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A hybrid bio-inspired approach for clustering and routing in UWSNs using MPA and HGS

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ABSTRACT

Underwater Wireless Sensor Networks (UWSNs) encounter serious challenges due to dynamic topology, energy constraints, and high latency underwater communication. Existing methods for clustering and routing often fail to strike an optimal balance between data delivery reliability, energy efficiency, and latency reduction. This paper overcomes these shortcomings by developing a hybrid model that integrates the Hunger Games Search (HGS) and Marine Predator Algorithm (MPA) for improved clustering and routing in UWSNs. The MPA was chosen due to its stability in selecting the first sensors/cluster heads and creating the clusters, drawing inspiration from the foraging strategies of marine predators, which guides it extensively in the balance of exploration and exploitation. Simulations demonstrate that the proposed method achieves significantly better results than classical methods. In particular, the HGS-MPA framework consumes 26.6 % less energy than GWO-PSO, increasing network lifetime by 22.1 % (FINOD) and 15.8 % (HANOD). The packet delivery ratio is improved by 3.1 % against the following best-performing method, reaching 92.4 %. A statistical test performed with ANOVA showed that these improvements are statistically significant at $P < 0.001$. The results reinforce how the HGS-MPA framework would help improve energy efficiency, network lifetime, and communication reliability in UWSN systems.

1. Introduction

UWSNs are essential for many uses, such as military operations [1,2], underwater research [3,4], and environmental monitoring [5]. These networks are made up of submerged sensor nodes and are used to gather and send data to a central point [6–8]. However, the distinct underwater environment presents several difficulties, including channel estimation [9], scarce energy supplies [10], high latency, reliability [11], and unstable communication links [12], which means that effective routing and clustering are crucial to the network's lifetime and effectiveness [13].

In UWSNs, traditional clustering and routing techniques frequently fail to balance these objectives successfully [14–17]. To tackle these issues, this work presents a novel hybrid strategy that combines the advantages of the HGS [18] with the MPA [19]. Inspired by the hunting tactics of marine predators, the MPA is incredibly good at generating well-organized clusters and choosing the best cluster heads. On the other hand, the HGS is skilled at determining the most effective paths for data transmission inside the network because it is based on competitive foraging behavior.

Our suggested approach combines MPA and HGS to improve UWSNs' overall performance. The MPA component ensures that clusters are created optimally, contributing to improved energy resource management and longer network lifetimes. At the same time, the HGS part finds the best routes to take to save energy usage and increase data delivery speeds.

In this work, we perform extensive simulations to assess our hybrid approach's efficacy. Compared to state-of-the-art techniques, the results show notable gains in energy efficiency, packet delivery ratio, and end-to-end delay, among other critical performance parameters. This study

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emphasizes how cutting-edge algorithms like MPA and HGS can be combined to address the unique difficulties of undersea communication networks.

The subsequent sections of this paper provide a comprehensive study of the suggested hybrid technique by detailing the methodologies, simulation setup, and outcomes. We also discuss how our results might affect practical uses and future studies in UWSNs.

2. Related works

Wireless sensor networks are essential for many uses, including military surveillance, underwater exploration, and environmental monitoring [20–22]. However, because of the challenging underwater environment, these networks confront major hurdles regarding energy efficiency, data routing, and node distribution [8,23,24].

Reference [25] suggests a wolf search algorithm that prioritizes coverage and energy efficiency. The algorithm imitates predator avoidance to avoid node invalidation and save energy. Energy conservation and efficient network coverage are among the benefits. However, the algorithm's complexity might prevent it from scaling in more expansive networks.

To improve data routing in UWSNs, the research [26] presents a hybridized cluster-based spatial opportunistic routing algorithm. The protocol includes sleep/wake scheduling and periodic beaconing to increase packet delivery and energy efficiency. The primary benefit is the notable increase in energy efficiency and network longevity. The drawback is that the intricate routing algorithms may increase processing overhead.

In the work [27], sink mobility-based data transmission and cluster head selection are optimized by combining Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). The hybrid strategy performs admirably when maximizing data routes and prolonging network lifetime. The benefit is the simultaneous optimization of data routing and CH selection. On the other hand, adding two meta-heuristic techniques could result in more computing complexity.

Utilizing A Whale Optimization Algorithm (WOA) for energy-efficient routing in UWSNs is presented in [28]. The algorithm's primary goals are to reduce energy usage and increase network longevity. The considerable decrease in energy use is the benefit. However, because the process is repetitive, it could not scale well in bigger networks.

To improve data transmission and energy efficiency, the [29] Research suggests an Ant Colony Optimization (ACO)-based adaptive clustering and routing system. The protocol offers resilience and adaptability by adapting to shifting network conditions, which is a benefit. The drawback is that ACO5's iterative structure may result in higher latency.

The work [6] integrates Simulated Annealing (SA) and Differential Evolution (DE) for energy-efficient clustering in UWSNs. The hybrid algorithm seeks to compromise exploration and exploitation for the best clustering. The longer network lifetime and increased energy efficiency are the benefits. However, the hybrid algorithm's complexity could present problems in real-time applications.

With an emphasis on data dependability and energy efficiency, the study [30] uses the Non-dominated Sorting Genetic Algorithm II (NSGA-II) for multi-objective optimization in UWSNs. The benefit is the capacity to manage several goals at once. The longer computing time needed for convergence is the drawback.

The goal of the study [31] is to improve data routing and energy efficiency in UWSNs by introducing a bio-inspired routing protocol based on the Firefly Algorithm (FA). The protocol uses firefly attraction mechanisms to determine the best pathways. The routing protocol's efficiency and simplicity are its advantages. However, in highly dynamic contexts, the algorithm might encounter difficulties.

For clustering in UWSNs, the research [32] combines Tabu Search (TS) and GA. The hybrid strategy seeks to increase network lifetime and clustering efficiency. The improved clustering performance is the benefit. The algorithm's hybrid design has the drawback of possibly increasing computational overhead.

The Bat Algorithm (BA) is used in the study's energy-aware routing strategy to optimize energy consumption and data transfer in UWSNs [33]. The benefit is a notable increase in energy efficiency. The algorithm might need to have its settings adjusted for best results.

The advantages of many existing methods can be combined with the Marine Predator Algorithm and Hunger Game Search for routing and clustering optimization in UWSNs. Although every algorithm has benefits, such as enhanced energy efficiency, longer network lifetimes, and greater adaptability, it also has drawbacks, like higher computational complexity and possible scaling problems. For UWSN optimization, a hybrid strategy that maximizes the benefits of several methods while minimizing their drawbacks may offer a reliable answer.

2.1. Research gaps, motivations, and contributions

Despite the progress made in UWSNs routing and clustering protocols, several obstacles still make them impractical. To start, water currents and other essential underwater environmental elements can impact the mobility of sensor nodes, yet many clustering techniques fail to account for them. Secondly, in bigger UWSNs, the scalability of current routing protocols is limited because they primarily provide single-hop communication. Finally, UWSNs still require effective clustering and routing techniques to guarantee energy conservation and increase their lifetime.

Our study is motivated by a desire to fill these gaps in the current literature and propose a novel, UWSN-specific, energy-efficient clustering and routing strategy [34]. Considering the marine environment's specifics, this protocol efficiently uses the restricted power supply available to sensor nodes. Two separate techniques, the MPA and the HGS, are utilized to accomplish this.

To optimize clustering and Cluster Head (CLH) selection, MPA takes cues from predator-hunting tactics in the ocean, which aim to avoid local optima and achieve rapid convergence. Simulating the motion of gas molecules in liquids, HGS improves routing efficiency and is based on concepts of gas solubility. HGS efficiently optimizes multi-hop routes by simulating the routing problem as gas molecules interact in a liquid.

Our methodology reduces computational complexity and improves convergence time by integrating MPA and HGS concurrently using a parallel hybrid structure. Clustering and CLH selection are the primary areas of concentration for MPA, whereas HGS simplifies routing. This hybrid strategy seeks to balance energy usage across nodes and achieve a longer operational lifetime of UWSNs.

The proposed approach addresses a key research gap by considering underwater environmental parameters and efficiently controlling sensor node energy. One possible approach to improving UWSN energy efficiency and operational lifetime is to combine MPA and HGS in a hybrid parallel architecture.

We present HGS-MPA, an innovative UWSN routing and clustering protocol that integrates MPA and HGS algorithms to address these issues. MPA and HGS find efficient multi-hop routing paths, while MPA improves cluster architectures and CLH selection. By distributing power fairly among sensor nodes and reducing the number of retransmissions, our protocol hopes to increase the network's lifetime and energy efficiency.

According to the experimental data, HGS-MPA achieves a better network lifespan and lower energy usage than current benchmark approaches. This research validates the effectiveness of our protocol through extensive simulations across varied scenarios. It advances energy-efficient clustering and routing protocols for UWSNs by exploiting the integration of MPA and HGS algorithms.

3. Methodology

This section describes the MPA and HGS techniques and explains how they are combined to create the hybrid HGS-MPA approach for routing and clustering UWSNs.

3.1. Marine predator algorithm (MPA)

A population-based strategy is employed in the MPA algorithm, which is typical of most metaheuristic algorithms. The algorithm starts with potential CLHs randomly dispersed over the search area. Each potential CLH is evaluated considering its distance from the base station (BS) and the number of sensor nodes within its coverage area.

The algorithm assigns a fitness value to each potential CLH based on the evaluated criteria. The potential CLH with the highest fitness value is selected as the leader or apex predator. Other potential CLHs are assigned to different levels of predators based on their fitness values. The predator-prey relationships are established based on the ranking of the potential CLHs.

After the predator-prey relationships are established, the algorithm simulates the hunting behavior of marine predators to optimize the clustering process. The predators move toward the leader, and the potential CLHs move toward the predators. This process continues until the algorithm converges and a set of optimal CLHs is selected.

Overall, the MPA algorithm employs a population-based strategy to optimize clustering in UWSNs, and the algorithm simulates the hunting behavior of marine predators to select efficient CLHs that can communicate effectively with the BS:

$$L_0 = lb + rand(ub - lb) \tag{1}$$

The lower and upper limits of variables are represented by *lb* and *ub*, respectively, where rand is a uniform random vector with a range of 0–1.

Several mathematical formulas intended to mimic the behavior of marine predators are at the heart of MPA:

- **Position update rule:** There is an iterative process for updating predators' positions utilizing

  $$x_i(t+1) = x_i(t) + \mathbf{SS}_i \cdot \mathbf{SM} \cdot \mathbf{Dir} \qquad (1 \quad ' \quad)$$

  Where, $x_i(t)$ denotes the position of a predator, $\mathbf{SS}_i$ adjusts step sizes, **SM**scales movement, and **Dir** denotes direction.
- **Fitness evaluation**: Each predator's fitness is evaluated using Eq. (2):

  $$f(x_i(t+1)) \tag{2}$$

  This function measures how well a predator's current position solves the optimization problem.
- **Swarm update mechanism**: Step sizes $\mathbf{SS}_i$ decrease over time, as shown in Eq. (3):

  $$\mathbf{SS}_i(t+1) = \mathbf{SS}_i(t) \cdot \exp(-\eta t / T) \tag{3}$$

  This adjustment balances exploration and exploitation during the search process.
- **Crossover operation**: Predators exchange information is performed using Eq. (4):

  $$x^{CV}{}_i(t+1) = \beta \cdot x_{i1}(t) + (1-\beta) \cdot x_{i2}(t) \tag{4}$$

  Where *B* denotes the crossover probability between two predators.

  To sum up, the primary phase of MPA can be summarized as follows:

1. **Initialization**: Set initial predator positions and parameters.
2. **Iterative search**: Update positions iteratively based on the position update rule until convergence.
3. **Fitness assessment**: Evaluate the fitness of each predator to gauge solution quality.
4. **Adaptation**: Adjust parameters dynamically based on fitness evaluations and convergence criteria.

MPA has effectively solved various optimization problems, including scheduling, routing, and clustering in challenging settings. Its advantages include adaptability to different problem domains, robustness against local optima, and rapid exploration of solution spaces.

The MPA is a powerful optimization technique inspired by natural predatory tactics. Its adaptive technique and mathematical foundations make it an essential tool for tackling complex optimization issues in various domains, including underwater wireless sensor networks. Fig. 1 shows the whole flowchart of MPA.

3.2. Hunger game search (HGS)

The population-based optimization paradigm, HGS, effectively resolves limited and unconstrained issues. The behavior and operations of animals driven by hunger serve as the foundation for the HGS. The HGS replicates the effect of hunger on every search phase by integrating hunger into the search method by using an adjustable weight dependent on hunger. Here is a description of the HGS mathematical model [35]:

$$\mathbf{X}(t+1) = \begin{cases} \mathbf{X}(t).(G(1)+1), \text{rand}_1 < \tau \\ \theta_1.\mathbf{X}_b + \boldsymbol{\eta}.\theta_2.|\mathbf{X}(t) - \mathbf{X}_b|\text{rand}_1 > \tau, \text{rand}_2 > \psi \\ \theta_1.\mathbf{X}_b - \boldsymbol{\eta}.\theta_2.|\mathbf{X}(t) - \mathbf{X}_b|\text{rand}_1 > \tau, \text{rand}_2 < \psi \end{cases} \tag{5}$$

Where the position of every predator is $\mathbf{X}(t)$, ξ and η can be expressed as Eqs. (9) and (10), respectively, G(1) is an arbitrary number with Gaussian distribution, $rand_1$, and rand2 are unknowns in the range of [0,1], and they indicate the hunger's weights. Additionally, t indicates the number of iterations that are currently underway [35]:

$$\xi = \frac{2}{e^{\alpha} + e^{-\alpha}}, \alpha = |Best - F(i)|, i \in 1, 2, \ldots, n \tag{6}$$

$$\begin{aligned} \boldsymbol{\eta} &= 2Ar - A, \\ A &= 2\left(1 - \frac{t}{T}\right), \end{aligned} \tag{7}$$

Where r is an arbitrary number in the interval [0,1], *Best* indicates the best fitness score determined in the present iteration, and *F*(*i*) indicates the fitness value of each person. The hunger of the searching agents is expressed mathematically using θ_1 and θ_2 [35]:

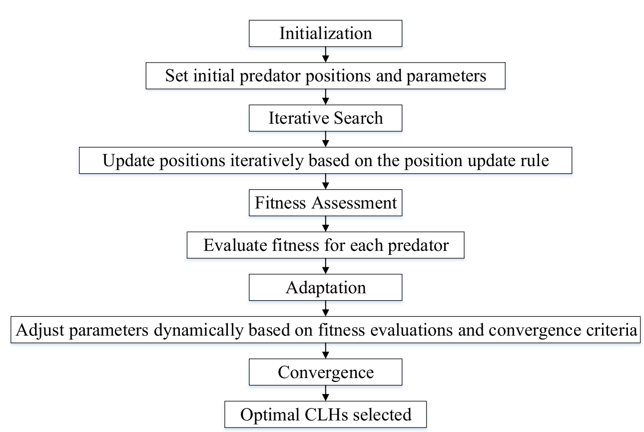

Fig. 1. The whole flowchart of MPA.

$$\theta_1(\tau) = \begin{cases} rand_4 \times \dfrac{N.hungry(i)}{SHungry}, rand_3 < \tau \\ 1 rand_3 > \tau \end{cases} \quad (8)$$

$$\theta_2(\tau) = 1 - 2 \times rand_5 \times \exp^{|hungry(i) - SHungry|} \quad (9)$$

In this equation, the number of searching agents is denoted by N, and random numbers in the interval [0,1] are rand3, rand4, and rand5, respectively, representing the hunger values of each individual and the total of all searching agents' hungry feelings. Eq. (13) describes the *hungry*(i) [35].

$$hungry(i) = \begin{cases} 0 AllFitness(i) == Best \\ H + hungry(i), AllFitness(i)! = Best \end{cases} \quad (10)$$

Each individual's fitness is saved in *AllFitness*(i) for the present iteration. Additionally, the H can be expressed as follows [35]:

$$H = \begin{cases} HT \mathrm{HT} \geq \mathrm{HL} \\ (1 + r) \times HL \mathrm{HT} < \mathrm{HL} \end{cases} \quad (11)$$

$$\mathrm{HT} = \frac{F(i) - Best}{Worst - Best}(ub - lb) \times 2rand_6 \quad (12)$$

Where $F(i)$ is the objective function score of each individual, lb, and ub stand for the lower and upper bounds of the search space, respectively, and $rand_6$ is a random number in the interval [0,1]. Best and Worst are the best and worst values for fitness. The whole flowchart of HGS is shown in Fig. 2.

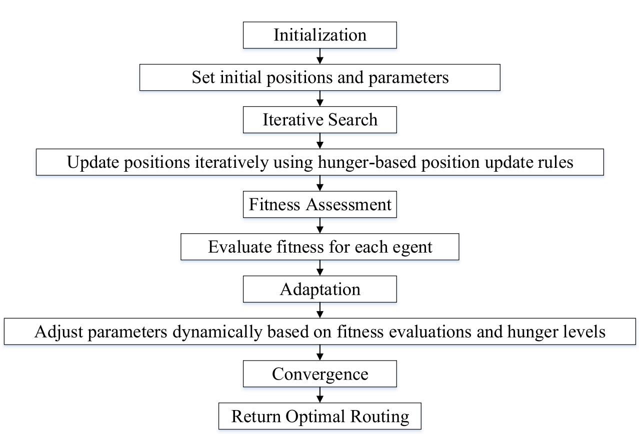

Fig. 2. The whole flowchart of HGS.

3.3. Proposed methodology

Following the clustering stage, the HGS technique is used for data routing in the HGS-MPA procedure. After setting up a large sensor field with numerous sensor nodes, the BS broadcasts a beacon signal to every nearby node. After receiving the signal, the nodes determine how far away they are from the BS. After exchanging a handshake signal, two nodes can share data concerning their local surroundings. After clustering the collected data, the MPA technique efficiently identifies and groups CLHs. The last stage is utilizing the HGS routing algorithm to determine the best routes throughout the network. The recommended HGS-MPA solution combines the advantages of the best clustering and routing techniques. The suggested method's block diagram is displayed in Fig. 3, and a detailed explanation of its several phases will follow.

3.3.1. The model of network

A group of N sensor nodes is continually observed in an underwater WSN. The different parts, such as the sensors, a module for communication (CM), a CLH, a BS, and others, are displayed in Fig. 4. The nodes monitor physical properties in sensing mode while communicating data instantly to the BS during communication mode. In addition, they gather information from other cluster members, and every sensor node is given an index determined by its position. After deployment, all sensors share the same starting energy, and the BS and sensor nodes stay in place. The nodes' connections are regarded as an individual entity.

3.3.2. lifetime of model

The lifetime of UWSN can be described using many definitions. Usually, the lifespan is expressed as the total number of rounds the network completes before a sensor node fails. Nevertheless, data integrity may deteriorate due to the network's initial node dying, and the system will ultimately terminate with the death of the final sensor node. The first node die (FINOD) and the half node die (HANOD) are two measures that can be used to estimate the lifetime of the UWSN [36]. When a network has many broken nodes, the HANOD is helpful since it makes it possible to evaluate its efficiency at its largest possible size. It is possible to determine the network's lifespan using Eq. (13).

$$\vartheta_{SN}^{AN} = Ns\left[\gamma = \frac{AN}{SN}\right] \quad (13)$$

According to this mathematical model, a network's sustained neighbor identification lifespan is defined as the time that passes when the total number of active nodes falls below a specific threshold. In this case, AN stands for all of the network's sensors, and SN for all its active nodes.

3.3.3. Clustering technique with MPA

The CLH column can be shown by Eq. (14), where R is the number of node sensors distributed throughout the region and randomly arranged into Nc clusters. The acronym $\overline{CLH}$indicates a non-CLH node, as should be noted. denotes a non-CLH node.

$$CLH = \{CLH_1, CLH_2, \ldots, CLH_R, \ldots, CLH_{CN}\} \quad (14)$$

The CH oversees data gathering inside the cluster, regulates communication amongst cluster nodes, and relays signals to the BS. The nodes' position and energy level determine which CLHs are chosen. The BS is urged to allocate CLHs to optimal spots with high residual workloads to sustain clusters at a constant node count. Therefore, this method can be viewed as an optimization problem, as represented by Eq. (15).

$$F_{CLH} = (1 - \alpha) \times \frac{\sum_{\forall node_i \in CLH} d(node_i, BS)/|\overline{CLH}|}{\sum_{\forall node_j \in \overline{CLH}} d(node_j, BS)/|CLH|} + \frac{\sum_{\forall node_j \in CH} E_{CLH}^{residual}(j)/|CLH|}{\sum_{\forall node_i \in \overline{CH}} E_{\overline{CLH}}^{residual}(i)/|\overline{CLH}|} \times \alpha \quad (15)$$

The $d(node_i, BS)$ indicates the distance calculated by Euclid between node i and BS, where $|CLH|$ and $|\overline{CLH}|$ represent the numbers of the CLH and non-CLH nodes, respectively. The equation aims to find a highly energy-efficient cluster topology and CLH for a typical UWSN. A node's capacity to produce power is directly related to how long it is expected to last. The data packet may contain this information. Usually, nodes near BS and with more labor are considered for CLHs. It is thought that this topic is an optimization process. Consequently, the procedure in a composite system is optimized using the HGS-MPA technique in the ensuing subsection.

3.3.4. The process of HGS routing

The suggested approach assigns a random number as an initial location for every gateway to the BS. Each outcome matches just one sensor node and a unique BS, and the value of the results remains constant with all gateways (Q).

$$S_{fh} = rand(0, 1), 1 \leq f \leq F_i, 1 \leq h \leq H \quad (16)$$

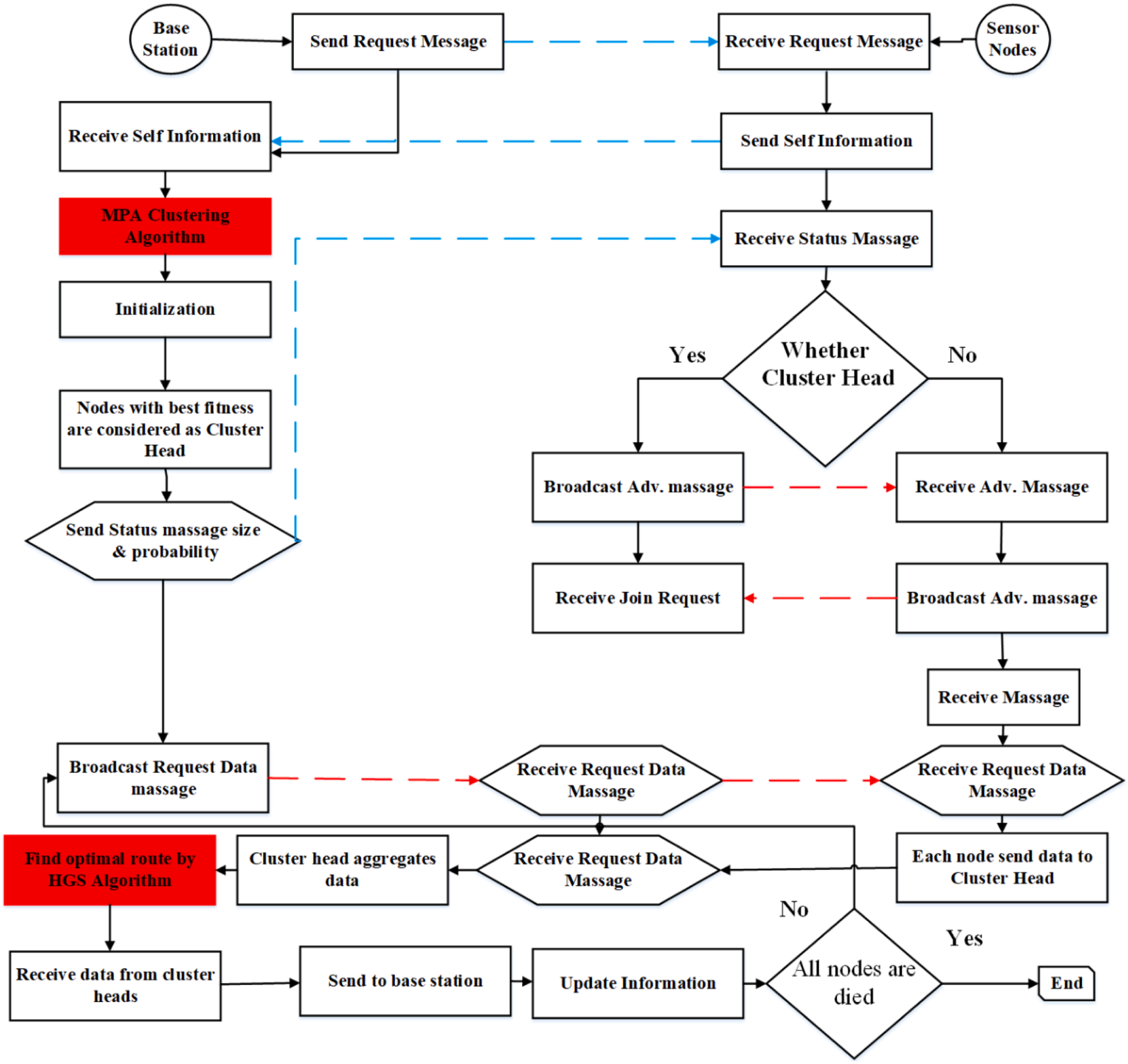

Fig. 3. The HGS-MPA Block diagram.

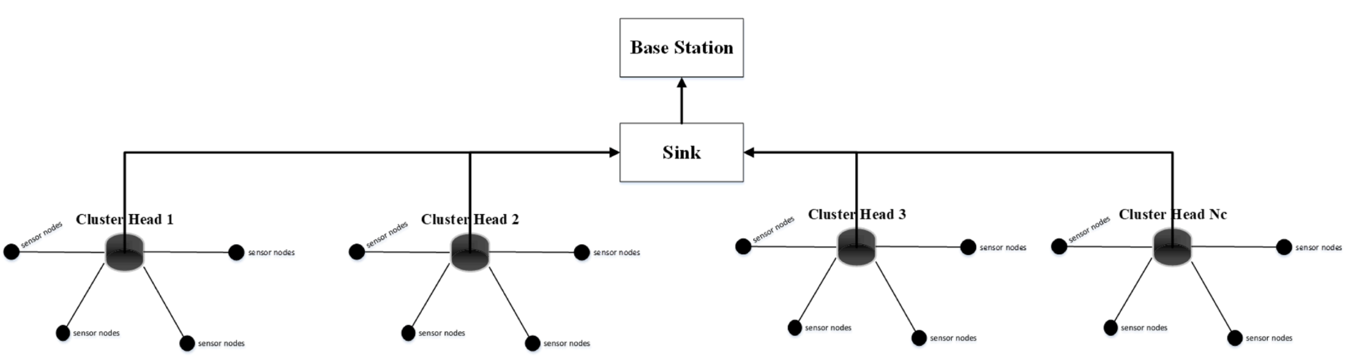

Fig. 4. A common UWSN's portrayal of multi-hop clustering.

The sensor number is indicated by h, and the letter f represents the gateway number. This section will detail the entrance GW and the path from the SN to the BS, concentrating on how Iq sends the data to the GW. In Eq. (17), the path-optimizing framework is explained [37].

$$GW = Idx(tL(I_q) \times SetN, Ceil(S_{fh} \times |tL(I_q) \times SetN|)) \tag{17}$$

The fitness function evaluates the gates based on the variables they include, and *Idx* is an index operator that finds the location of the nth gateway. Fitness function-based routing techniques now allow routes between BS and GW to be constructed. The distance (D) that gate units span is defined by Eq. (18), while the gateways that are dispersed throughout the model are represented by Eq. (19) [37].

$$D = \sum_{q=1}^{Q} dis(tL(I_q) \times N, I_q) \tag{18}$$

$$GW = \sum_{p=1}^{N} Count(I_p) \times NxtL \tag{19}$$

The two primary considerations in routing are the minimum number of hops and the shortest distance. Higher levels of the routing objective function are related to shorter paths and fewer hops, which indicates that overall distances are lower and there are fewer hops. This is the way to go for an ideal search agent for an individual. The fitness function is derived from Eq. (20) [38].

$$Fitness\_Function(Routing) = \lambda \frac{1}{(\theta_1 \times D + \theta_2 \times G_N)}, \tag{20}$$
$$\theta_1 + \theta_2 = 1, \theta_1, \theta_2 \in [0,1], \lambda : \text{ProportionalConstant}$$

4. Experimentation

Energy efficiency, First Node Dead (FINOD), and Half Nodes Dead (HANOD) are the three main measures used to assess the HGS-MPA algorithm's performance [39]. Energy efficiency calculates each node's power during a specific period to gain insight into the network's total energy consumption. First Node Dead, or FINOD for short, is the round number in which the network's first node goes down, a measure of the network's resilience and durability [40]. The HANOD condition occurs when 50 % of the network's nodes are inoperable [41]. These measures thoroughly assess the algorithm's performance in preserving energy-efficient and durable UWSNs.

4.1. Experimental implementation

An extensive set of simulations is used to represent the UWSN under different situations, with a particular emphasis on the BS location, to assess the hybrid HGS-MPA technique. As shown in Fig. 5, the examination encompasses three separate scenarios, each of which signifies a unique BS placement. An equitable distribution of communication load and possible minimization of energy usage across the network are anticipated in the first scenario, T1, where the BS is situated in the middle of the target area. The second scenario, T2, puts the algorithm to the test in less-than-ideal conditions by placing the base station (BS) at the corner of the target area, which would increase communication distances for many nodes. In the third possible outcome, T3, the base station is located far from the intended destination, which causes further problems, including longer communication delays and more energy consumption for the nodes far from the base station.

The usual 200 × 200 square meter area with 300 sensors is used to evaluate these scenarios, which simulate the conditions found in UWSNs. This setup enables a comprehensive evaluation of the HGS-MPA method's efficiency in both ideal and challenging settings. Table 1 summarizes the ideal parameters found during the validation phase to conduct simulations in conditions that closely resemble real-world deployments.

A thorough evaluation of the HGS-MPA approach is conducted by comparing its results to those of four well-known clustering algorithms: LEACH [42], efficient weight-based clustering algorithm (EWBCA) [43], Adaptive k-means (AKM) [44], hierarchical chimp optimization (HCHOA) [45], and GWO-PSO [37].

This study will showcase HGS-MPA's advantages in energy efficiency, network lifetime, and adaptation to diverse BS sites by comparing it to these methodologies. Given the importance of energy efficiency and network robustness in real-world UWSN applications, this comparison research is essential to grasping the possible advantages of HGS-MPA.

4.2. Energy efficiency

The proposed Hybrid HGS-MPA system's power consumption is evaluated in three separate situations, as shown in Figs. 6 through 8. These scenarios help understand the system's energy dynamics under different conditions. Using the average energy efficiency of the sensor

Table 1
Initial values for parameters.

Parameters	Value
E_{elec} (*nJ/bit*)	500
ε_{fs}(*pJ/bit/m*^{2})	100
Area (m^2)	200 × 200
E_0 (J)	0.5
Packet size (Kbits)	4

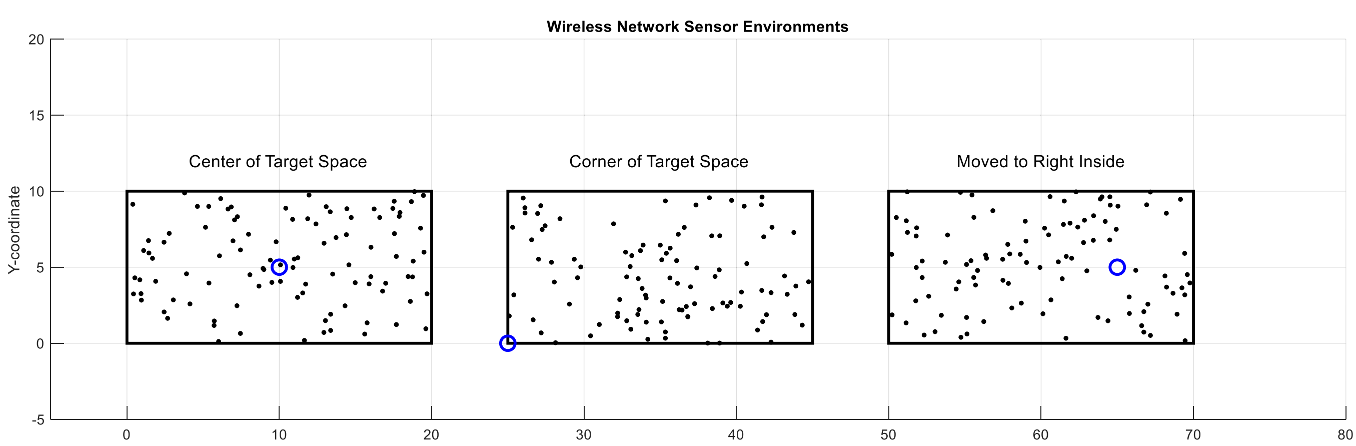

Fig. 5. The possible positions for the base station.

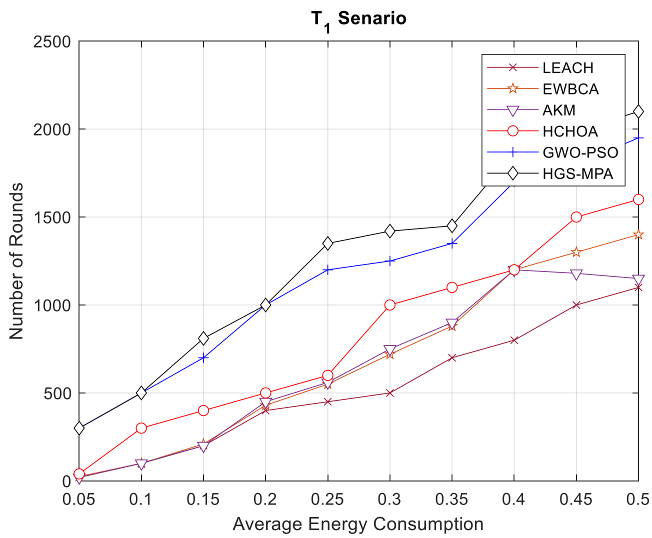

Fig. 6. First scenario (T_1).

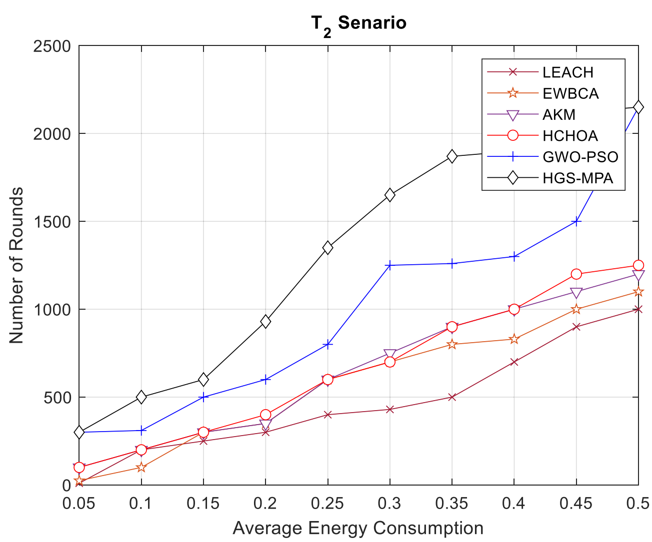

Fig. 7. Second scenario (T_2).

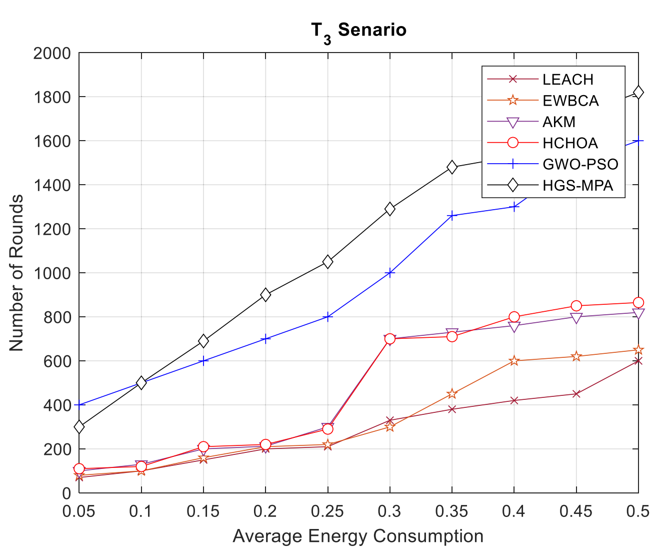

Fig. 8. Third scenario (T_3).

nodes across 2500 iterations, we calculate the total power consumed to find the energy usage. Considering aspects like algorithmic efficiency in energy management, communication overhead, and sensor node density, this evaluation thoroughly studies the system's performance.

As part of the detailed analysis, the total energy dissipation of each node in every iteration, incorporating energy used for sensing, processing, and communication tasks, is computed. The system's energy efficiency can be assessed by taking the mean of these values over 2500 iterations, which is likely reasonably accurate. Different situations with network configurations, sensor spatial distribution strategies, and communication protocols affect aggregated power consumption differently (Figs. 6, 7, and 8).

In the first scenario, shown in Fig. 6, the sensor nodes are densely spaced over the network. Because of the more excellent rates of interference and collisions, this arrangement typically has higher communication overhead, which in turn causes higher energy usage. In Fig. 7, Scenario 2 examines a sparse network topology where nodes are further dispersed. This topology usually leads to reduced communication energy but more significant energy expenditure for data aggregation and routing. Scenario 3, as shown in Fig. 8, integrates sparse and dense topology features to maximize the trade-offs between processing power and communication.

These cases aid in determining the most energy-efficient deployment and operations for the HGS-MPA system, ensuring the sensor network's long-term sustainability and enhancing overall efficiency.

In Scenario T1 (Fig. 6), each algorithm has unique performance features when looking at energy usage versus the number of operational rounds. The LEACH algorithm shows a steady but inefficient performance, with a slight rise in energy usage. EWBCA and AKM are not efficient in the long run as they have higher than average energy consumption during startup, and their g% rate is almost identical. The same cannot be said about GWO-PSO, which consumes significantly during mid-rounds, reflecting possible problems. At the same time, HCHOA uses up much energy in the beginning before significantly stabilizing during the following rounds. The lowest energy usage is regularly shown by HGS-MPA, which indicates that it is more efficient and makes the best use of its resources.

Even though the circumstances in Scenario T_2 (Fig. 7) are different, the patterns in the algorithms' performance remain consistent. EWBCA's performance improves slightly compared to the results obtained in T_1, but overall, it still does worse than the LEACH model, which, though it has a lower starting value, has a constant energy usage. In the case of AKM, there is a gradual increase in energy consumption over rounds, which becomes slightly high, whereas HCHOA's performance starts to be steady at around T_1. Once again, persistent inefficiencies are shown by GWO-PSO's considerable rise in energy consumption. HGS-MPA maintains its lead over other algorithms by consistently using the least energy over rounds and demonstrating its efficiency and resilience in different operating environments.

Fig. 8 shows the energy consumption trends of Scenario T_3, which supports the earlier findings even more. While EWBCA's trend is somewhat higher but comparable, LEACH's beginning energy consumption is higher and grows at a steady rate. The energy profile of AKM is consistent, but it falls short compared to the best algorithms in terms of efficiency. Moving forward, energy usage levels that HCHOA utilized at the beginning of each round are set downwards, as was expected. Further, substantial increases in energy consumption that GWO-PSO faces, particularly in the mid to later rounds, uncover inefficiencies. In varying network topologies and the presence of different troubleshooting conditions, HGS-MPA optimally consumes the least amount of energy. All these consistent relations suggest that HGS-MPA is a reliable manager of energy resources, which explains the role it can play in wireless sensor networks and similar low-power scenarios.

By integrating MPA and HGS into clustering and routing processes, the HGS-MPA method achieves exceptional energy efficiency. With this method, we may use one-hop transmission and random CH allocation to reduce power usage during data transfer inside the cluster. In contrast, EWBCA's ineffective CH selection approach and one-hop transmission mean it performs poorly. Although it lags behind the GWO-PSO and HGS-MPA models, the reactive HCHOA approach uses less energy than EWBCA. While HCHOA can always reduce transmission costs, it suffers from the quality of its CH selection methods, which can be pretty harmful. GWO-PSO and HGS-MPA improve energy efficiency by selecting the first CLHs, which are the most energy-efficient and usable methods. Regarding data transfer, in any reasonably examined environment, HGS-MPA is the most energy-efficient model among these models.

4.3. Data transmission quantity

The evaluation of UWSN performance mainly depends on the communication efficiency between CLHs and BSs. The HGS-MPA model enhances the network's HANOD by integrating a sophisticated routing protocol with an advanced clustering algorithm. This HANOD increment guarantees that the network operates optimally for quite sometime before the energy resources are depleted, enhancing data throughput.

In Fig. 9, the HGS-MPA method is compared to other network models regarding the total number of data transmissions. The picture shows that networks using the HGS-MPA technique have more successful data transmissions. The model's approach to cluster management relativity and routing strategies has resulted in low energy consumption and transmission lag, breeds an increase in data rate. Thus, the HGS-MPA model achieves better results by ensuring that the UWSN communication lines remain intact.

The HGS-MPA method is superior as it has spread the data load across sensor nodes, increasing network stability and reducing node failure chances. The HGS-MPA model gives confidence in the optimal use of energy and bandwidth resources by gravitational search algorithms and multi-path routing techniques. This enhances both the data transmission speeds and the network's operational lifespan. Fig. 7 shows that the HGS-MPA model maximizes data transmission efficiency in UWSNs.

The efficient transmission of information between CLHs and BSs is typically used to evaluate the efficacy of a UWSN. The HGS-MPA paradigm is distinct from other models as a consequence of its clustering and routing mechanisms, which significantly contribute to the enhancement of a network's HANOD, also as demonstrated in Fig. 9. It can outperform competing models such as EWBCA and HCHOA; moreover, its routing and clustering capabilities enable the delivery of more data over an extended period. All of these alternative models have a problem with an effective transfer of communications between nodes and the BS because they transmit fewer frames per incident and have issues with CLH control.

The intended life of a UWSN can best be evaluated in terms of its FINOD and HANOD levels. The impact of the FINOD metric on the overall network performance is minimal, while the influence of the HANOD measure on the data transmission quality is considerable. Figs. 10, 11, and 12 demonstrate the reduction in data transmission performance with the decrease of the HANOD metric. Once the last operative UWSN node dies, there will be no further communications instigated with the base station, and the transferring of information will flicker out.

To ensure the continuity of the network and the seamless transmission of information, the HGS-MPA model does an excellent job of extending FINOD and HANOD. The system diminishes the probability of nodes going offline, thus increasing stability through its unique load balancing and energy management designs. It has been made feasible with HGS-MPA to optimize data transfer velocity and the operating life span due to the appropriate usage of resources in the form of gravitational search algorithms and multi-path routing schemes. Figs. 9, 10, and 11 show that the HGS-MPA model outperforms the alternatives for keeping information transmission efficient in UWSNs.

One standard metric for gauging a UWSN's performance is how well data is transmitted between the network's CLHs and BSs. Fig. 9 shows that the HGS-MPA paradigm dramatically increases the network's HANOD compared to other models. This is because of its efficient routing approach and diversified clustering process. This model outperforms rivals like EWBCA and HCHOA because of its better routing and clustering capabilities, which allow it to send more data over an extended duration. These competing models have trouble regulating CHs, which hinders effective communication between nodes and the BS, and they send fewer frames to each incident.

It is critical to take into account both the FINOD and HANOD levels when assessing the predicted lifetime of a UWSN [46,47]. Even though FINOD little affects the overall performance of the network, UWSN techniques are shown in the figures according to two critical metrics: HANOD and FINOD [48]

The HGS-MPA algorithm's capacity to extend the network's lifetime

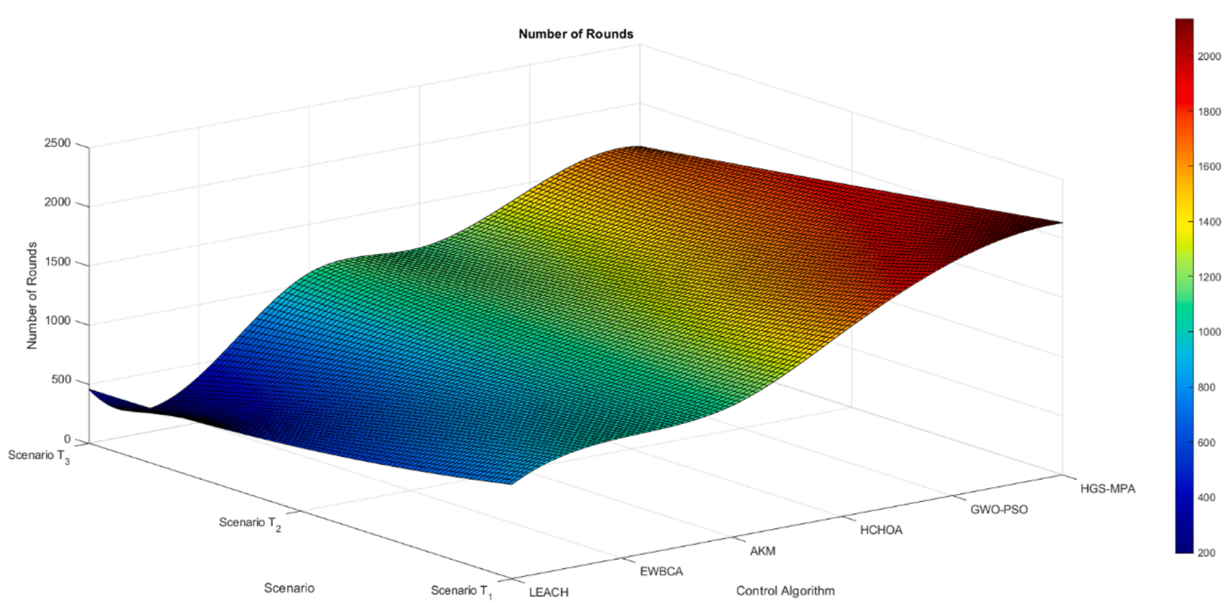

Fig. 9. The number of packets sent to the BS until the HANOD is triggered.

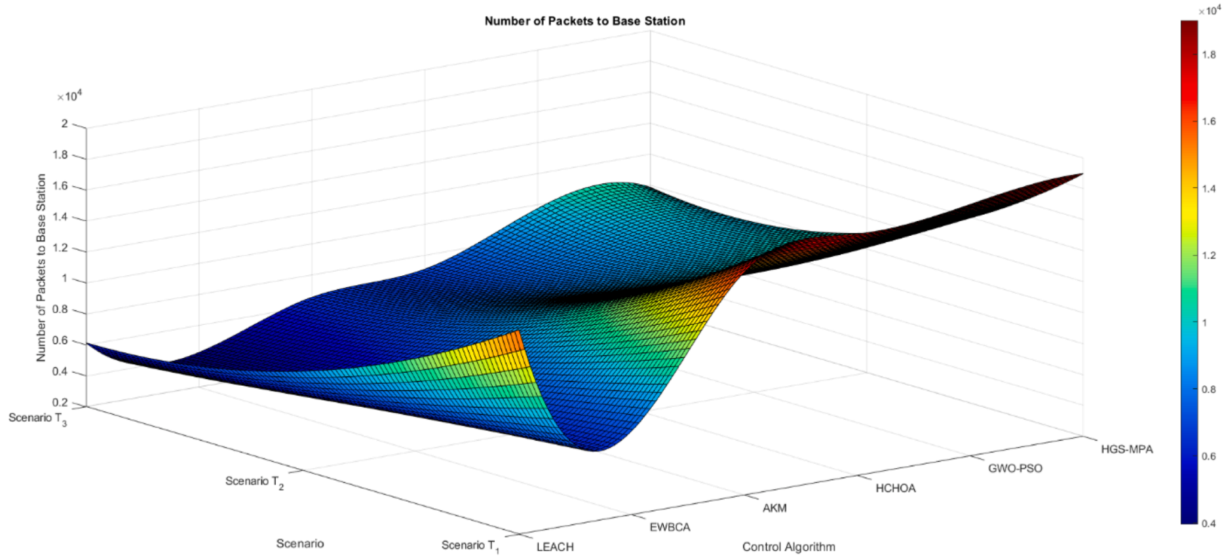

Fig. 10. FINOD values for different scenarios.

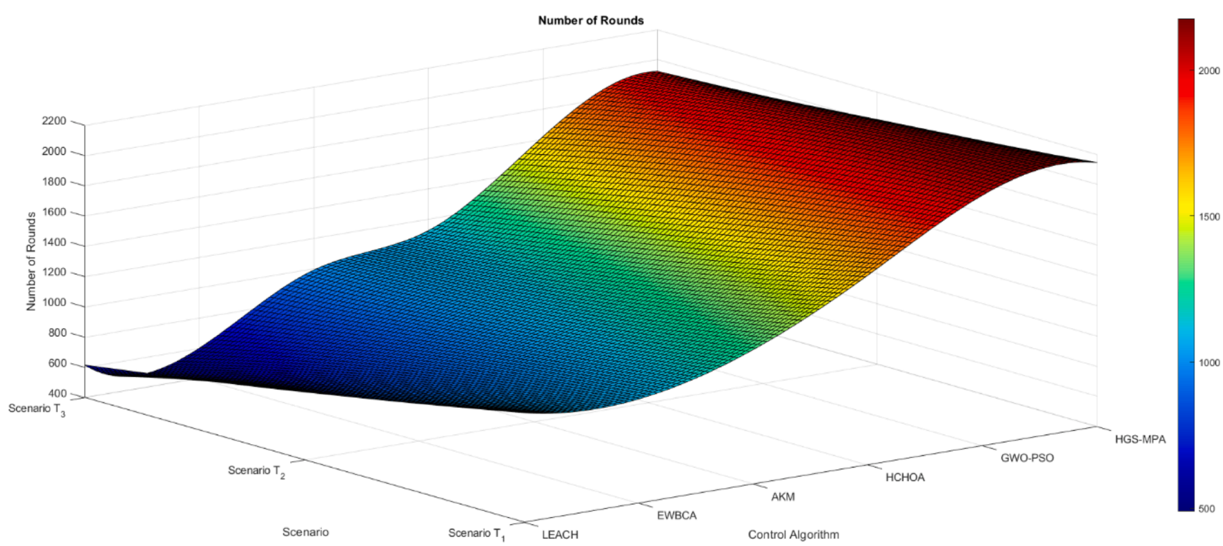

Fig. 11. HANOD values for different scenarios.

is consistently emphasized by Fig. 12, portraying the findings of the FINOD across the T_1, T_2, and T_3 scenarios. More particularly, it performs significantly better than competing algorithms, such as GWO-PSO and HCHOA, concerning such scenarios as energy management and control of node efficiency. It is interesting to note that T_1 has the best FINOD values and shows the most control over the network, while T_3 points out the least strengths in how the network will operate over time.

The results of HANOD are provided in Fig. 12, which seeks to portray the overall effectiveness of the algorithms in maintaining communication between the sensor nodes and the base stations. HGS-MPA also triumphed, obtaining the best HANOD figures across all scenarios. This illustrates its capability to ensure reliable information transmission across channels, which is necessary information for data collection in real-time, specifically in underwater conditions. A key observation was that Scenario T_2 performed worse than T_3 concerning the maintenance of communications links for extended periods due to rapid transmission in T_2, while T_2 exhibited superior communication reliability than Scenario T_3.

The study stresses the significance of choosing appropriate algorithms to strengthen and improve the efficiency of UWSN: HGS-MPA's strong node and communication protocols suggest that such algorithms are needed to tackle the issues encountered underwater.

Future work could further enhance the applicability of these findings to real UWSN systems by refining these algorithms even more and incorporating actual environmental information into the simulation models. In short, these results facilitate the technological advancement of UWSN systems, from which underwater communication systems of higher integrity and are environmentally friendly are developed. The data transmission quality is considerably affected by performance through HANOD. Data may be impeded when the level of HANOD is low, as demonstrated in Figs. 10 and 11. A UWSN is inoperative when the last active node of the system is deactivated, as information can no longer be sent out, and the connection to its base is lost. The system is shut down at this time.

In our context, the HGS-MPA model is exceptional and excellent for expanding FINOD and HANOD. It also guarantees that network operations will be sustained and data flowing. The complex load balancing and energy management algorithms increase the networks' resiliency by reducing the chances of node failure.

HGS-MPA also optimizes data transmission and prolongs the

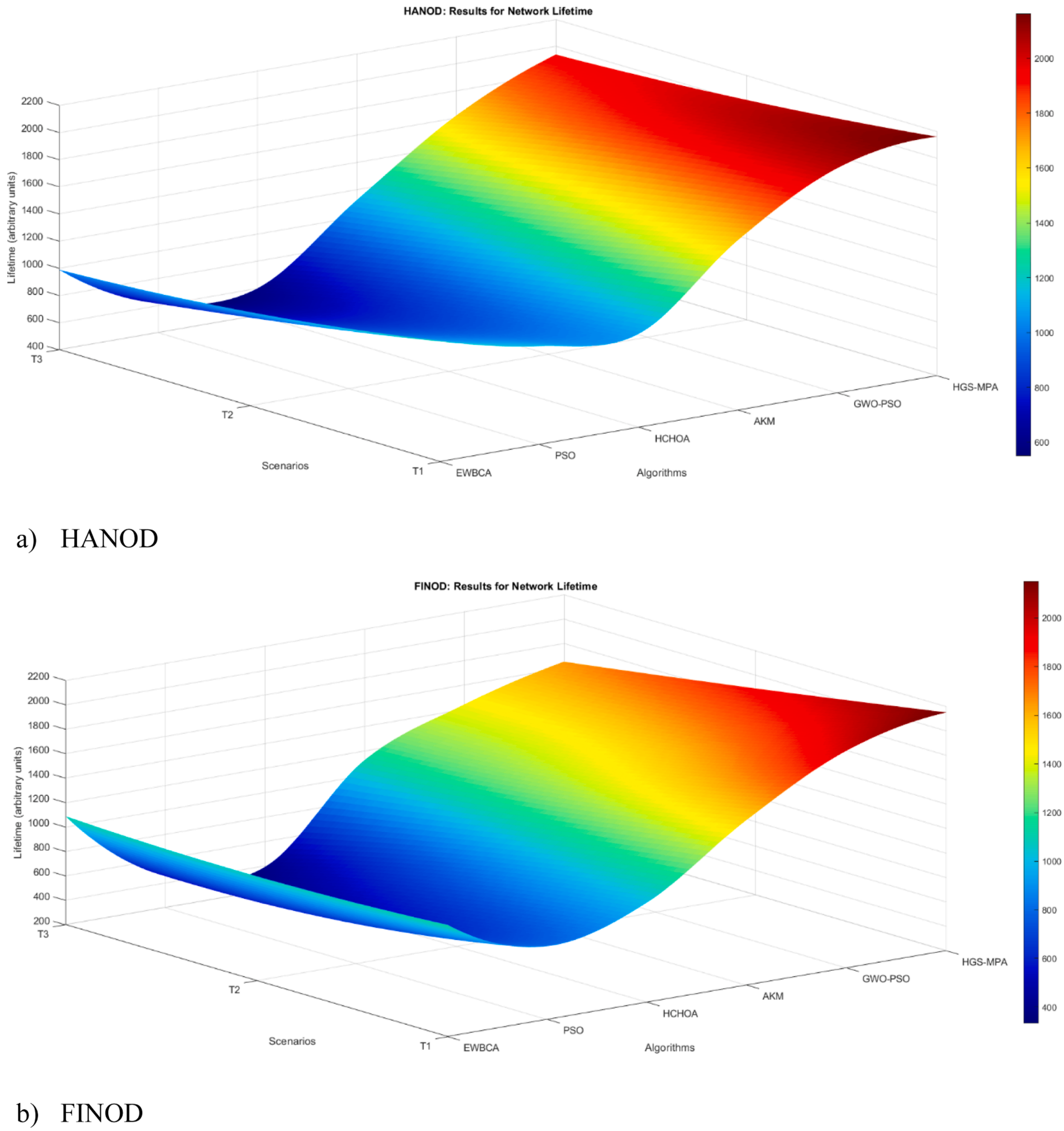

Fig. 12. Network lifetime outcomes.

network's lifetime by implementing multipath routing architectures and gravitational search algorithms, which minimize energy consumption and maximize bandwidth utilization. From the comparison results seen in Figs. 9, 10, and 11, the HGS-MPA model is by far the most appropriate model for enhancing the data transfer effectiveness in UWSNs because it is highly effective.

The optimization feature of our hybrid HGS-MPA approach has the best chance for scalability. Due to the hybrid structure of MPA and HGS, the components can be assimilated into the current designs of UWSN for differing node densities and harsh underwater conditions. On the other hand, for ultra-dense networks, additional approaches such as hierarchical clustering or dynamic load balancing will need to be implemented in conjunction with inter-cluster interference management to guarantee even energy distribution. These issues need to be investigated by future work so that this framework can be more useful in practice.

4.4. Statistical analysis and results

To validate the performance of the HGS-MPA framework, a detailed statistical analysis was performed, and the numerical and visual results were presented. This part displays the average energy consumption for several methods using boxplots and one-way ANOVA for testing statistical differences. These studies again illustrate that HGS-MPA is the best in terms of energy efficiency, duration of the network, and reliability. The performance metrics of the proposed HGS-MPA method vis-a-vis other existing algorithms, such as LEACH, EWBCA, AKM, HCHOA, and GWO-PSO, are summarized in Table 2. Each of the performance metrics was computed using five independent simulation experiments. The difference between the means was statistically tested by analyzing one-factor variance and its post-hoc test for pairwise comparisons.

Fig. 13 shows a box plot representing the energy spent by all the methods. The plot indicates the variability and distribution of data such

Table 2
Statistical significance test.

Metrics	EWBCA	LEACH	GWO-PSO	AKM	HCHOA	HGS-MPA (Proposed)
Network Lifetime (HANOD)	328 ± 12	312 ± 14	342 ± 9	331 ± 10	338 ± 11	**396 ± 11**
Network Lifetime (FINOD)	138 ± 10	123 ± 8	149 ± 8	141 ± 7	146 ± 9	**182 ± 6**
Packet Delivery Ratio (%)	86.8 ± 1.5	85.2 ± 1.7	89.5 ± 1.3	87.3 ± 1.2	88.9 ± 1.4	**92.4 ± 1.1**
Energy Consumption (J)	19.8 ± 1.5	21.3 ± 1.2	16.9 ± 1.0	18.6 ± 1.1	opposed	**12.4 ± 0.8**
P-value (ANOVA)	0.0001	0.00002	0.00011	0.00021	0.0001	**N/A**

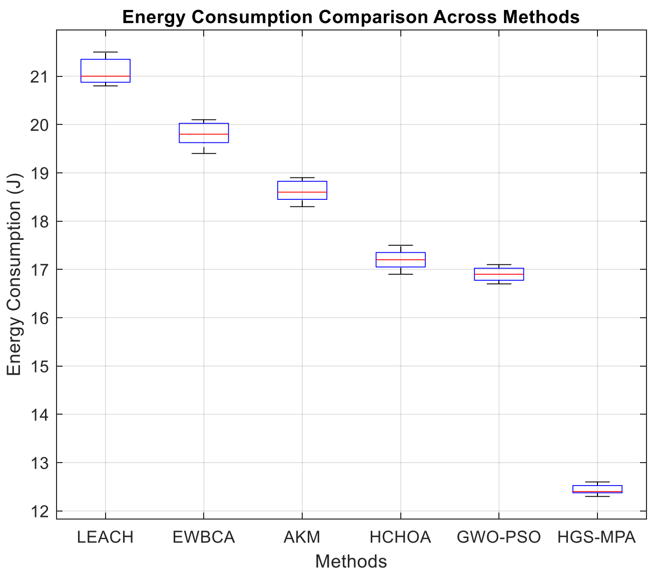

Fig. 13. Energy consumption comparison.

as energy consumption, and HGS-MPA depicts upper and consistent performance commendably.

Compared with existing frameworks, the HGS-MPA framework displays lower energy consumption, thus proving its greater energy efficiency. This is achieved by combining the MPA and HGA for separate energy-efficient clustering and routing. Average power consumption has decreased by 26.6 %, with the HGS-MPA averaging 12.4 J while the subsequent best GWO-PSO averages 16.9 J.

The methodology used to monitor network lifetime refers to the FINOD and HANOD, and it undeniably proves the sturdiness of the HGS-MPA framework as the latter increases the network life by 22.10 % and 15.80 %, respectively. It guarantees the delicate underwater framework network functions persistently while severely limited on resources. Such progress is advantageous for continuous use over extended periods, for instance, while monitoring the environment or exploring the sea bed.

Another crucial pointer is communication accuracy, which establishes strength in the HGS-MPA framework. Measuring the packet loss ratio, the new framework averaged 92.4 %, with GWO-PSO and the other standard methods averaging 89.5 %. Reliability, specifically in underwater settings, is essential due to the cost of rerouting created by the high latency and energy needed.

Further corroborating the noted enhancements, statistical significance testing (ANOVA) shows P-values < 0.001 across all metrics. Post-hoc analysis verifies the differences between HGS-MPA and other approaches and strengthens the results as it proves them to be statistically significant.

The statistical analyses and visualization together illustrate the advantages of the proposed HGS-MPA framework in terms of energy optimization, network lifetime expansion, and improved data transmission reliability. Such studies confirm that the framework has the potential to be a notable contribution to underwater wireless sensor network optimization.

4.5. Comparison with state-of-the-art clustering and routing algorithms

This subsection aims to evaluate the efficiency of the HGS-MPA framework against existing advanced algorithms for the clustering and routing of UWSNs. These include LEACH [42], TEEN [49], DEEC [50], and GWO-PSO [37]. The selected algorithms were included in the evaluation due to their relevance and popularity concerning energy-efficient cluster routing methodologies in UWSNs. The comparison is made by assessing core performance indicators, including network longevity (as determined by FINOD and HANOD), energy utilization, packet delivery ratio, and computational complexity. In this calculation, computational complexity is a function of the number of sensor nodes, *N*. The results from the HGS-MPA framework are summarized together with the other state-of-the-art competing algorithms in Table 3.

4.5.1. The network lifetime (FINOD and HANOD)

The HGS-MPA algorithm demonstrates the maximum network lifetime, achieving a FINOD of 182 ± 6 and a HANOD of 396 ± 11. That means the network lifetime is still operational longer than that of other algorithms. Conversely, LEACH is the worst performer at 138 ± 10 and 328 ± 12 for FINOD and HANOD, respectively. The LEACH performance is poor because of the broad clustering approach and the efficient routing of LEACH. Approaches for multi-hop\clusters active and HGS-MPA active routing are the Efficient Step. Multi-hop clustering and routines. These approaches consume fewer resources than traditional methods, increasing network operational lifetime. HGS-MPA has extended the network's operational lifetime through newer approaches due to its optimized energy-consuming clustering approach based on energy and network efficiency.

4.5.2. Energy consumptions

HGS-MPA is also the lowest in other estimates of efficiency—operational energy. Lowering consumption to 12.4 ± 0.8 J, HGS-MPA is 26.6 % lower than GWO-PSO (16.9 ± 1.0 J) or 37.5 % lower than LEACH (19.8 ± 1.5 J). Energy consumption is reduced in HGS-MPA, which is enabled by a more complex mechanism determined to energy-aware cluster head selection and efficient routing, and those optimize paths through the transmissions and evasive an undoing of superfluous retransmissions.

4.5.3. Packet delivery ratio

As for the packet delivery ratio, the best performer is HGS-MPA, with 92.4 ± 1.1 %. This suggests excellent reliability in transmitting data. The worst performer is LEACH, with a delivery ratio of 86.8 ± 1.5 %. This poor performance is mainly due to LEACH's lack of adaptive routing and clustering techniques. TEEN and DEEC are slightly better than LEACH, with delivery ratios of 87.8 ± 1.2 % and 88.2 ± 1.4 %, respectively, but still do not reach the level of HGS-MPA.

4.5.4. Computational complexity

The computational complexity of the algorithms is also essential in assessing their practicality for implementation within large-scale UWSNs. Both LEACH and TEEN have linear complexity that can be represented as $O(N)$, where N is the number of sensor nodes within the network. This indicates that their computational costs increase with the

Table 3
Comparison results for HGS-MPA and the state-of-the-art algorithms.

Algorithm	Energy Consumption (J)	FINOD	HANOD	Packet Delivery Ratio (%)	Computational Complexity
DEEC	18.2 ± 1.1	160 ± 6	375 ± 9	88.2 ± 1.4	$O(N^2)$
TEEN	17.5 ± 1.3	140 ± 7	335 ± 8	87.8 ± 1.2	$O(N)$
LEACH	19.8 ± 1.5	138 ± 10	328 ± 12	86.8 ± 1.5	$O(N)$
GWO-PSO	16.9 ± 1.0	149 ± 8	342 ± 9	89.5 ± 1.3	$O(N^2)$
HGS-MPA (Proposed)	12.4 ± 0.8	182 ± 6	396 ± 11	92.4 ± 1.1	$O(N^2)$

number of nodes. LEACH has a simple clustering scheme, while TEEN has some control over its operation using threshold values, which contribute to their linear complexity. Both are good for small to moderate-sized networks, but they can contend with more extensive networks.

The DEEC protocol is different because it relies on clustering based on residual energy levels it has already utilized and its relationships with base stations for optimization, creating a communication overhead. This increases its complexity to $O(N^2)$ for computation. Even though DEEC is more energy efficient than LEACH, the additional computational complexity could limit its scalability to large networks.

As previously noted, the GWO-PSO hybrid algorithm combines two optimization techniques, GWO and PSO. It is also $O(N^2)$ with GWO-PSO with its superior performance in clustering and routing compared to LEACH and TEEN. Its performance can be detrimental in dynamic scenarios with plenty of nodes because its complexity will hinder environments like GWO-PSO's efficiency.

These algorithms respond to a dynamic environment, like the proposed framework HGS-MPA, which has $O(N^2)$ complexity due to iterative optimization steps like the predator-prey paradigm in the MPA, plus multi-hop routing in the HGS. While this approach is more costly in computations than other simpler algorithms like LEACH and TEEN, the gains in energy efficiency, network lifetime, and reliable packet delivery justify these costs. HGS-MPA is particularly well suited for medium to large-scale UWSNs where the performance gain supersedes the additional computational expense.

4.5.5. *Summary of results*

To summarize, HGS-MPA, alongside its dimensional reductions and clustering, has the best results compared to LEACH, TEEN, DEEC, and GWO-PSO algorithms. Even though its computational time is quadratic, $O(N^2)$, its energy efficiency, network lifetime, and packet delivery ratio outperform. Optimizing UWSNs. Analysis in Table 2 informs us that HGS-MPA has the best performance and value for medium to large-scale deployments.

5. Discussion

5.1. *The effects of network setup and node density in HGS-MPA's usability*

HGS-MPA's performance in UWSNs is directly related to network configurations such as node density, deployment strategy, and network topology. To check the robustness, we tested the effect of these parameters with simulation scenarios.

- **Influence of node density**

  Changes in node density have a considerable effect on cluster formation and routing efficiency. In dense networks, greater energy efficiency arises as many CHs result in lower clusters and shorter transmission distances. On the other hand, node density can contribute to congestion and interference, increasing packet transmission delays. HGS-MPA mitigates this problem by electively choosing CHs with the necessary distance and residual energy, thus balancing the energy consumption among all nodes.

  In sparse networks, lower CHs available increase the energy needed, leading to higher clusters where individual nodes must transmit data over longer distances. HGS-MPA has multi-hop routing that is efficient in these cases by improving the transmission path, thus lowering the power consumption while enabling stable communication links despite the lower node density.

- **Effect of the network design on performance**

The network node's arrangement is equally significant regarding the performance of HGS-MPA. In the case of uniform node distribution, HGS-MPA performs well because stable clusters are formed, allowing the energy consumption to be optimized and the network's lifetime to be maximized. On the contrary, some regions may be energy hotspots in randomly deployed networks because of the excessive data traffic in some areas. The adaptive CH re-selection mechanism in HGS-MPA solves this problem by altering load distribution and postponing the exhaustion of nodes manipulated too much with data transmissions.

Sparse topologies also introduce problems like additional multi-hop delays. On the other hand, HGS-MPA's ability to recognize optimal relay nodes ensures that data is transmitted without incurring unnecessary energy costs. These features make HGS-MPA the most appropriate for the different configurations and strategies of network deployment.

5.2. *Energy harvesting and future improvements*

An additional remark for this research is the lack of attention on implementing energy harvesting (EH) methods, which are becoming familiar with enhancing the lifespan of the UWSN.

- **Possible implementation of energy harvesting in HGS-MPA**

  The integration of energy harvesters into HGS-MPA energy harvesting technologies like solar panel installations on the surface nodes or piezoelectric energy harvesting for underwater nodes that are exposed to the motions of waves and ocean currents can be utilized by UWSNs. Combining battery power with harvested energy increases the longevity of the energy systems.

  An energy harvesting approach to HGS-MPA can allow higher harvested energy level nodes for CH selection, lessening the burden on battery-dependent nodes. Furthermore, excellent power conservation in non-harvesting nodes may occur if dynamic relay routing strategies assign relay roles to nodes with higher harvested energy.

- **Challenges and future work**

Significant variability of harvested energy from the ocean makes it challenging to ensure sustainability. As a result, varieties in energy harvest could result in variability of CH selection and routing stability. It is suggested that future research modifies HGS-MPA by including an energy prediction module that automatically alters clustering and routing strategies based on predicted energy levels. Integrating network configuration analysis with energy harvesting expands the applicability of HGS-MPA to real-world underwater sensor networks. It contributes towards the development of energy-efficient, self-sustainable UWSNs.

5.3. *Practical investigation*

Even though the simulation results prove the efficiency and effectiveness of the designed HGS-MPA framework, the HGS-MPA framework simulation environment poses some limitations. The internal simulations assume idealized acoustic propagation models, with fixed sensor placements post-deployment and non-uniform energy consumption patterns, which differ from real-world underwater conditions. Many other environmental factors, such as water current, wildly varying acoustic interference, and hardware limits, can affect the network performance.

To close the divide between simulations and real-life applications, the following steps will be to implement the framework in staged submerged testbeds before moving to uncontrolled waters. Validation can first occur in controlled water tanks with fixed node locations to measure energy expenditure, clustering, and routing efficiency. After this, field tests in lakes or coastal waters will help determine how well the framework performs in more complex underwater ecosystems. Also, implementing adaptive clustering and feedback strategies will make it easier to operate the proposed approach in real-world circumstances.

6. Conclusion

In conclusion, this research integrated MPA with the HGS to propose a new hybrid technique to enhance clustering and multi-hop routing for UWSNs. In all circumstances, the proposed HGS-MPA system was more efficient than the reference systems when several measures, like network lifetime and energy consumption, were compared.

The performance of the proposed HGS-MPA methodology is supported comprehensively by the simulation results, but validation in real life is needed to substantiate its claims further. Focusing on the following studies, an experimental setup could be built or deployed to test the method in a realistic underwater environment where external factors highly influence the components. For example, a framework that seeks signal interference could be used to test its performance in non-static acoustic channels. In contrast, a moving node simulator would test its displacement in strong underwater currents. In addition, real deployments would allow one to measure the energy dynamics within the constraints of the operational battery and energy harvesting capabilities. Investigations such as these would broaden the understanding of the HGS-MPA framework, its practical application, and its scalability and reliability in different underwater settings. Secondly, the simulations were performed using the NS2 simulator; however, testing the proposed method on practical UWSN is better to check its applicability and efficiency.

Like many other studies, this study contributes to UWSN research, especially in improving the optimization techniques of multi-hop routing and clustering; however, it has its limitations. Exploiting the proposed approach would provide great insight into the problems associated with UWSNs, such as mobile nodes, sparse networks, and limited bandwidth. Exploring the effects of alternative network configurations and node density variations on the devised technique's functionality would also be a worthwhile pursuit. There are possibilities to improve UWSN's effectiveness and efficiency by combining the proposed approach with other optimization methods, such as AI and ML.

Authors' contributions

All authors approved the submitted version. All authors read and approved the final manuscript.

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Martín Diego: Writing – review & editing, Visualization, Validation, Software, Resources. **Khishe Mohammad:** Writing – original draft, Supervision, Project administration, Methodology, Conceptualization. **Hernando-Gallego Francisco:** Resources, Investigation, Formal analysis, Data curation. **Li Haitao:** Writing – review & editing, Visualization, Validation, Data curation.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

References

[1] K. Wu, X.-M. Li, Deep learning for retrieving omnidirectional ocean wave spectra from spaceborne synthetic aperture radar, Remote Sens. Environ. 314 (2024) 114386.
[2] X. Zhang, H. Zhang, L. Liu, Z. Han, H.V. Poor, B. Di, Target detection and positioning aided by reconfigurable surfaces: reflective or holographic? IEEE Trans. Wirel. Commun. (2024).
[3] G. Li, Y. Zhang, S. Fan, F. Yu, Y. Wang, Dynamic-wave interference suppression based on angular increment assistance for underwater Imaging Polarization Sensor, IEEE Trans. Instrum. Meas. (2024).
[4] D. Zhao, et al., A distributed and parallel accelerator design for 3-D acoustic imaging on FPGA-based systems, IEEE Trans. Comput. Des. Integr. Circuits Syst. 43 (5) (2023) 1401–1414.
[5] T. Kavitha, M. Venkatesan, S. Gopalakrishnan, S.R. Chand, M. Gopianand, S. Abirami, Underwater wireless sensors increase routing performance using impact efficient localization-based routing protocols, Babylon. J. Netw. 2024 (2024) 69–77.
[6] D. Zhao, et al., Design of forward-looking sonar system for real-time image segmentation with light multiscale attention net, IEEE Trans. Instrum. Meas. 73 (2023) 1–17.
[7] L. Sun, Y. Wang, X. Hui, X. Ma, X. Bai, M. Tan, Underwater robots and key technologies for operation control, Cyborg Bionic Syst. 5 (2024) 89.
[8] F. Ding, R. Wang, T. Zhang, G. Zheng, Z. Wu, S. Wang, Real-time trajectory planning and tracking control of bionic underwater robot in dynamic environment, Cyborg Bionic Syst. 5 (2024) 112.
[9] H. Chu, X. Pan, J. Jiang, X. Li, L. Zheng, Adaptive and robust channel estimation for IRS-aided millimeter-wave communications, IEEE Trans. Veh. Technol. (2024).
[10] Y. Ma, T. Li, Y. Zhou, L. Yu, D. Jin, Mitigating energy consumption in heterogeneous mobile networks through data-driven optimization, IEEE Trans. Netw. Serv. Manag. (2024).
[11] M. Zhou, et al., Reliability enhancement for V2V communications: via AF relay versus via passive RIS, IEEE Trans. Commun. (2024).
[12] J. Zhuang, Y. Zheng, B. Guo, Y. Yan, Globally deformable information selection transformer for underwater image enhancement, IEEE Trans. Circuits Syst. Video Technol. (2024).
[13] J. Luo, Y. Chen, M. Wu, Y. Yang, A survey of routing protocols for underwater wireless sensor networks, IEEE Commun. Surv. Tutor. 23 (1) (2021) 137–160.
[14] S. Gupta, N.P. Singh, Underwater wireless sensor networks: a review of routing protocols, taxonomy, and future directions, J. Supercomput. 80 (4) (2024) 5163–5196.
[15] F. Jiang, T. Li, X. Lv, H. Rui, D. Jin, Physics-informed neural networks for path loss estimation by solving electromagnetic integral equations, IEEE Trans. Wirel. Commun. (2024).
[16] G. Sun, Y. Zhang, H. Yu, X. Du, M. Guizani, "Intersection fog-based distributed routing for V2V communication in urban vehicular ad hoc networks,", IEEE Trans. Intell. Transp. Syst. 21 (6) (2019) 2409–2426.
[17] G. Sun, L. Song, H. Yu, V. Chang, X. Du, M. Guizani, V2V routing in a VANET based on the autoregressive integrated moving average model, IEEE Trans. Veh. Technol. 68 (1) (2019) 908–922, https://doi.org/10.1109/TVT.2018.2884525.
[18] P. Mehta, B.S. Yildiz, S.M. Sait, A.R. Yildiz, Hunger games search algorithm for global optimization of engineering design problems, Mater. Test. 64 (4) (2022) 524–532.
[19] A. Faramarzi, M. Heidarinejad, S. Mirjalili, A.H. Gandomi, Marine predators algorithm: a nature-inspired metaheuristic, Expert Syst. Appl. (2020), https://doi.org/10.1016/j.eswa.2020.113377.
[20] Y. Gong, H. Yao, A. Nallanathan, Intelligent sensing, communication, computation and caching for satellite-ground integrated networks, IEEE Netw. (2024).
[21] Y. Gong, D. Yu, X. Cheng, C. Yuen, M. Bennis, M. Debbah, Computation offloading and quantization schemes for federated satellite-ground graph networks, IEEE Trans. Wirel. Commun. (2024).
[22] L. Wang, et al., Research on high precision localization of space target with multi-sensor association, Opt. Lasers Eng. 184 (2025) 108553.
[23] B. Chen, J. Hu, Y. Zhao, B.K. Ghosh, Finite-time observer based tracking control of uncertain heterogeneous underwater vehicles using adaptive sliding mode approach, Neurocomputing 481 (2022) 322–332.

[24] B. Saemi, F. Goodarzian, Energy-efficient routing protocol for underwater wireless sensor networks using a hybrid metaheuristic algorithm, Eng. Appl. Artif. Intell. 133 (2024) 108132.

[25] P. Jiang, Y. Feng, F. Wu, Underwater sensor network redeployment algorithm based on wolf search, Sensors 16 (10) (2016) 1754.

[26] B. Ragavi, V. Baranidharan, K.Ramash Kumar, A novel hybridized cluster-based geographical opportunistic routing protocol for effective data routing in underwater wireless sensor networks, J. Electr. Comput. Eng. 2023 (1) (2023) 5567483.

[27] B.M. Sahoo, H.M. Pandey, T. Amgoth, GAPSO-H: a hybrid approach towards optimizing the cluster based routing in wireless sensor network, Swarm Evol. Comput. 60 (2021) 100772.

[28] A. Wahid, S. Lee, D. Kim, An energy-efficient routing protocol for UWSNs using physical distance and residual energy. OCEANS 2011 IEEE-Spain, IEEE, 2011, pp. 1–6.

[29] X. Xiao, H. Huang, A clustering routing algorithm based on improved ant colony optimization algorithms for underwater wireless sensor networks, Algorithms 13 (10) (2020) 250.

[30] Y. Hu, Z. Bie, T. Ding, Y. Lin, An NSGA-II based multi-objective optimization for combined gas and electricity network expansion planning, Appl. Energy 167 (2016) 280–293.

[31] M. Ali, "Nature Inspired Data Dissimination Routing Protocol for Wireless Sensor Networks," 2023.

[32] D. Anuradha, N. Subramani, O.I. Khalaf, Y. Alotaibi, S. Alghamdi, M. Rajagopal, Chaotic search-and-rescue-optimization-based multi-hop data transmission protocol for underwater wireless sensor networks, Sensors 22 (8) (2022) 2867.

[33] R.D. Jalal and S.A. Aliesawi, "Enhancing TEEN Protocol using the Particle Swarm Optimization and BAT Algorithms in Underwater Wireless Sensor Network," in *2023 15th International Conference on Developments in eSystems Engineering (DeSE)*, IEEE, 2023, pp. 504–510.

[34] X. Zhang, D. Hou, Z. Xiong, Y. Liu, S. Wang, Y. Li, EALLR: energy-aware low-latency routing data driven model in mobile edge computing, IEEE Trans. Consum. Electron. (2024).

[35] Y. Yang, H. Chen, A.A. Heidari, A.H. Gandomi, Hunger games search: visions, conception, implementation, deep analysis, perspectives, and towards performance shifts, Expert Syst. Appl. 177 (2021) 114864.

[36] G. Sun, Y. Zhang, D. Liao, H. Yu, X. Du, M. Guizani, Bus-trajectory-based street-centric routing for message delivery in urban vehicular ad hoc networks, IEEE Trans. Veh. Technol. 67 (8) (2018) 7550–7563, https://doi.org/10.1109/TVT.2018.2828651.

[37] M. Elhoseny, R.S. Rajan, M. Hammoudeh, K. Shankar, O. Aldabbas, Swarm intelligence–based energy efficient clustering with multihop routing protocol for sustainable wireless sensor networks, p. 1550147720949133, Int. J. Distrib. Sens. Netw. 16 (9) (2020), p. 1550147720949133.

[38] J.-Y. Xia, S. Li, J.-J. Huang, Z. Yang, I.M. Jaimoukha, D. Gündüz, "Metalearning-based alternating minimization algorithm for nonconvex optimization,", IEEE Trans. Neural Netw. Learn. Syst. 34 (9) (2022) 5366–5380.

[39] A. Mohammadzadeh, H. Taghavifar, Y. Zhang, W. Zhang, A fast nonsingleton type-3 fuzzy predictive controller for nonholonomic robots under sensor and actuator faults and measurement errors, IEEE Trans. Syst. Man, Cybern. Syst. (2024).

[40] L. Yin, et al., U-Net-STN: a novel end-to-end lake boundary prediction model, Land 12 (8) (2023) 1602.

[41] L. Yin, et al., U-Net-LSTM: time series-enhanced lake boundary prediction model, Land 12 (10) (2023) 1859.

[42] S.N. Sajedi, M. Maadani, M.Nesari Moghadam, F-LEACH: a fuzzy-based data aggregation scheme for healthcare IoT systems, J. Supercomput. 78 (1) (2022) 1030–1047.

[43] S. Tamizharasu, P. Kalpana, An intelligent AODV routing with energy efficient weight based clustering algorithm (EEWCA) in wireless Ad hoc network (WANET), Wirel. Netw. 29 (6) (2023) 2703–2716.

[44] Q. Zhou, B. Sun, Adaptive K-means clustering based under-sampling methods to solve the class imbalance problem, Data Inf. Manag. (2023) 100064.

[45] S. He, Q. Li, M. Khishe, A. Salih Mohammed, H. Mohammadi, M. Mohammadi, The optimization of nodes clustering and multi-hop routing protocol using hierarchical chimp optimization for sustainable energy efficient underwater wireless sensor networks, Wirel. Netw. 30 (1) (2024) 233–252.

[46] A. Mohammadzadeh, H. Taghavifar, C. Zhang, K.A. Alattas, J. Liu, M.T. Vu, A non-linear fractional-order type-3 fuzzy control for enhanced path-tracking performance of autonomous cars, IET Control Theory Appl. 18 (1) (2024) 40–54.

[47] A. Mohammadzadeh, C. Zhang, K.A. Alattas, F.F.M. El-Sousy, M.T. Vu, "Fourier-based type-2 fuzzy neural network: Simple and effective for high dimensional problems,", Neurocomputing 547 (2023) 126316.

[48] S.-R. Yan, W. Guo, A. Mohammadzadeh, S. Rathinasamy, Optimal deep learning control for modernized microgrids, Appl. Intell. 53 (12) (2023) 15638–15655.

[49] A. Manjeshwar and D.P. Agrawal, "TEEN: ARouting Protocol for Enhanced Efficiency in Wireless Sensor Networks.," in *ipdps*, 2001, p. 189.

[50] S. Singh, A. Malik, R. Kumar, Energy efficient heterogeneous DEEC protocol for enhancing lifetime in WSNs, Eng. Sci. Technol. Int. J. 20 (1) (2017) 345–353.