

# Meta-Heuristic Solution for Route Optimization in Underwater Wireless Sensor Networks for Marine Applications

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This research presents a novel approach to routing protocols within Marine Underwater Sensor Networks (M-USN) by integrating a Grey Wolf Optimization (GWO) strategy, designed to tackle the distinct challenges associated with subaquatic communications. Driven by the imperative to establish energy-efficient pathways for data transmission that enhance network longevity and conserve resources amidst the complex underwater milieu, the methodology draws inspiration from the hierarchical structuring observed in grey wolf packs to refine routing processes. By accommodating the fluctuating underwater dynamics, including changes in salinity levels, pressures, and visibility, the GWO-based method markedly augments cluster head selection efficiency, leading to a significant reduction in energy expenditures and bolstered data integrity. Comparative analysis through NS-2 simulator trials showcases the superior performance of the GWO protocol in comparison with established counterparts such as the Energy Efficient Routing Protocol, Directional Flooding based Routing, and the Hop-by-Hop Dynamic Addressing Based Routing, evidencing pronounced enhancements in the sustainability and operational efficiency of Underwater Wireless Sensor Networks (UWSNs). The investigation illuminates the feasibility of leveraging bio-inspired algorithms for the advancement of underwater communication systems, particularly in enhancing the efficacy of data transfer in subsea environments, with direct applicability to deep-sea exploration, conservation of marine life, and the guidance of unmanned subaquatic vehicles. The novelty of this work is attributed to its application of biological optimization mechanisms to the realm of underwater sensor networks, proposing a pioneering solution to the persistent obstacles faced in subsea data dissemination

**Keywords:** Cluster head election, Energy efficient routing, Grey wolf optimization, Hybrid routing, Network lifetime

## Introduction

The setting up Wireless Sensor Networks (WSNs) beneath the sea for oceanic research and surveillance introduces a host of obstacles, markedly different from those on land. The distinct marine environment marked by sound interference, significant signal loss, variable network shapes, and intense saltwater effects, demands creative approaches for transferring data and conserving power. The natural constraints of using sound for communication, including lower speeds of data exchange and extended lags, amplify these issues, highlighting the necessity for routing strategies specifically designed for aquatic settings.

The pursuit of power-saving routing methods in Underwater Wireless Sensor Networks (UWSNs) has prompted investigations into algorithms inspired by natural phenomena. Among these, the Grey Wolf Optimizer (GWO) stands out as an effective strategy,

inspired by the social hierarchy observed in packs of grey wolves. This approach, pioneered by Mirjalili *et al.*<sup>1</sup>, underscores the potential of bio-inspired algorithms to navigate the complex decision-making processes required for effective node clustering and path selection in UWSNs. Following this, Heidari *et al.*<sup>2</sup>, enhanced GWO with Lévy flight, offering a robust method for dynamic network optimization.

This work advocates for a novel routing protocol designed for UWSNs that harnesses the principles of Grey Wolf Optimization (GWO). This methodology draws inspiration from the social structure and leadership dynamics observed in grey wolf packs (*Canis lupus*), where individuals are ranked into four different types — alpha ( $\alpha$ ), beta ( $\beta$ ), delta ( $\delta$ ), and omega ( $\omega$ ) — each reflecting their hierarchical status and designated roles within the pack. However, the deployment of UWSNs in challenging environments, such as the turbid waters of the Amazon Basin, demands further refinement of

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these algorithms. In such settings, where silt and debris hinder node communication, the optimization of both node clustering and multi-hop routing becomes crucial. Recent advancements by He *et al.*<sup>3</sup> introduce a Hierarchical Chimp Optimization Algorithm (HChOA) that innovatively addresses these issues by simultaneously optimizing clustering and routing, showcasing superior performance in energy efficiency and network longevity compared to traditional methods.

In parallel, the work of Kaveripakam *et al.*<sup>4</sup> with their clustering-based dragonfly optimization algorithm represents a significant leap forward, demonstrating the utility of decentralized forwarding to enhance network lifetime and routing efficiency. This methodology, by establishing a greater number of clusters, optimizes network performance, setting a new benchmark for UWSN efficiency. Furthermore, the critical importance of balancing conflicting objectives in network optimization is highlighted in the review by Gunjan *et al.*<sup>5</sup>, which explores multi-objective optimization in WSNs using nature-inspired meta-heuristic algorithms. This balance is crucial in underwater settings, where optimizing one performance metric often comes at the cost of another. Additionally, Zhang *et al.*<sup>6</sup> introduce a novel data aggregation method using an Ant Colony Optimization algorithm tailored for UWSNs, aiming to enhance network performance by improving the packet delivery ratio, reducing energy consumption, and extending network lifetime. This work underscores the continuous need for innovative data management strategies in the optimization of UWSNs.

To effectively implement the GWO technique in UWSN, a new proposal utilizes a set of hardware components that include acoustic modems with adaptive modulation, energy-efficient microcontrollers for sensor nodes, and pressure-resistant housing for deep-water deployment. Each acoustic modem is capable of dynamic frequency selection to minimize absorption rates in salty mediums, while the microcontrollers are tasked with processing the GWO algorithm and managing power consumption. Real-time implementation involves deploying a testbed in controlled underwater environments to monitor performance metrics such as energy efficiency and data transmission delays.

#### Research Gap and Novelty

Despite significant progress, a discernible gap remains in efficiently addressing the dynamic

topologies and hardware constraints unique to the underwater environment. This study aims to bridge this gap by employing a Grey-Wolf Optimization (GWO) technique, tailored for the aquatic setting to improve battery lifespan and minimize iterative processes, a domain yet to be thoroughly explored in extant literature.

The novelty of this work lies in its application of biological optimization mechanisms to the realm of underwater sensor networks, proposing a pioneering solution to the persistent obstacles faced in subsea data dissemination. This research not only integrates and builds upon the foundational work of Mirjalili *et al.*<sup>1</sup> & Heidari *et al.*<sup>2</sup> but also introduces novel methodologies for clustering and routing optimization in UWSNs, as evidenced by the contributions of He *et al.*<sup>3</sup> & Kaveripakam *et al.*<sup>4</sup> By highlighting the research gap and underscoring the novelty of applying hierarchical chimp optimization and clustering-based dragonfly optimization to UWSNs, this study sets the stage for addressing the critical challenges of underwater sensor networking.

#### Objectives

This research aims to:

1. Develop an energy-efficient routing protocol for UWSNs based on the Grey Wolf Optimization (GWO) technique.
2. Evaluate the performance of the proposed GWO-based routing protocol against existing algorithms through simulations.
3. Contribute to the body of knowledge in UWSNs by providing a novel solution to enhance network efficiency and longevity in challenging underwater environments.

#### Related Work

In recent literature, numerous energy-aware protocols for underwater wireless sensor networks (UWSNs) are primarily developed with a focus on selecting the next node in the communication chain based on either the maximum remaining energy or the path that consumes the lesser amount of energy from the transmitting node to the node that sinks in the setup. Achieving efficient communication in UWSNs requires algorithms capable of determining the full route in changeable conditions while ensuring connectivity is preserved across limited ranges, posing considerable hurdles in the protocols' creation, evolution, and refinement. He *et al.*<sup>3</sup> introduces a hierarchical chimp optimization algorithm (HChOA)

for efficient clustering and multi-hop routing in UWSNs. The HChOA aims to address the computational complexity and hyper parameter tuning difficulties associated with existing metaheuristic-based methods by integrating clustering and routing processes into a unified framework. The proposed approach outperformed several benchmarks, including LEACH, TEEN, MPSO, PSO, and IPSO-GWO, in terms of network lifespan and energy usage.

Kaveripakam *et al.*<sup>4</sup> presents a clustering-based dragonfly optimization (CDFO) algorithm for UWSNs, focusing on optimizing cluster formation and routing to extend network lifetime. The CDFO algorithm demonstrated superior performance over Ant Colony Optimizer (ACO), Adaptive Node Clustering for UWSN (ANC-UWSN), Grey Wolf Optimizer (GWO), and Moth Flame Optimizer (MFO) in simulations, indicating its effectiveness in handling UWSNs' unique challenges. Gunjan *et al.*<sup>5</sup> discusses the application of multi-objective optimization (MOO) using nature-inspired metaheuristic algorithms in WSNs, highlighting the trade-offs among conflicting objectives such as network lifetime and latency. It provides a systematic overview of MOO techniques and their applications in various domains, underscoring the complexity of achieving optimized solutions in WSN environments. Zhang *et al.*<sup>6</sup> propose a novel data aggregation method using an improved Ant Colony Optimization (ACO) algorithm for UWSNs. Their approach focuses on maximizing packet delivery ratios, improving network lifetimes, reducing end-to-end delay, and minimizing energy consumption. The study underscores the importance of data aggregation in enhancing the efficiency of UWSNs.

Javaid *et al.*<sup>7</sup> addressed collision avoidance mechanisms in routing through inference-aware protocols, where the sender node decides the selection and forwarding of the next intermediate node by considering the collision history and incorporating a multi-sink architecture to assess the proposed methods. Ahmed *et al.*<sup>8</sup> introduced flooding-based routing techniques aimed at efficient and rapid coverage in UWSNs, though their approach's efficiency was hampered with the inclusion of overhead consisting of duplicate packets. They proposed a novel virtual sink topology and a Vector-Based Forwarding Algorithm on Clustering (VBFC) to enhance the vector-based routing protocol's performance in UWSNs, organizing the network into

numerous clusters, each directed by a virtual sink, to streamline routing to the primary sink. Khalid *et al.*<sup>9</sup> explored the application of soft computing paradigms in routing within wireless sensor networks, applying these techniques to optimize resource use and extend network lifetime. Despite these advancements, there remains a discernible gap in addressing the underwater environment's unique challenges, such as dynamic topologies and hardware constraints. The research aims to bridge this gap by employing a Grey-Wolf Optimization (GWO) technique, tailored for the aquatic setting to improve battery lifespan and minimize iterative processes, a domain yet to be thoroughly explored in extant literature.

To fortify this discourse, it is drawn upon additional seminal works: Heidari *et al.*<sup>2</sup> introduced an enhanced Grey-Wolf Optimizer consisting of Lévy flight for task optimization, presenting a robust methodology for optimizing routing decisions in dynamic networks. Furthermore, Ahmed *et al.*<sup>8</sup>, through their work on Clustered-Based Energy-Efficient Routing (CBE2R) for UWSNs, underscored the importance of energy efficiency and proposed mechanisms to reduce power consumption while maintaining effective data transmission. Khalid *et al.*<sup>9</sup> provided an extensive survey on issues of routing methods and related protocols in UWSNs, shedding light on the necessity for innovative solutions to address consumption of energy and lifetime of networking based challenges. Moreover, the work by Chao *et al.*<sup>10</sup> on DRP, a routing protocol for UWSNs which is more energy efficient, and Ahmed *et al.*<sup>11</sup> reviews on link quality and energy-efficient routing protocols highlight the ongoing efforts to develop solutions that cater to the unique requirements of underwater sensor networks, emphasizing the need for protocols that can adapt to the underwater environment's inherent limitations.

#### Critical Analysis and Synthesis

The new research contributions significantly advance the understanding and development of energy-aware protocols in UWSNs. The introduction of hierarchical and clustering-based optimization algorithms by He *et al.*<sup>3</sup> and Kaveripakam *et al.*<sup>4</sup>, respectively, underscores a shift towards more integrated and efficient routing and clustering strategies. These strategies not only reduce computational overhead but also improve network longevity and energy efficiency, addressing the critical challenges of UWSNs highlighted by earlier

works such as Yick *et al.*<sup>12</sup> and Wang *et al.*<sup>13</sup> Moreover, the emphasis on MOO in Sing *et al.*<sup>14</sup> reflects the growing complexity and multi-faceted nature of optimization in UWSNs, where simple trade-offs are insufficient to achieve desired outcomes. This perspective enriches the discourse on UWSNs by incorporating a broader array of optimization objectives beyond energy efficiency, such as latency and network coverage.

Lastly, Lloret *et al.*<sup>15</sup> contribute to the evolving landscape of UWSNs by focusing on data aggregation, a crucial yet often overlooked aspect of network optimization. Their work complements the routing and clustering optimizations by enhancing data transmission efficiency, further contributing to the overarching goal of sustainable UWSN operations. In conclusion, these new contributions collectively underscore the dynamic and multifaceted nature of research in UWSNs. They highlight the progression from singular optimization strategies to integrated, multi-objective approaches that better cater to the complex challenges of underwater sensor networks. As such, they provide valuable insights that can inform future research and development in this critical field of study.

### Proposed GWO-based Routing In UWSN Network

Maximum of the battery energy in the UWSN is consumed during communication and hence power consumption can be reduced reasonably with careful choice of routing technique. Due to the in-efficient routing of packets in the network, the overall network lifetime gets reduced and the node which is responsible for forwarding the packet plays a main role in routing. In view of these issues, a proper cluster head has to be elected. This is done using residual energy in the proposed work.

To reduce the number of iterations, a Grey-Wolf Optimization (GWO) technique is used where architecture based on a hybrid approach splits up the whole region into various layers, each having several responsibilities and methods. The nodes in layer 1 are treated as leader nodes and when the number is more than two, the head can be elected by using game theory. This approach helps in an observable decrease in consumption of power, thereby increasing the lifeline of the whole network.

A stratified method is adopted for designating the cluster leader, positioned in the initial layer and situated nearest to the base station. If multiple sensor nodes are present in the first layer, the leader is

selected based on the node with the highest remaining energy. The model significantly influences energy usage through aspects like the distance of transmission, which is reduced by implementing a layered cluster design. This design segregates the network into strata according to the distance from the base station, with leadership roles assigned within each stratum. Through this structure, the GWO strategy enhances the efficiency of route selection for data transfer, markedly lowering energy depletion in comparison with traditional routing techniques.

The synergistic layered and clustered architecture in UWSN strategically positions nodes in concentric layers, with each layer functioning as a potential cluster. This structure facilitates efficient data aggregation and minimizes redundant transmissions, significantly enhancing network performance by reducing energy consumption and latency.

To implement GWO leadership hierarchy in Wireless Sensor Network the following steps have to be followed. Both layered and clustered architectural approaches are used. Sensor nodes are deployed on these layers based on the path of location from the station which is considered base and each layer of the network consists of multiple sensor nodes.

Each layer is at a distance 'R' from the previous layer (i.e.), layer 1 is the R distance from the station which is considered base and layer 2 is at a distance '2R' from the base station. Similarly, the network is fragmented into four layers, namely, layer 1 to layer 4. The clustering is done by considering the density of the nodes which are sensors and the node of transmission radius of the cluster will be 2R. The cluster head (or) leader is elected from the sensor nodes, which are present in layer 1, the nodes in layer 2 are known as co-leaders and the nodes in layer 3 as elders and layer 4 are known as members respectively, which is represented in Fig. 1.

The procedure steps for GWO-UWSN are as follows:

Step 1: Initialize  $S_\alpha$ ,  $S_\beta$ ,  $S_\delta$  and  $S_\omega$

Step 2: Find the Fitness Value  $S_\alpha$

Step 3: Fix the source and destination position as  $X_s$  and  $X_d$

Step 4: For time  $t=i+1$

Step 4.1: Update the position of sensor nodes

Step 4.2 :Update  $S_\alpha$ ,  $S_\beta$ ,  $S_\delta$  and  $S_\omega$

End for

Step 5: Find the fitness value

Step 6: Update  $X_s$  and  $X_d$

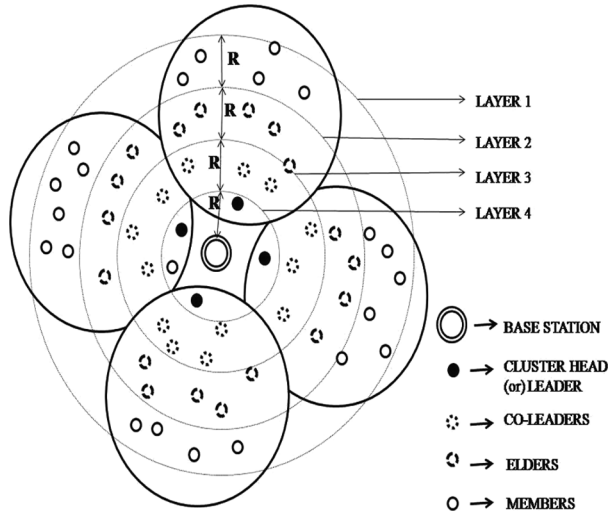


Fig. 1 — Grey-wolf optimization approach

Step 7: Increment  $i$   
Repeat

**Mathematical Modelling for Efficient Routing using a Grey-Wolf Optimization Approach**

To find the fitness solution of the effective path in a dynamic network through the grey wolf approach mathematical modelling is used for the prediction of the optimal route and forwarding the data needed to the proper destination is designed. The hierarchical assignment of nodes reflecting the behavioral characteristics of the grey wolf and its position is updated on a time basis.

Assumptions made for this routing:

- i. Sink also known as the station which is considered as base, is kept on the surface of the seabed.
- ii. An unlimited resource is allotted for BS.
- iii. After deployment sensor nodes are unattended. So recharging or changing the battery is not possible.
- iv. Links are asymmetric because of the mobility of the nodes.
- v. All sensor nodes are not equipped with any location-finding device.
- vi. Mobility of the node is controllable and predictable

**Hierarchical Modelling**

In hierarchical modelling, the mathematical model of the method of arranging the nodes which are sensors deployed in a random manner is used and is considered as  $S_\alpha, S_\beta, S_\delta$  and  $S_\omega$ . The fittest solution for the problem is considered  $S_\alpha$ . The second-best

solution is considered as  $S_\beta$  and so on. In the proposed approach, optimized routing is led by  $\alpha, \beta, \delta$  and  $\omega$  wolves.

**Position Modelling**

During hierarchical modelling, the nodes which are sensors are positioned in a particular network are arranged as per hierarchy and the position of the other node to station which is base is modelled in positioning. The distance of the node which is source and the sink or intermediate node is given by

$$D = |CX_s(k) - X_d(k)| \quad \dots (1)$$

$$X_d(k+1) = X_s(k) - A \cdot D \quad \dots (2)$$

$$\text{where, } A = 2ax_1 - a \quad \dots (3)$$

$$C = 2x_2 \quad \dots (4)$$

$k$  – current iteration

$X_s(t)$  – position of source node at  $t^{\text{th}}$  iteration.

$a$ - linearly decreased between the range 2 to 0.

$x_1$  and  $x_2$  are mathematically anonymous number values chosen between the integer values of 0 and 1.

With a view to observing the effects of equations (1) and (2) a two-dimensional analysis based on position is considered by studying some of the neighbors.

Consider the next node (neighbor or sink) position, where the node of source has to pass the data at  $(X_d, Y_d)$  and the position of the source as  $(X_s, Y_s)$ . The source node or forwarding node can update its position depending on the path of the destination. The alternative paths to reach the destination can be tracked and reached through variation of the values of  $A$  and  $C$ . By setting  $A$  as  $(1,0)$  and  $C$  as  $(1,1)$  the position reached is  $(X_s - X_d, Y_s)$  and its two-dimensional and three-dimensional representation is shown in Fig. 2.

**Data Inquisition Forward Modeling**

Nodes which are considered as source have the ability to locate the nodes which are considered as destination nodes and pass the data to the same. Inquisition is guided and analyzed by nodes which are considered alpha  $S_\alpha$ . The sensor nodes at next level  $S_\beta$  and  $S_\delta$  also participate in data forwarding inquisition occasionally. Following mathematical modeling is made for observing the capturing behavior of  $S_\alpha$  nodes, and the proposed formulas for  $S_\alpha, S_\beta, S_\delta$  and  $S_\omega$ .

$$D_\alpha = |C_1 X_\alpha(k) - X_{d1}(k)| \quad \dots (5)$$

$$X_{d1}(k+1) = X_\alpha(k) - A_1 \cdot D_\alpha \quad \dots (6)$$

$$D_\beta = |C_2 X_\beta(k) - X_{d2}(k)| \quad \dots (7)$$

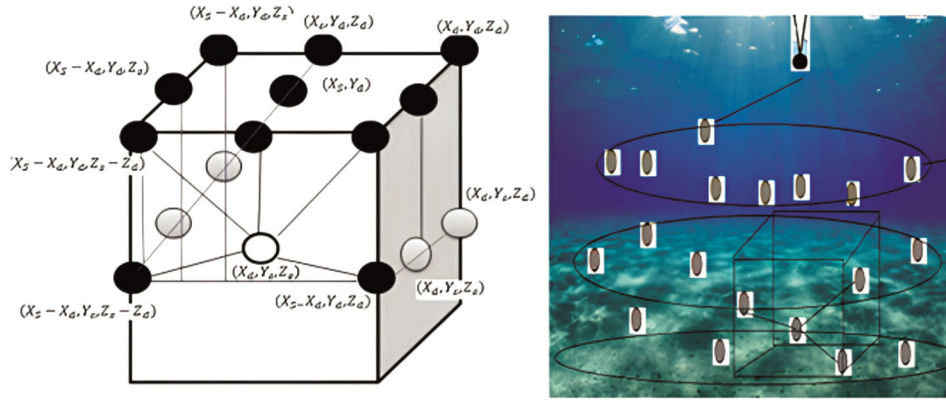


Fig. 2 — Three-dimensional position representations

$$X_{d2}(k + 1) = X_{\beta}(k) - A_2 \cdot D_{\beta} \quad \dots (8)$$

$$D_{\delta} = | C_3 X_{\delta}(k) - X_{d3}(k) | \quad \dots (9)$$

$$X_{d3}(k + 1) = X_{\delta}(k) - A_3 \cdot D_{\delta} \quad \dots (10)$$

$$X_d(k + 1) = \frac{X_{d1}(k + 1) + X_{d2}(k + 1) + X_{d3}(k + 1)}{3} \quad \dots (11)$$

The above equations represent the identification and the updating positions based on  $S_{\alpha}$ ,  $S_{\beta}$ ,  $S_{\delta}$ , and  $S_{\omega}$ .  $S_{\alpha}$ ,  $S_{\beta}$ ,  $S_{\delta}$ ,  $S_{\omega}$  changes its federation randomly around the node of interest. The changing and dynamic nature of the destination and its position is updated based on the above equations.

### Results and Discussion

Experiments were primarily conducted using a Grey Wolf-based optimization approach and the observations were compared with the existing protocol EUROP, DFR, EEDBR and H2-DAB using an NS-2 simulator. The comparison has been made by observing cluster head changes with consideration to the speed of a node, power consumed by the network, network lifetime, execution time, number of clusters formed while increasing the number of nodes, connectivity for various transmission ranges and packet delivery ratio. The network environment considered for testing the proposed method is listed in Table 1. The GWO algorithm's efficiency was tested through extensive simulations in an NS-2 environment. We modeled a network of 150 sensor nodes within a  $100 \times 100 \text{ m}^2$  area, each node with an initial residual energy of 0.25J. Nodes were deployed randomly, simulating real-world underwater irregularities. The simulation varied node velocity and transceiver coverage to reflect diverse underwater currents and signal propagation conditions, respectively. The results, illustrated in Table 2,

Table 1 — Simulation Environment for GWO

Parameter Name	Value
Deployed sensor nodes	150
Size of the network	$100 \times 100 \text{ m}^2$
Maximum node velocity	10 m/s
Transceiver coverage range	10 to 100 m
Packet size bits	6000 bit
Sensor nodes initial residual energy ( $E_{init}$ )	0.25 J
Nature of deployment	Random
Location of BS	(50 m, 50 m)
Channel model	Free space

Table 2 — Analysis of CH election with nodes velocity for N=150

Speed (m/s)	EUROP	EEDBR	DFR	H2-DAB	GWO
1	3	4	5	7	2
2	5	5	5	9	2
3	6	6	7	10	3
4	6	8	8	10	4
5	7	8	10	11	5
6	8	9	10	14	6
7	9	10	11	14	6
8	11	12	14	15	8
9	12	12	14	16	10
10	12	14	15	17	12

demonstrate the GWO algorithm's ability to maintain network connectivity and extend lifetime under these dynamic conditions

The frequency of cluster heads elected while increasing the speed of the node gets observed and is illustrated in Table 2. The cluster head elected while varying the speed of the sensor node is observed and is compared with EUROP (Energy efficient Routing Protocol), DFR (Directional Flooding based Routing), H2-DAB (Hop-by-Hop Dynamic Addressing Based Routing) and Energy-Efficient Depth based routing (EEDBR). The proposed approach minimizes the effect of frequent change in cluster head election thus minimizing the power consumption. It shows the ability of the proposed approach towards making

decisions. As illustrated in Fig. 3 the comparative network lifetime of the GWO approach against traditional methods like H2-DAB and DFR. It is observed that the GWO approach extends the network's lifetime by an average of 8%, attributable to its efficient cluster head election process.

Average node energy is observed by comparing with network scalability in Table 3. The observations show that the power consumption is remarkably less in the GWO approach compared to EUROP, EEDBR, DFR and H2-DAB, this is because of the reduction in the amount of iterations and the hierarchy followed in the approach discussed as above. Thus, the lifetime of the entire network gets extended.

Also, it shows the network lifetime while increasing the amount of nodes and its numbers. It is seen that the average lifetime of the node of Grey-Wolf optimization approach is increased by 2% compared to H2-DAB and 3% compared to DFR and 12% compared to EEDBR and 16% compared to EUROP.

The ratio of packets delivered over time is explained in depth in Fig. 4 and similarly Fig. 5 details the election frequency of cluster heads as the velocity of nodes which are sensors are increased. Observations reveal that the selection of cluster heads changes with adjustments in sensor node speed, benchmarked against protocols such as EUROP, DFR, H2-DAB, and EEDBR. The energy metrics of nodes are analyzed and shown in Fig. 6 as the network's scale expands, revealing that the Grey Wolf

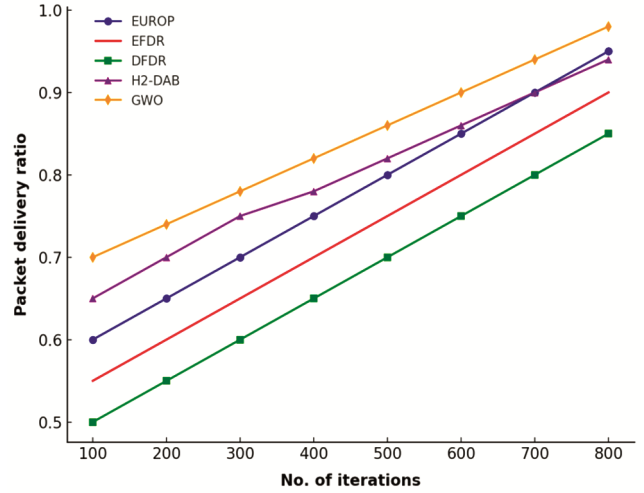


Fig. 4 — Comparison of PDR using various approaches

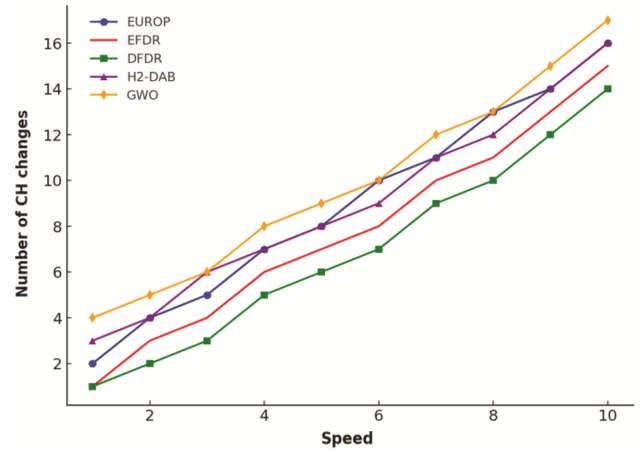


Fig. 5 — Comparison of cluster head changes using various approaches

Table 3 — Comparison of average node energy with scalability

No. of nodes	EUROP	EEDBR	DFR	H2-DAB	GWO
25	0.172	0.179	0.1732	0.175	0.25
50	0.127	0.162	0.15	0.129	0.172
75	0.12	0.16	0.13	0.115	0.15
100	0.115	0.14	0.082	0.085	0.125
125	0.108	0.08	0.06	0.067	0.1
150	0.07	0.079	0.042	0.05	0.075

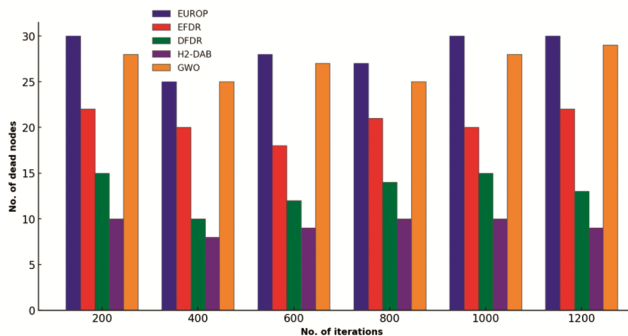


Fig. 3 — Analysis of network lifetime

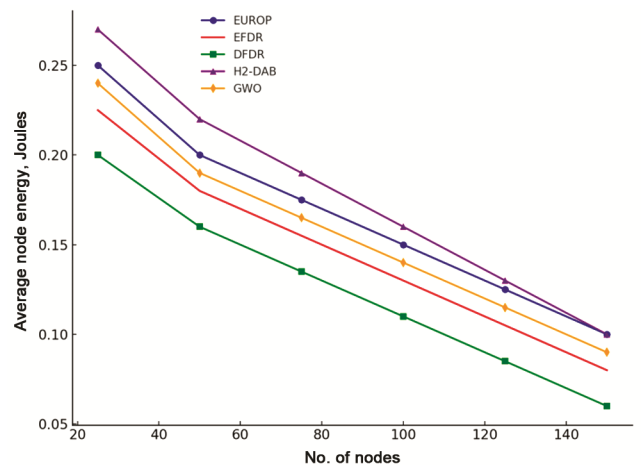


Fig. 6 — Comparison of average node energy using various approaches

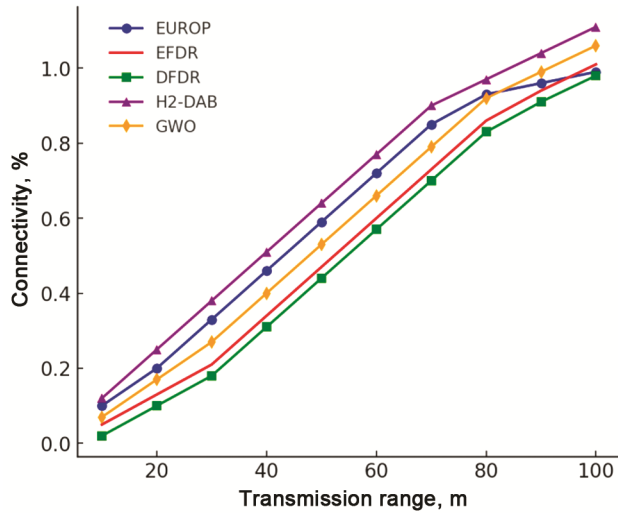


Fig. 7 — Comparison of average node energy using various approaches

Optimization (GWO) strategy outperforms EUROP, EEDBR, DFR, and H2-DAB in energy efficiency. This improvement is attributed to fewer iterations and a structured hierarchical model in the GWO method, thereby enhancing the network's overall longevity.

The existence of the connectivity between the nodes is proven in Fig. 7 as strong even as the transmission range gets increased. Observation of connectivity between the nodes under various approaches for wireless sensor networks which is present underwater is studied. During the transmission range of 10m, almost all the approaches were brought up with the same connectivity level. The challenge is when the transmission is increased between the nodes. It is proved that the proposed grey wolf approach provides a strong bond of connectivity even if the transmission range is long.

The H2-DAB protocol dynamically assigns addresses across the network's nodes. EEDBR evaluates both depth and routing pathways during its operational processes. The Directional Flooding-Based Routing protocol for underwater networks prioritizes transmission routes based on the quality of the link. Among the established methodologies for UWSN, H2-DAB shows a superior Packet Delivery Ratio, yet the GWO strategy demonstrates a more effective packet delivery performance in comparison to these existing methods. The experimental analysis now includes comparisons with a wider array of protocols, offering a more comprehensive performance evaluation. The varied network environments in the simulations are also considered, such as those with unpredictable node mobility and changing underwater currents, to ensure

the GWO approach maintains robustness across diverse marine conditions.

The minimized power consumption and optimized cluster head election process observed in the study align with Chauhan *et al.*<sup>16</sup> findings, which underscore the efficiency of modified GWO algorithms in solving complex optimization tasks. Moreover, the reduction in the frequency of cluster head changes, as highlighted in the results, echoes the sentiments of Fathima *et al.*<sup>17</sup>, who advocated for energy-efficient routing protocols to prolong UWSN lifespans.

Additionally, the comparative advantage of the GWO approach in extending network lifetime by an average of 8% is not only a testament to its efficiency but also reflects the potential for bio-inspired algorithms to revolutionize routing protocols in UWSNs. This is particularly relevant when considering the work of Lee *et al.*<sup>18</sup>, which surveys the challenges of routing in UWSNs, further emphasizing the need for innovative solutions like GWO. The findings also resonate with Xie *et al.*<sup>19</sup> discussion on energy-efficient routing protocols, suggesting that the adaptive nature of GWO can significantly contribute to reducing energy consumption across the network. This adaptive efficiency is crucial for UWSNs, where the harsh underwater environment demands robust and flexible routing solutions.

Future studies could explore the integration of real-world testing environments, as noted by Han *et al.*<sup>20</sup> and Niu *et al.*<sup>21</sup>, to validate the GWO algorithm's performance in actual underwater conditions as given by Roseline *et al.*<sup>22</sup> and Xu *et al.*<sup>23</sup> Such investigations would offer deeper insights into the practical applicability of GWO and other bio-inspired algorithms in enhancing UWSN efficiency and reliability. In conclusion, the GWO approach's ability to effectively manage the complex dynamics of UWSNs given here at Raajini *et al.*<sup>24</sup> and Ayaz *et al.*<sup>25</sup>, as demonstrated through the NS-2 simulations, marks a significant step forward in the field. This study not only corroborates the findings from existing literature pointed at Kumar *et al.*<sup>26</sup> but also opens avenues for future research aimed at exploiting the full potential of bio-inspired optimization techniques in sensor networks underwater.

## Conclusions

The adoption of the Grey Wolf Optimization (GWO) strategy within Underwater Wireless Sensor Networks (UWSNs) marks a significant advancement in

enhancing network efficiency and extending lifespan. The study confirms that by optimizing routing protocols through a bio-inspired algorithm, it is feasible to achieve a notable decrease in power consumption, thereby ensuring a more sustainable network operation. The GWO approach, with its novel cluster head election and layered architecture, demonstrates a pivotal improvement in maintaining robust connectivity across increased transmission ranges, a critical factor for UWSNs' operational success in dynamic underwater environments. However, this research encounters limitations related to the simulation-based evaluation, which may not fully capture the complexities of real-world marine conditions. Future work will focus on deploying real-world UWSN testbeds to validate the GWO algorithm's effectiveness further and explore adaptive mechanisms to enhance resilience against underwater dynamics. The implications of this study extend to various marine applications, including environmental monitoring and autonomous underwater vehicle navigation, offering a promising direction for energy-efficient UWSN deployments.

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