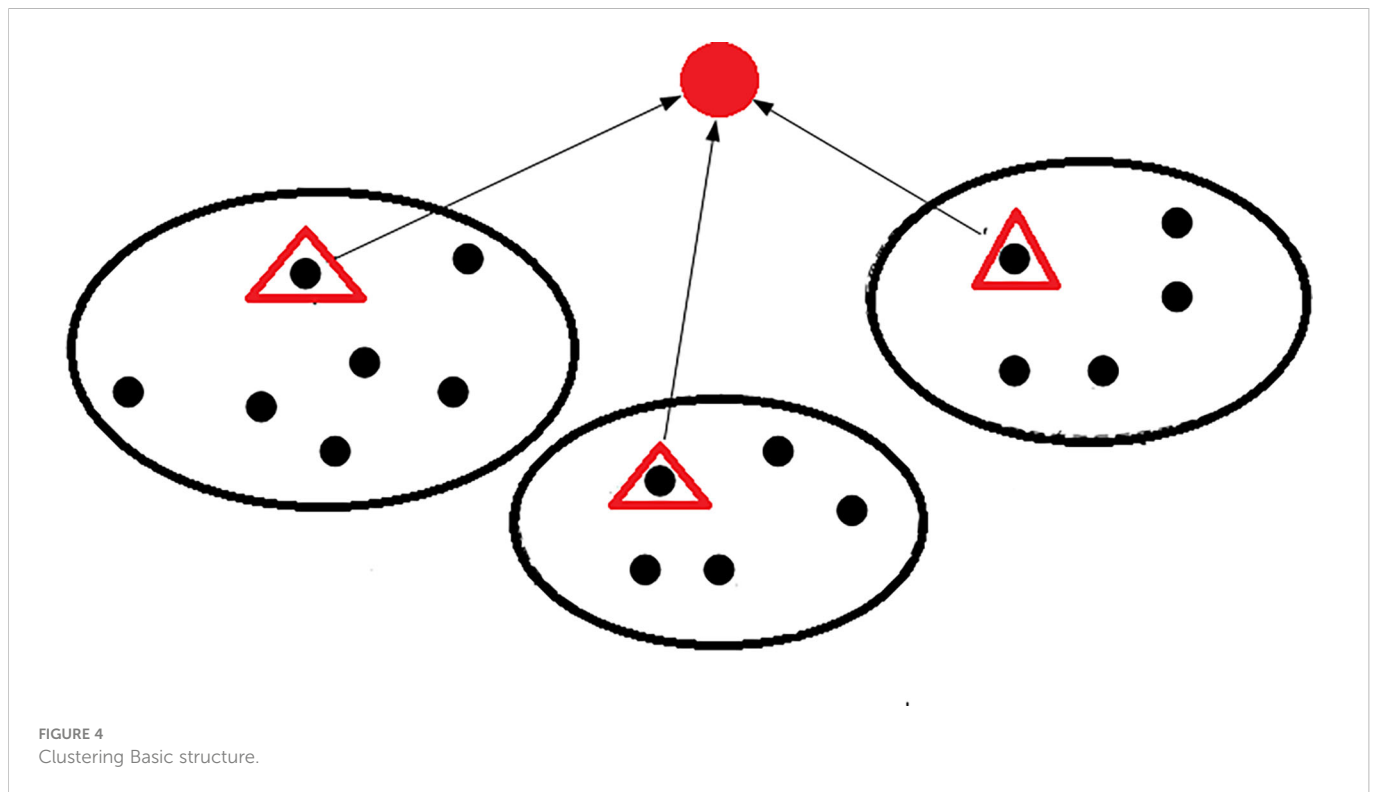
The function for luciferin value is given by:

$$f_2 = Luci_i(t+1) \text{ by Eq. (1)} \tag{10}$$

$$f_3 = ReSE_i \tag{11}$$

In our proposed algorithm, Eq. 6 is used to calculate the fitness of each UWSN in the cluster formulation mechanism, as seen in Figure 4. The weighted sum of the luciferin value and the total energy spent and residual energy from Equations. 8, 10, and 11 is used to compute the fitness. In addition to its fitness, each UWSN sends a "Hello Message" along with its fitness to all the other nodes. When the SNs get a Hello message, the received fitness is compared by the nodes with its own. When a "Hello" message is received, the UWSN creates and updates a neighbour table using the UWSN's entries. The UWSN then sorts the neighbour table by decreasing fitness values. The closest node to the base station is the "Cluster Head". This would be the best place for CH. However, when there is just one node in the range of the base station or more than one, the UWSN with the most significant fitness value is designated as the cluster head and sends a Cluster Formation message to all nearby nodes. By sending a cluster-joining message from all nodes with lower fitness values, they can recognize their CH. The UWSN coalition of *ad-hoc* nodes is created on-demand when a UWSN wants to transfer data but is out of range of the base station. In order to get the information to its final destination, the Nodes use an intermediate UWSN to make many hops (Khan et al., 2019; Bharany et al., 2021; Khan et al., 2021). The remainder of the UWSN nodes will become superficial nodes or cluster members after the election of the CH, which will be purely based on a fitness function. The Luciferin level values of each glowworm in each cluster are updated according to their position and fitness function. Members of the cluster must keep track of the CH's movement and alter their locations accordingly. The CH keeps track of the cluster's topology by receiving location data from all UWSNs and updating the topology





database accordingly. Suppose a UWSN travels out of the cluster's range based on its updated position (as determined by the luciferin value). In that case, it is no longer considered a part of the cluster. In the next step, the CH transmits the updated topology table to the cluster members and maintains the cluster (Bharany et al., 2021). This method also includes a technique for managing the topology of clusters, which is described in detail below. Using a topology configuration message, each CM communicates its luciferin value to the other CM UWSNs. Upon receipt of the topology configuration message, the cluster head of UWSN modifies the location of the cluster member nodes following the luciferin values stored in the cluster topology table. Once the position information for each CM of UWSN has been updated, the cluster head sends this cluster topology table to all the cluster members. This way, all the CM behave like a swarm and move to keep up with the CH.

### 2.3 Optimal path selection and UWSN communication

The best path selection for information transmission in an efficient routing mechanism result in lower energy consumption in the network and enhances the cluster's lifetime. Every UWSN node in the proposed system follows the location of CH and adjusts its position in response to that of CH. Once the sensor nodes are in clusters, each group's head node (CH) makes a TDMA schedule and sends it to the other cluster members. In order to save energy, each node sends its data to the cluster head during the time slot defined in the TDMA table and then switches off its radio transmitter while waiting for the next transmission slot as stated in the TDMA table. In the TDMA table, the priority of allotting a slot is determined by the UAV's neighbor range, residual energy, and location, which are used

for load balancing and congestion management purposes. When allocating TDMA slots, the UWSN in the neighborhood range of the source UWSN (close to the source UAV) and having the lowest residual energy will be prioritized over the other UWSNs, as this would be necessary to retrieve the data from this node. Therefore, a node with low residual energy will be assigned to the first available TDMA slot before any other node with high residual energy. On the other hand, the cluster heads keep their radios turned on to receive data from cluster members, and they perform an XOR operation on that data to reduce the amount of duplicate data. As soon as a cluster head gets data from its members, it performs data aggregation and sends it to the surface station near the water's edge. As the primary base station on the ground is typically located a long distance away, employing these strategies will prevent a high-energy transmission since sending it straight to the primary base station on the ground would result in high energy consumption and a high risk of data loss. This method sends information through the surface station to the primary base station to save energy and transmission costs.

## 3 Results

This section investigates the performance of the SS-GSO method, utilizing other modern approaches in a range of scenarios. Table 2 has some simulation parameters considered in our experimentation setup.

### 3.1 Network lifetime

In Figure 5, we can see the number of alive nodes (NAN) analysis of the SS-GSO method compared to older methods is done. The

TABLE 2 Simulation parameters.

Parameters	SS-GSO	ACO	GWO	MFO	LEACH
Number of UWSN	20–200	20–200	20–200	20–200	20–200
Max Iterations	100	100	100	100	100
Simulation Runs	20	20	20	20	20
Nodes Positions	Fixed	Fixed	Fixed	Fixed	Fixed
Simulation Area	500 × 2000 m <sup>2</sup>	500 × 2000 m <sup>2</sup>	500 × 2000 m <sup>2</sup>	500 × 2000 m <sup>2</sup>	500 × 2000 m <sup>2</sup>
Mobility	Static	Static	Static	Static	Static
Inertia Weight	0.694	0.694	0.694	0.694	0.694
Transmission Range	Fixed	Fixed	Fixed	Fixed	Fixed
Distance between Nodes(max)	5 m	5 m	5 m	5 m	5 m
Distance between Nodes(min)	2m	2m	2m	2m	2m
W <sub>1</sub> , W <sub>2</sub> , W <sub>3</sub>	0.5	0.5	0.5	0.5	0.5

experiment was carried out using the 2018a version of MATLAB programming, and it was completed on a 7th generation core i5 machine with DDR4 8 GB of RAM. An experimental grid size ranging from 500 meters to 2000 meters was used for this investigation. The number of nodes used ranged from 0 to 300, and each node’s transmission range was between 25 m and 200 m. Nodes are made to stay in the same place or move very slowly so they do not get in the water flow (Bharany et al., 2022). It was equated to different state-of-the-art evolutionary clustering algorithms, such as the ant colony optimizer (ACO), the grey wolf optimizer (GWO), the moth flame optimizer (MFO), and LEACH. In Table 2, we can see all the simulation metrics. The experimental results suggest that the low-energy adaptive clustering hierarchy (LEACH) technique delivers poor outputs with the least feasible NAN. The MFO technique obtained a more significant NAN value than the LEACH procedure. Accordingly, the ACO techniques do not produce a

favorable outcome either. While the GWO approach sought to create a respectable NAN compared to the other, Figure 5 revealed that the SS-GWO strategy outscored them all in terms of NAN. We can also see in the figure that the LND (the last node died) is best for our proposed algorithms. In Table 3, we can see the results of the network node analysis of all the techniques.

### 3.2 Clustering time

It is common practice to refer to the computational complexity of a clustering algorithm as the time it takes to complete the clustering process using that approach. Typically, clustering algorithms input a set of nodes and associated fitness ratings and output a subset of CH nodes and other related nodes. The time it takes for an algorithm to go from receiving inputs to generating outputs is known as its “cluster

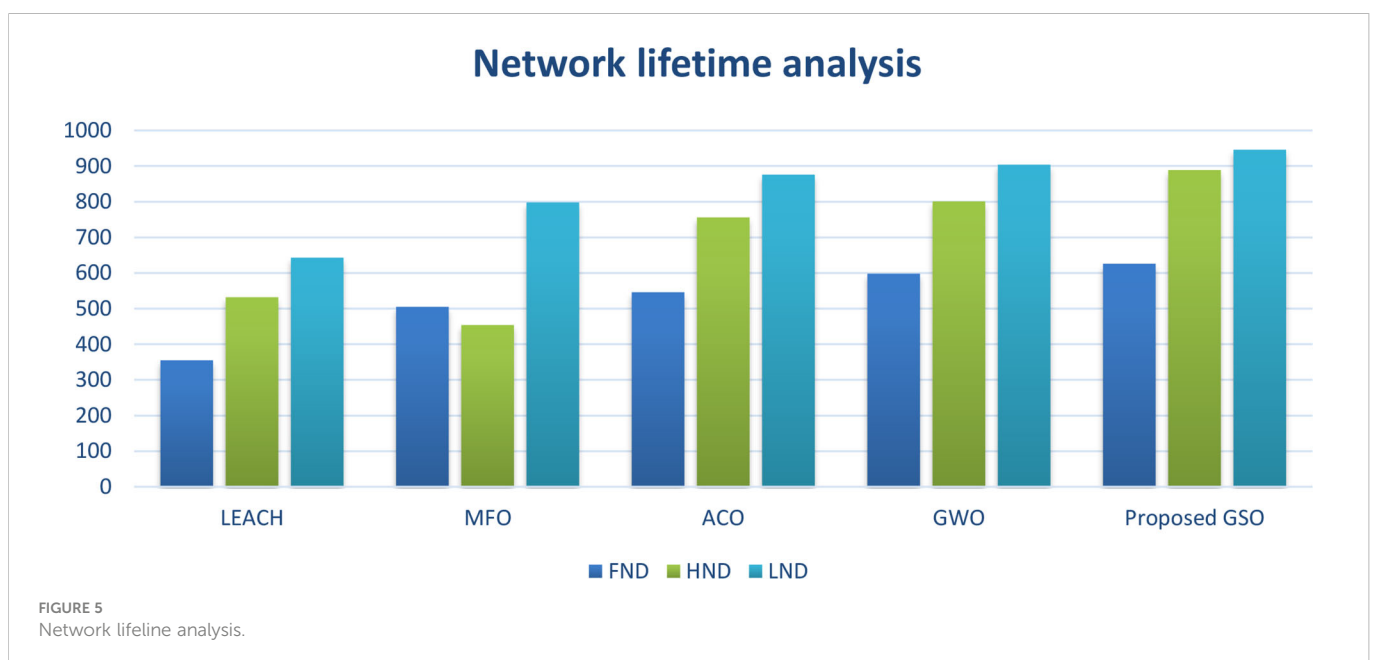


FIGURE 5 Network lifeline analysis.

TABLE 3 Network lifespan analysis of various algorithms.

Methods	FND	HND	LND
LEACH	355	532	643
MFO	515	724	804
ACO	578	784	898
GWO	599	802	904
PROPOSED SS-GSO	704	899	987

building time.” Since the UWSN has little memory and processing power, a longer cluster formation time will harm WSN performance. Increasing the time required to create a cluster uses more energy, reducing the time SNs in a network can remain in operation. Figure 6 shows that our proposed SS-GSO performs better than LEACH, ACO, MFO, and GWO because, in contrast to ACO and GWO, which begin with several solutions and converge to the optimal through iteration, our SS-GSO always quickly converges towards the best solution. Using the SS-GSO method, the time it takes to build a cluster and the time it takes to choose a path is kept to a minimum. This makes it possible for SNs to do complex calculations with much less energy.

### 3.3 Total energy consumption

It is shown in Figure 7 that our suggested method, SS-GSO, compares favorably to other strategies in terms of total energy consumption (TEC). The LEACH procedure could have been more efficient than alternative techniques with a maximum TEC. It was also seen in Figure 7 that the MFO approach had a lower TEC than the LEACH method. Regarding TECs, MFO approaches were slightly better throughout several iterations than the LEACH method. It is worth noting that while the GSO performed better in all other elevation parameters, in TEC, the ACO strategy had the second-lowest TEC and surpassed the GWO strategy. Finally, our projected

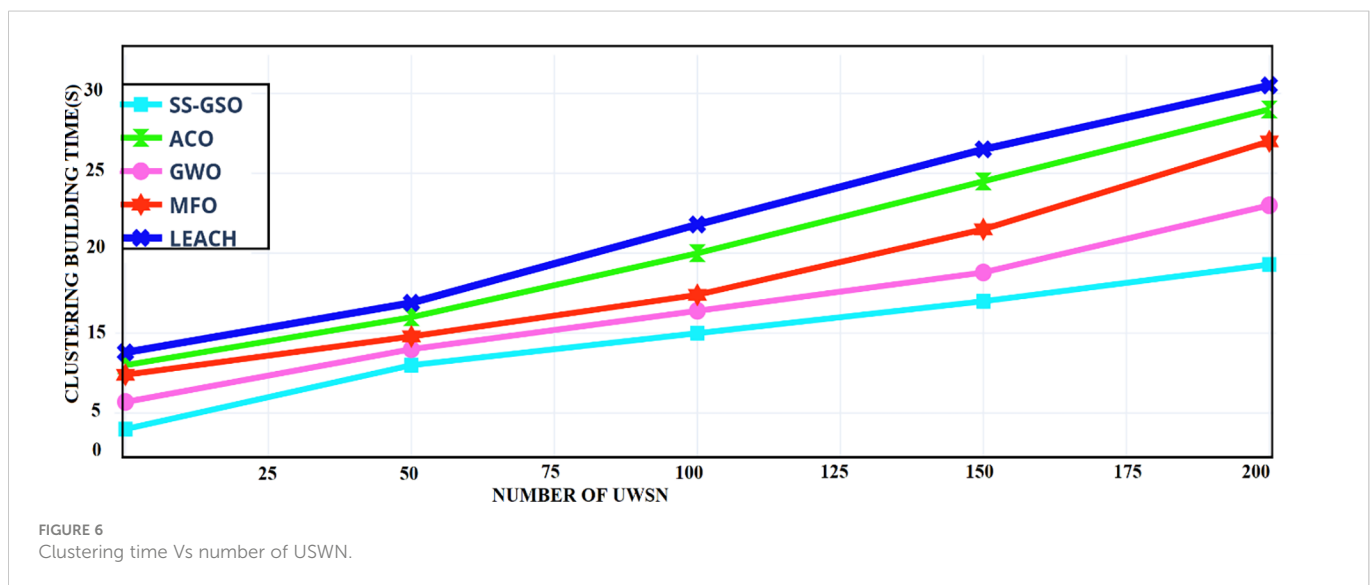
SS-GSO executes better than all other techniques (He et al., 2016; Bharany et al., 2022), as only ACO competes with SS-GSO.

### 3.4 Cluster head count

The number of cluster head nodes substantially influences the efficiency of the protocol, as there will be an increase in node energy consumption and overall energy consumption. As a result, if the count of CHs is low, the number of SNs per CH will be high, and the time of SN data transmission will be affected (Okoth et al., 2022; Srivastava et al., 2022). The total energy consumed by each round of networks increases and is directly proportional to the number of CH. Figure 8 shows that our proposed SS-GSO clustering protocols’, outperform LEACH, ACO, GWO, and MFO protocols in headcount fluctuation frequency. In this case, we are considering only 1000 rounds for evaluation. It is simple to see that the cluster headcount in the LEACH protocol swings between  $4 \leq T \leq 17$  and  $5 \leq T \leq 14$  in GWO,  $6 \leq T \leq 14$  in ACO, and  $3 \leq T \leq 17$  in MFO, and that the cluster headcount in our suggested protocol swings between  $3 \leq k \leq 13$  which is the most desirable.

### 3.5 Number of packets received

This section compares the number of packets received (NOPR) analysis of the SS-GSO technique to other methods in various iterations. The experimental findings indicated that the LEACH strategy produced inferior results with a lower NOPR than the conventional approach. The MFO approach obtained a NOPR marginally more significant than the LEACH procedure. After that, ACO approach rounds resulted in a NOPR that was only marginally closer to the original last NOPR. While the GWO method was trying to get a reasonable NOPR, the SS-GSO



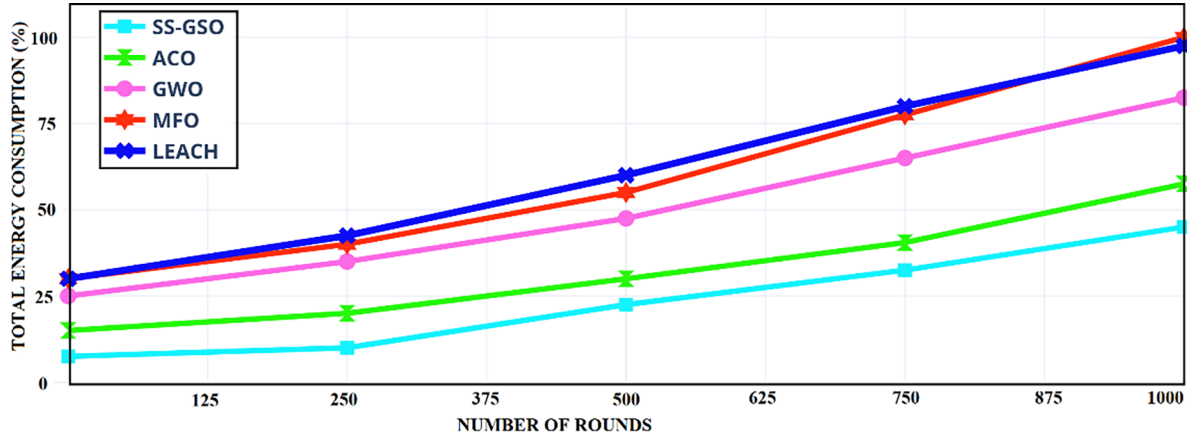


FIGURE 7 Total energy consumption by USWN.

method could get a higher NOPR than other methods (Mohamed et al., 2019; Arshad et al., 2020; Asif et al., 2020; Mehmood et al., 2020; Ahmad et al., 2022; Mazhar et al., 2022; Zeb et al., 2022).

As seen in Figure 9 and Table 4, the SS-GSO approach is a good strategy for maximizing energy efficiency and longevity in the UWSN context. Overall, the results of the experiments showed that the LEACH method performed poorly across all comparison criteria (Mohamed and Mohamed, 2017; Mohamed and Suganthan, 2017; Ahmad et al., 2021; Mehmood et al., 2021; Saleem et al., 2021; Ahmad et al., 2022). Finally, our proposed method has performed better than all other techniques.

### 4 Discussion

From the information shown in the Figure 10 tables and figures above, it is clear that the SS-GSO approach is very effective at getting the highest possible energy efficiency and durability in the UWSN context. Based on the initial results, the number of packets received (NOPR) analysis of the SS-PSO technique is compared to that of other methods in multiple iterations. The experimental data showed that the LEACH method performed poorly in all rounds, with a lower NOPR, the longest time to build clusters, and the most energy used. After that, the NOPR for the GWO model was higher than that for the LEACH method. In all

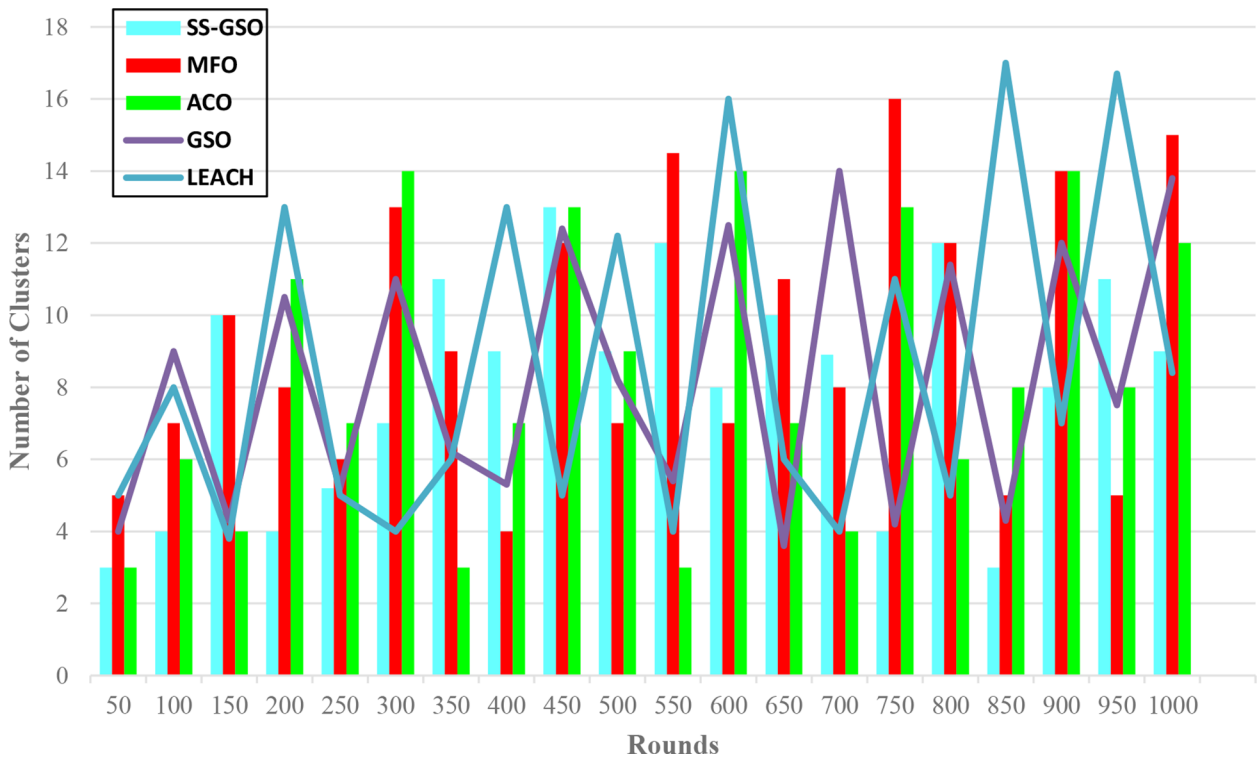


FIGURE 8 consistency of USWN cluster head cou.

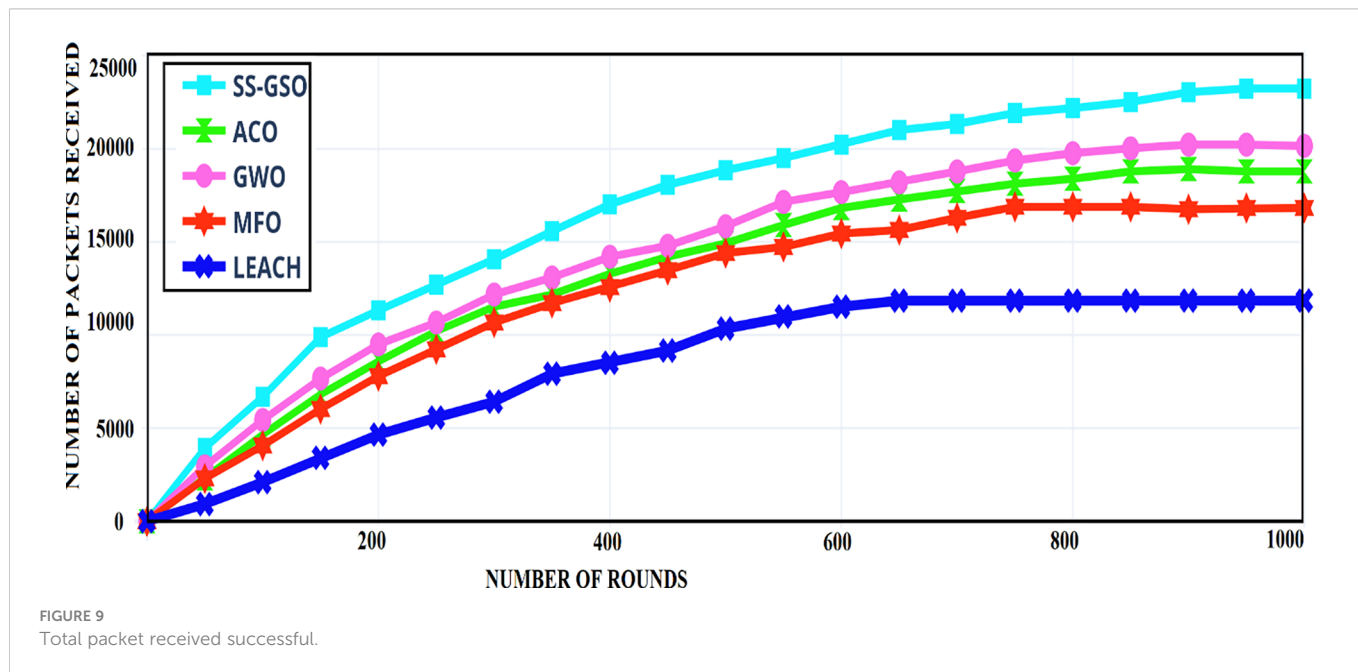
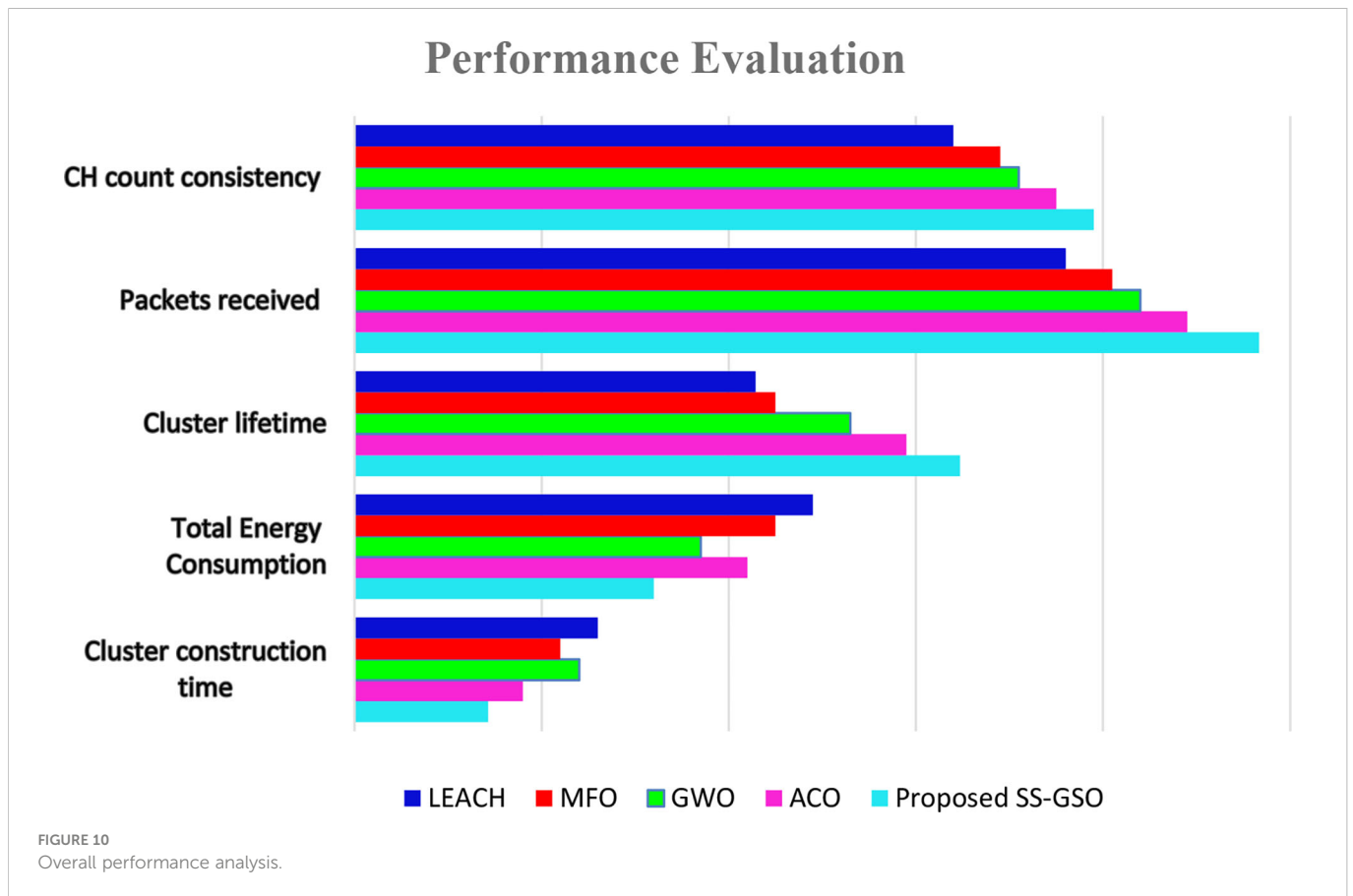


TABLE 4 Number of packets received analysis.

No. of Rounds	LEACH	MFO	ACO	GWO	Proposed SS-GSO
0	0	0	0	0	0
50	945	2302	2312	2951	3989
100	2215	4175	4756	5512	6765
150	3548	6245	6901	7785	9912
200	4846	7845	8645	9501	11,402
250	5894	9345	10,456	10,745	12,801
300	6589	10,785	11,715	12,223	14,156
350	8012	11,845	12,256	13,189	15,645
400	8614	12,678	13,313	14,312	17,156
450	9234	13,745	14,345	14,856	18,178
500	10,545	14,512	15,001	15,956	18,934
550	11,012	14,845	15,945	17,238	19,536
600	11,522	15,678	16,856	17,759	20,400
650	11,945	15,785	17,345	18,223	21,102
700	11,995	16,345	17,786	18,978	21,512
750	11,995	16,915	18,245	19,450	21,989
800	11,995	16,989	18,465	19,885	22,307
850	11,995	16,887	18,856	20,156	22,645
900	11,995	16,989	18,923	20,148	23,185
950	11,995	16,989	18,779	20,148	23,348
1000	11,995	16,989	18,779	20,139	23,234



of the evaluated parameters except for the total amount of energy used, GWO is behind our proposed algorithm. The ACO works better than GSO, so the level of acceptance for GWO changes. We cannot put any algorithm at the second position from all the above experiments.

An SS-GSO for UWSN has been proposed in the current study. It has proven to be a very effective and scalable clustering protocol that works in a search space and chooses the optimal number of clusters to be deployed. It makes use of the GSO approach to accomplish this. For UWSN, GSO works iteratively in a defined search space to discover a better potential solution to improve its energy efficiency and longevity. As the number of clusters required decreases, the amount of energy consumed eventually reduces the cost of routing and the conservation of power in the nodes. On average, ten simulation runs were executed to see how well the suggested method worked. The algorithm was tested using a variety of assessed parameters. The findings demonstrate that SS-GSO is an excellent clustering technique for underwater environments. Clustering techniques such as GWO, MFO, and ACO are compared with our suggested algorithm for clustering. The results reveal that the SS-GSO is superior to all these algorithms in terms of performance, energy consumption, and other evaluating parameters. Incorporating data aggregation tactics early on in the design process has been shown to further increase the energy efficiency of SS-GSO approaches. Also, metaheuristic methods could be utilized to maximize resource utilization after being distributed to other nodes.

## Data availability statement

The original contributions presented in the study are included in the article/supplementary material. Further inquiries can be directed to the corresponding author.

## Author contributions

Conceptualization SB. Methodology SB. Software NA, EE and NG. Validation SB, SS. Formal analysis NA, EE and NG. Investigation SB. Resources SS, EE. Data Curation NA, EE and NG. Writing - Original Draft SB. Writing - Review & Editing SB, NA, EE and NG. Visualization SB, EE. Supervision SS, EE. Project administration NA, EE and NG. Funding acquisition NA, EE and NG. All authors contributed to the article and approved the submitted version.

## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The reviewer AM declared a shared affiliation with the author NG to the handling editor at the time of review.

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