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Research Article

Secured Multi-Objective Optimisation-Based Protocol for Reliable Data Transmission in Underwater Wireless Sensor Networks

Mostfa Albdair [1,3], Zainab Rustum mohsin[2], Ahmed Saihood,*[2], Aqeel M. Hamad[2], Aqeel Sahi [4]

[1] *Alayen Iraqi University, Engineering Technical College, Iraq.*
[2] *Faculty of Computer Science and Mathematics, University of Thi-Qar, Nasiriyah 00964, Thi-Qar, Iraq.*
[3] *Misan University, College of Engineering, Iraq.*
[4] *School of Mathematics, Physics and Computing, University of Southern Queensland, QLD 4350, Australia.*

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ABSTRACT

Underwater wireless sensor network (UWSN) requirements have increased beyond applications in environmental monitoring and underwater exploration to military surveillance. The complex underwater environment raises many challenges due to high propagation delays, limited bandwidth, high error rates, and dynamic underwater currents. Most traditional clustering algorithms do not consider the multifaceted requirements of UWSNs. In most cases, a single objective is optimised at the cost of other essential factors, such as energy consumption, network robustness, and data transmission reliability. This paper proposes a new UWSN protocol based on the tiger beetle optimisation (TBO) algorithm for multiobjective K-means clustering (TBO-MOK). The protocol comprises adaptive search procedures motivated by tiger beetle hunting behaviors and lightweight AES-based encryption for data security. TBO-MOK is excellent in multiobjective optimisation since it simultaneously considers performance metrics of more than one aspect. Many problems are resolved by TBO-MOK, which optimises all the involved performance metrics to provide balanced energy usage and robust communication links. Comprehensive simulations demonstrate that TBO-MOK outperforms the traditional LEACH, PSO, and GA approaches in grossly enhancing network lifetime, energy efficiency, load balancing, and data transmission reliability. These results show the potential of TBO-MOK to provide a more effective and resilient solution for UWSNs.

1. INTRODUCTION

Another crucial technology has emerged as UWSNs for environmental, underwater exploration, and military surveillance applications. The different nodes of these networks are engaged in water to gather information and transmit it back to the stations on the surface or to other nodes, as depicted in Figure 1. Additionally, a new environment presents the challenges of high propagation delays, limited bandwidth, and high error rates. In contrast, efficient and reliable data transmission protocols should be expanded to protect against robust variability in water currents and guarantee long-lasting processes. UWSNs are considered critical for several applications, such as environmental monitoring, underwater exploration, and military surveillance. These networks contain sensor nodes distributed underwater to collect and transfer data to stations. Despite their growing significance, UWSNs face challenges due to the essence of the underwater environment. High propagation delays, limited bandwidth, and high error rates cause data transmission complexity, whereas dynamic underwater currents exacerbate network instability. This makes the development of efficient and reliable protocols for UWSNs a pressing research demand. [1].

Conventional clustering algorithms, such as K-means [2], [3], cannot cope with the complex conditions of UWSNs. Traditional algorithms have a monoobjective function; the objective is to reduce the distance between nodes and cluster centers without considering other important factors—energy consumption, network robustness, and data transmission reliability [4], [5].

Genetic algorithms [6] tend to imitate the process of natural selection and attempt to solve complex optimisation issues by maturing solutions over generations, making them practical for multiobjective optimisation in UWSNs in terms of energy

*Corresponding author. Email: ahmed.alisiehood@utq.edu.iq

efficiency, robustness, and reliability of data transmission. Particle swarm optimisation, which is illuminated by the social manners of birds and fish, modifies parameters around candidate solutions, improving those iteratively balances different performance metrics in the UWSN. Multiobjective evolutionary algorithms, such as NSGA-II, optimise multiple objectives simultaneously and allow the Pareto optimal solutions in UWSNs to be found. Simulated annealing (SA) [9] is a probabilistic technique that approximates the global optimum by incorporating multiple performance criteria into the cost function. Ant colony optimisation (ACO) [10][39], inspired by ant foraging behavior, finds optimal graph paths, can minimise energy consumption, and can maximise network lifetime in UWSNs.

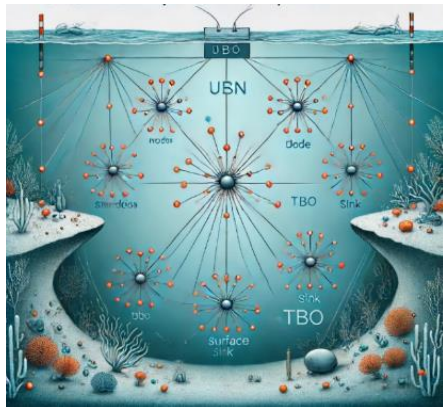


Fig. 1. UWSN environment

Multiobjective optimisation techniques can overcome these limitations since several performance metrics can be optimised simultaneously for more efficient and resilient network designs. Nonetheless, they may be very computationally intensive, resulting in high computational overhead. Most of them suffer from slow convergence speed and usually become stuck in some local optima. Maintaining diversity in the solutions and scalability with increasing objectives is a problem.

Classic clustering algorithms, such as K-means clustering, focus on mono-objective optimisation, often prioritising the immediacy between nodes and cluster centers. However, these techniques account for critical factors such as energy consumption, network robustness, and data transmission reliability. While multiobjective algorithms such as particle swarm optimisation and genetic algorithms often suffer from slow convergence, local optima, and high computational overhead, they are less beneficial for dynamic and resource-constrained underwater environments. Acquiring a balanced tradeoff between energy efficiency, load balancing, and connectivity remains a significant burden for UWSN protocols.

Tiger beetle optimisation (TBO) [11] is a bioinspired optimisation algorithm modelled after tiger beetle hunting and survival strategies and is renowned for its exceptional speed, agility, and adaptability in dynamic environments. Unlike traditional optimisation methods, which often focus on a single objective, TBO excels in multiobjective optimisation by simultaneously considering multiple performance metrics. It achieves this by employing a population-based search mechanism, where individual solutions, akin to beetles, explore the search space guided by adaptive strategies that balance exploration and exploitation. Owing to its ability to self-adjust its search patterns, TBO is efficient for complex, multidimensional problems and, therefore, highly suitable for the intricate requirements of UWSNs. It outperforms state-of-the-art, existing LEACH and PSO- and GA-based methods that easily achieve trade-offs in a multiobjective scenario by optimising multiobject energy consumption, network lifetime, and data transmission reliability. TBO thus ensures, with its adaptiveness and robustness, the equal distribution of energy expenditure across a network for these sensor nodes so that more resistance to node failures is developed and reliable links are maintained for communication, providing an overall more effective solution for UWSNs.

This paper proposes the TBO-based multiobjective K-means clustering (TBO-MOK) protocol to address the shortcomings in reliable data transmission within UWSNs. Inspired by the exceptional hunting and survival strategies of one of the fastest-moving and most adaptable insects, our approach is based on TBO. The TBO algorithm's ability to navigate effectively and find optimality within complex, multidimensional search spaces represents a fitting solution for solving the multiobjective optimisation required in UWSNs.

The TBO-MOK protocol addresses some critical failures in existing processes for simultaneously optimising multiple performance metrics, such as energy consumption, network lifetime, and data transmission reliability. Indeed, traditional clustering algorithms such as K-means typically cannot handle these conflicting objectives, resulting in suboptimal network performance. However, TBO-MOK is enabled with a population-based search mechanism that allows adaptive balancing in exploring and exploiting the solution space. It makes energy usage uniform throughout the network, preventing nodes from failing early and preventing the collapse of communication links in dynamic underwater environments. By handling these critical issues, the TBO-MOK protocol significantly enhances the overall efficiency and reliability of UWSNs compared with existing methods such as LEACH, PSO, and the GA.

This study combines the use of the TBO algorithm with UWSNs for the first time and performs multiobjective optimisation of energy efficiency, load balancing, and connectivity. In the case of conventional approaches such as PSO or GA, TBO presents a bioinspired mechanism that balances exploration and exploitation. Moreover, the combination of AES-based encryption and dynamic key management via elliptic curve cryptography (ECC) provides secure and efficient data transmission, enabling the handling of security intervals in prior studies.

In this study, energy efficiency, load balancing, and connectivity performance are managed, and critical security problems intrinsic to UWSNs are addressed. By combining AES-based encryption and ECC-based dynamic key control, the proposed TBO-MOK protocol provides secure and reliable data transmission, reducing exposures such as eavesdropping and tampering. This work provides a comprehensive method that balances security and performance, making it practical for real-world applications.

This investigation's dual focus is to optimise the performance and improve the security of UWSNs, which are inclined toward unique exposures under dynamic underwater conditions. By combining cutting-edge encryption mechanisms and dynamic key management with a bioinspired optimisation framework, this work guarantees data confidentiality and integrity while maintaining energy efficiency and network robustness.

The main contributions of this article are as follows:

- A new protocol, TBO-MOK, is used for cluster identification, energy dissipation, and the selection of cluster heads in UWSNs. The protocol uses the strengths of the TBO algorithm's efficient adaptive searching to enhance performance and lifespan.
- Extensive evaluations compared TBO-MOK with the baseline LEACH, PSO, and GA methods. The results for critical metrics, such as network lifetime, energy consumption, load balancing, and data transmission reliability, showed improvements in the workings of TBO-MOK over other algorithms in most situations under study.
- A lightweight encryption mechanism based on the advanced encryption standard (AES) is integrated to ensure the confidentiality and integrity of fitness data during the clustering process in the TBO-MOK protocol for the UWSN.
- The strength and flexibility of the protocol for different conditions in UWSNs are demonstrated. The TBO-MOK protocol copes well with multiple contradictory goals and adapts to environmental changes.

Section 2 summarises the related articles regarding the routing protocols in WSNs and UWSNs. Section 3 details the proposed TBO-MOK protocol. This section elaborates on the fundamental aspects related to cluster identification, energy dissipation, and selection of a cluster head. Section 4 presents a complete performance evaluation of the proposed protocol through extensive simulations against traditional schemes such as LEACH, PSO, and the GA. The results are presented in Section 5, which outlines the vast improvements achieved by TBO-MOK in balanced workload distribution, enhanced connectivity, and energy efficiency. Finally, the conclusion in Section 6 summarises how the TBO-MOK protocol contributes to the area of UWSNs, reiterating its superiority over existing methods and its potential for future applications in various underwater sensing and monitoring scenarios.

2. RELATED WORKS

Different routing protocols have been suggested over the past few years to address the unique challenges of underwater wireless sensor networks. Notably, among them could be the stretched holding time difference (SHTD). This protocol prevents collisions and minimises energy consumption but demonstrates limited scalability and increases delay in the case of an extended network [12]. Another technique combines multiple sinks for secure data aggregation and authentication in cluster-based underwater vehicular wireless sensor networks. Although this technique optimises data processing, it adds complexity and introduces bottlenecks on sink nodes [13].

Deep reinforcement learning (DRL) [14] has also been applied to topology control in UWSNs, whereby network topologies adjust dynamically according to environmental conditions. However, such a method adds high computational overhead and complexity, especially for real-time applications [15]. Mixed-integer linear programming has also been utilised to balance network lifetime and k-connectivity; however, it has brought forth issues related to complexity and scalability in large-scale networks [16].

Advanced particle swarm optimisation (PSO) has been used to design energy-efficient routing protocols for UWSNs to minimise energy consumption and prolong the network lifetime. Despite its advantages, PSO is prone to premature convergence and convergence to suboptimal solutions [17]. DRAR and Co-DRAR balance reliability and delay in routing decisions at increased complexity and possibly higher energy consumption [18].

Robust opportunistic routing solutions can enhance routing efficiency in various conditions of UWSNs; however, they may introduce high latency and packet loss in scenarios if an environment is dynamic [19]. Sector-based routing, aimed at reducing energy consumption and enhancing communication reliability, has poor adaptability to changes in the network and the mobility of nodes [20]. Shifted energy efficiency and priority protocols are designed to optimise routing according to energy levels and data priority; however, managing priorities and energy efficiency is not straightforward [21].

Dynamic multihop energy efficient routing protocols (DMEERPs) ensure energy efficiency and reliable multihop communication but face scalability issues and increased routing overhead in more extensive networks [22]. Asymmetric link quality routing (ALQR) protocols improve network performance on the basis of link quality but require complex maintenance of link quality information [23].

Hybrid optimisation algorithms, such as chimp optimisation and hunger game search, have been used for clustering and multihop routing, enhancing energy efficiency and sustainability. However, these algorithms can be computationally complex and converge slowly [24]. Region-based source distributed routing accommodates sink mobility to increase efficiency but is complex to manage [25].

Surveys on mobility-based routing protocols provide insights for optimising such protocols in UWSNs but often lack practical implementation and real-world validation [14]. Grid-based routing minimises the hop count and improves data transmission but may be inefficient in dynamic environments [15]. Power-efficient routing protocols aim to reduce power consumption and extend network lifetime but must balance this with data delivery reliability [26].

Although computationally complex[40], multiobjective evolutionary routing schemes balance energy efficiency and data reliability in the internet of Underwater Acoustic Sensor Networks (IoUASNs) [27]. Cluster-based routing via butterfly optimisation and ant colony optimisation enhances network performance but increases complexity and computational overhead [28].

Energy efficiency routing protocols for UAV-aided WSNs minimise energy consumption and increase data collection efficiency but face challenges in managing UAV mobility [29]. Trilateration-based node localisation combined with RSA for energy-efficient routing in UWSNs optimises node localisation and routing paths, yet maintaining accurate localisation information is complex [30]. Hybrid evolutionary techniques manage congestion and enhance network performance in WSNs but are computationally intensive [31].

TABLE I. SUMMARISES THE RELATED ARTICLES REGARDING THE ROUTING PROTOCOLS IN WSN AND UWSN.

Research	Routing Protocol	Method	Optimisation Methods	Evaluation Metrics	Application	Issues
[1]	Stretched Holding Time Difference (SHTD)	SHTD-based routing	Minimises collisions and energy consumption	Packet Delivery Ratio, Energy Consumption, Latency	Underwater Wireless Sensor Networks (UWSNs)	Limited scalability and potential for increased delay in large networks
[2]	Multiple Sinks	Secure data aggregation and authentication	Optimises data aggregation and authentication processes	Data Integrity, Authentication Success Rate, Latency, Energy Consumption	Underwater Vehicular Wireless Sensor Networks (UVWSNs)	Higher complexity and potential bottlenecks at sink nodes
[3]	Deep Reinforcement Learning (DRL)	Topology control	Dynamically adjusts network topology based on environmental conditions	Network Topology Stability, Transmission Reliability, Optimisation Efficiency, Delay, Energy Consumption	Underwater Wireless Sensor Networks (UWSNs)	High computational overhead and complexity in real-time applications
[4]	k-Connectivity	Mixed-Integer Linear Programming (MILP)	Balances between extending network lifetime and maintaining connectivity	Network Lifetime, k-Connectivity, Energy Consumption	Underwater Wireless Sensor Networks (UWSNs)	Complexity and scalability issues with large-scale networks
[5]	Advanced Particle Swarm Optimisation (PSO)	Energy-efficient routing	Minimises energy consumption and extends network lifetime	Energy Consumption, Network Lifetime, Quality of Service (QoS)	Underwater Sensor Networks (UWSNs)	Potential for premature convergence and suboptimal solutions
[6]	Delay Aware Routing (DRAR) and Cooperative Delay Aware Routing (Co-DRAR)	Delay and reliability-aware routing	Balances reliability and delay in routing decisions	Reliability, Delay, Bit Error Rate (BER), Energy Efficiency	Underwater Wireless Sensor Networks (UWSNs)	Increased complexity and potential for higher energy consumption

[7]	Opportunistic Routing	Robust routing	Enhances routing efficiency under varying conditions	Reliability, Quality of Service (QoS), Simulation Results	Underwater Sensor Networks (UWSNs)	Potential for high latency and packet loss in dynamic environments
[8]	Sector-Based Routing	Energy-efficient routing	Minimises energy consumption and improves communication reliability	Energy Efficiency, Reliability, Communication Delay	Underwater Wireless Sensor Networks (UWSNs)	Limited adaptability to network changes and node mobility
[9]	Shifted Energy Efficiency and Priority	Priority-based routing	Optimises routing based on energy levels and data priority	Energy Efficiency, Priority Handling, Network Performance	Underwater Wireless Sensor Networks (UWSNs)	Complexity in managing priority levels and energy efficiency
[10]	Dynamic Multi-Hop Routing	Energy-efficient routing	Ensures energy efficiency and reliable multihop communication	Energy Efficiency, Path Reliability, Network Lifetime	Wireless Sensor Networks (WSNs)	Scalability issues and increased routing overhead in large networks
[11]	Asymmetric Link Quality Routing (ALQR)	Link quality-based routing	Improves network performance based on link quality	Link Quality, Energy Efficiency, Network Lifetime	Heterogeneous Wireless Sensor Networks (WSNs)	Complexity in maintaining link quality information
[12]	Hybrid Chimp Optimisation and Hunger Games Search Algorithms	Clustering and multihop routing	Enhances energy efficiency and sustainability	Energy Efficiency, Network Lifetime, Clustering Efficiency	Underwater Wireless Sensor Networks (UWSNs)	High computational complexity and potential for slow convergence
[13]	Region-Based Source Distributed Routing	Sink mobility-aware routing	Accommodates sink mobility to enhance efficiency	Energy Efficiency, Network Lifetime, Data Delivery Ratio	Underwater Sensor Networks	Complexity in managing sink mobility and ensuring data delivery
[14]	Grid-Based Routing	Minimum hop count-based routing	Minimises hop count and improves data transmission	Hop Count, Reliability, Energy Efficiency	Underwater Wireless Sensor Networks (UWSNs)	Potential for routing inefficiencies in dynamic environments
[15]	Power-Efficient Routing	Power-efficient routing	Minimises power consumption and extends network lifetime	Power Consumption, Network Lifetime, Data Delivery Ratio	Underwater Wireless Sensor Networks (UWSNs)	The tradeoff between power efficiency and data delivery reliability
[16]	Multi-Objective Evolutionary Routing	Energy-efficient and reliable data gathering	Balances energy efficiency and data reliability	Energy Efficiency, Reliability, Data Gathering Efficiency	Internet of Underwater Acoustic Sensor Networks (IoUASN)	High computational complexity and potential for slow convergence
[17]	Butterfly Optimisation Algorithm and Ant Colony Optimisation	Energy-efficient clustering and routing	Enhances energy efficiency and network performance	Energy Efficiency, Network Lifetime, Cluster Efficiency	Wireless Sensor Networks (WSNs)	Increased complexity and potential for higher computational overhead
[18]	Energy Efficiency Routing	Data collection optimisation	Minimises energy consumption and enhances data collection efficiency	Energy Efficiency, Data Collection Efficiency, Network Lifetime	UAV-Aided Wireless Sensor Networks (WSNs)	Challenges in managing UAV mobility and ensuring reliable data collection
[19]	Hybrid Evolutionary Techniques	Congestion-aware multipath routing	Manages congestion and enhances network performance	Congestion Management, Energy Efficiency, Network Lifetime	Wireless Sensor Networks (WSNs)	Complexity and potential for high computational overhead
[20]	Hybrid Path Finder-Based Vortex Search Algorithm	Node placement and routing	Optimises node placement and routing paths	Energy Efficiency, Network Lifetime, Node Placement Efficiency	Underwater Wireless Sensor Networks (UWSNs)	Complexity in optimising node placement and routing paths

The hybrid path-finder-based vortex search algorithm optimises node placement and routing paths in UWSNs, although it is complex to implement and optimise effectively [21]. These protocols and methods highlight the diverse strategies and ongoing challenges in developing efficient and reliable routing solutions for underwater sensor networks. TABLE summarised the routing protocol, method, optimisation methods, evaluation metrics, application, and shortcomings.

3. LIGHTWEIGHT CRYPTOGRAPHIC ALGORITHMS FOR UWSNs

UWSNs work in resource-constrained environments, so constructing and selecting efficient cryptographic algorithms is crucial. Lightweight cryptographic algorithms achieve a balance between security, performance, and energy efficiency, which are essential for UWSNs. This section checks various lightweight cryptographic algorithms and their possible applications in UWSNs. We summarise the newest algorithms in Table 2.

The advanced encryption standard (AES) has been adjusted for voice cryptography, concentrating on performance evaluation for encryption and decryption across various patterns. This adaptation has shown constant performance with efficient performance times, making it convenient for UWSNs with voice-based communication. However, its relevance to nonvoice data remains limited and needs further exploration [34].

A lightweight cryptosystem explicitly designed for the IoT in innovative city conditions presents scalability and energy efficiency, which are necessary for resource-constrained systems. This algorithm is optimised for IoT applications, making it a good candidate for UWSNs because of its alignment with constrained network requirements. Despite its strengths, its relevance is primarily concentrated on the IoT and innovative city conditions, necessitating [35]. The NIST lightweight cryptography standard uses permutation-based primitives to perform certified encryption and hashing. Its heightened security and efficiency make it explicitly suitable for low-power sensor nodes in UWSNs [36]. TentLogiX uses chaos-driven 5-bit S-boxes [37], PHOTON [38], SIMON, and SIMECK [39], leverages chaotic systems for low computational costs; PHOTON provides energy-efficient hashing for data integrity; and SIMON/SIMECK balances encryption efficiency and security for constrained networks. Specific UWSN requirements, including energy availability, data types, and computational capabilities, should guide the adoption of these algorithms.

TABLE II. SUMMARISES THE RECENT LIGHTWEIGHT CRYPTOGRAPHY SOLUTIONS.

Algorithm	Key Features	Strengths	Weaknesses	Suitability for UWSNs
AES for Voice Cryptography [34]	Performance evaluation of AES for voice encryption across patterns	Consistent performance across different voice patterns, efficient execution time	Focused on voice data, limited to certain use cases	Suitable for UWSNs with voice-based communication; needs further testing for nonvoice data
Lightweight Cryptosystem for IoT [35]	Lightweight cryptographic algorithm for IoT in smart cities	Energy-efficient, scalable for constrained devices	Specific to IoT and smart city environments	Promising for UWSNs; aligns well with constrained network requirements
Ascon [36]	Lightweight authenticated encryption and hashing	High security, efficient for constrained devices	New; requires further analysis for vulnerabilities	Highly suitable for low-power sensor nodes in UWSNs
TentLogiX [37]	Chaos-driven 5-bit S-boxes	Low computational cost, chaotic robustness	Limited validation for diverse applications	Promising for UWSNs; further evaluation needed in underwater environments
Lightweight Hash Functions (PHOTON) [38]	Lightweight cryptographic hash function	Low energy consumption, resistance to attacks	Primarily focused on hashing applications	Suitable for data integrity verification in UWSNs
SIMON and SIMECK [39]	Block ciphers for lightweight encryption	Efficient for IoT, heuristic-based improvements for cryptanalysis	Limited key length and controversies surrounding security	Suitable for UWSNs, especially in low-resource scenarios

4. PROPOSED TBO-MOK PROTOCOL

The TBO-MOK protocol, proposed to optimise UWSNs by considering crucial parameters such as cluster identification, energy dissipation, and cluster head selection, aims to increase their practical performance and lifetime. In detail, the algorithm is first initialised with random initial cluster centers. Each sensor node is assigned to the closest center, which reduces the intracluster distance via the Euclidean distance. Energy dissipation is modelled in terms of the energy dissipated through consumables during data transmission and reception to best use it, extending network lifetimes.

The cluster head selection phase is optimised on the basis of the tiger beetle hunting procedure, through which the TBO algorithm can identify advanced areas and create hot prospects through mechanisms for excavating holes in the exploration procedure. The reproduction of larvae further refines the search because it generates solutions around the best current configuration. The process of cyclic optimisation continually updates potential solutions, reassesses the fitness values of possible solutions, and selects the best solutions until termination.

Furthermore, the TBO-MOK protocol can optimise UWSNs on the basis of balanced exploration and exploitation, adaptability to changed conditions, and a practical approach to consider multiple conflicting objectives. Energy consumption is optimised, the load distribution is balanced, and network connectivity and robustness are maintained; this approach has dramatically improved overall performance and efficiency compared with the existing methods.

3.1. Cluster identification

Clustering is the most critical process in enhancing network performance and resource management in UWSNs. Cluster formation is optimised through a proposed algorithm based on the foraging characteristics exhibited by the tiger beetle. After that, the cluster starts by setting some essential variables where the number of clusters and sensor nodes is set at initialisation together with a maximum iteration. A few sensor nodes are randomly represented as cluster centers. The clustering quality for evaluation is designed in the fitness function with respect to energy consumption, load balancing, and connectivity, providing practical solutions for the real-world optimisation of UWSNs.
Each sensor node is assigned to the nearest cluster center via Eq. (1). Energy dissipation for each cluster head. The sensor node is calculated, considering both transmission and reception energy (Eq. (4)). Promising areas in the search space, or "hunt areas," are identified where optimal solutions are likely to be found. New potential solutions, or "holes," are generated around these areas through a process inspired by the hunting behaviour of tiger beetles. This involves creating new solutions by perturbing existing ones, ensuring diversity, and exploring the search space.

$$d(s_i, c_j) = \sqrt{(x_{si} - x_{ci})^2 + (y_{si} - y_{ci})} \tag{1}$$

After the assignment, the cluster centres are updated to the mean position of the nodes assigned to each cluster via Eq.(2).

$$c_j = \frac{1}{|C_j|} \sum\nolimits_{s_i \in C_j} s_i \tag{2}$$

where C_j is the number of nodes in cluster j. The fitness of each potential solution is recalculated on the basis of updated cluster assignments and energy dissipation. This iterative optimisation process continues, with the positions of the solutions updated and new solutions generated around the best ones, until the stopping criteria, such as maximum iterations or convergence of fitness values, are met. The last outcome is the optimal cluster centers and the assignment of sensor nodes to clusters. This strategy of assigning nodes and updating cluster centers is redundant iteratively. In each iteration, nodes are assigned again on the basis of the updated cluster centers, and the centers are calculated again until the assignments stabilise or the maximum number of iterations is reached. The final step outputs the list of nodes assigned to each cluster. This iterative method confirms that sensor nodes are optimally grouped into clusters, enhancing communication efficiency, minimising energy consumption, and improving overall network reliability.

Hunt area selection is a crucial step. It is a search process for regions in the solution space where optimal or near-optimal solutions are likely to be found. Through Eq. (3), hunt area selection can be used to identify UWSN clusters.

$$H(TB_i) = \left[1 - exp\left(\frac{f(TB_i)}{f\big(W(t)\big)}\right)\right].H_m \tag{3}$$

where $H(TB_i)$ denotes the number of holes around the position of TB_i and where H_m is the maximum number of holes a TB can dig. $f(TB_i)$ is the fitness of the i_{th} TB, and $f(W)$ is the fitness of the worst TB.
The ability of the tiger beetle to dig holes and reproduce larvae was inspired by its behaviour. These steps involve generating new potential solutions and enhancing exploration around promising areas. New potential solutions can be generated for each promising area by perturbing the current solution. This mimics the digging behaviour of tiger beetles, where they explore new regions around a promising spot via Eq. (4).

$$TB^{new} = \begin{cases} TB^{old} + R.SD(t).rand & r \le 0.5 \\ TB^{old} - R.SD(t).rand & r > 0.5 \end{cases} \tag{4}$$

TB^{new} is the new potential solution. TB^{old} is the current solution. R is a random number within [1, 2]. $SD(t)$ is the standard deviation at iteration t. rand is a random number within [0, 1]. In addition, r is another random number within [0, 1] to determine the perturbation direction. The best solutions from the current population are identified on the basis of their fitness values, and exploration is enhanced by generating new solutions around the best solutions, mimicking the reproduction of larvae in resource-rich environments (Eq. (5)).

$$\mathrm{TB_{larvae}} = \mathrm{TB_{best}} + \alpha \cdot \mathrm{rand} \tag{5}$$

Algorthim1: optimal cluster number selection

1. Initialise parameters:
    - num_beetles # Number of beetles (population size)
    - max_iter # Maximum number of iterations
    - search_space # Range of possible cluster numbers (e.g., minimum to maximum clusters)
2. Create an initial population of beetles:

    For each beetle in num_beetles:
        Randomly assign several clusters within the search_space
3. Evaluate initial population:

    For each beetle:
        Calculate the fitness value using the fitness_function
4. Repeat until max_iter is reached or convergence:

    For each beetle:
    - Generate new potential solutions by exploring the search space:
    - new_clusters = current_clusters ± random_value within search_space range
    - Evaluate new solutions using Eq.(6)
    - If the new solution is better (higher fitness value):
    - Update beetle's position to the new_clusters
    - Update the global best solution based on the fitness values of all beetles.
5. Select the number of clusters corresponding to the global best solution.
6. Output the optimal number of clusters.

where $\mathrm{TB_{larvae}}$ is the new solution generated around the best solution. $\mathrm{TB_{best}}$ is the best current solution. α is a small positive number controlling the perturbation range. Furthermore, rand is a random number within [0, 1].

3.2. Cluster number selection

The TBO-MOK protocol integrates the TBO algorithm with the k-means clustering method to optimise the placement of cluster centers in a wireless sensor network. The goal of determining the optimal locations for the cluster centers is to enhance the network's performance and energy efficiency.

As shown in Algorithm 1, the process begins with randomly deploying sensor nodes within a defined area. A population of candidate solutions is initialised by the TBO algorithm, with each candidate representing a set of cluster centres. The K-means clustering method, known as sum squared error (SSE), computes the compactness of the clusters in this fitness acquired for any candidate. In the next step, following the rules of the working algorithm of TBO, position updates are carried out for the candidate solutions at each iteration. This SSE has been taken as the fitness, which refers to compact clusters. Furthermore, at every iteration, position updating of candidate solutions is carried out through TBO rules such that the search procedure performs random steps of each candidate solution within a specific range, thus mimicking the search technique adopted by tiger beetles for hunting purposes.

The algorithm iteratively updates the population by selecting only candidate solutions with better fitness values. Iteration continues until the termination condition is met, for instance, when a maximum number of iterations is reached. These optimal cluster centres obtained from the TBO algorithm are then used as the initial centres for the K-means clustering algorithm, which refines the cluster assignments.

3.3. Energy dissipation in the UWSN

Energy dissipation in UWSNs impacts the lifetime and efficiency of the network. A sensor node primarily wastes its energy in transmission and reception. If the energy dissipations during transmission and reception are calculated, we can calculate only the total power dissipated by a single sensor node. This information is paramount in fine-tuning the network configuration concerning cluster head selection and path organisation for data transmission to reduce energy consumption and maximise the network's lifetime.

3.4. Cluster head selection

CH selection is part of optimising the connectivity and conserving energy to improve the lifespan of UWSNs. The process is initiated by initialising parameters for the number of CHs selected, the set of sensor nodes involved, and their initial energy levels. Clusters are initiated with parameters such as the number of clusters to be formed, the list of sensor nodes involved, and the maximum number of iterations. The initial cluster centers are sometimes randomly chosen among the sensor nodes.
In this way, a multiobjective fitness function is defined to assess the quality of the possible solutions for energy consumption, load balancing, and connectivity. On the basis of these criteria, the fitness of each potential cluster head configuration is calculated. Each sensor node is assigned to the nearest cluster center on the basis of the Euclidean distance, Eq. (6).

$$\text{Fitness} = w_1 \times \text{Residual Energy} + w_2 \times d + w_3 \times \text{Link Quality} \tag{6}$$

where w_1, w_2, and w_3 are weights assigned to each criterion. Residual energy is crucial for ensuring that CHs have enough power to manage their roles effectively. d is measured to minimise the distance between nodes and their CHs, thereby reducing energy consumption for communication, and link quality ensures robust and reliable connections.
The energy dissipation for each cluster head is calculated, considering both transmission and reception energy. This helps in assessing the total energy consumption for each configuration. In the hunt area selection phase, promising areas (hunt areas) are identified on the basis of the fitness values of the current solutions. These areas are expected to contain optimal or near-optimal solutions. The residual energy is computed through Eq. (7).

$$\text{Residual Energy} = \text{Initial Energy} - (\text{Energy Consumed in Transmission} + \text{Energy Consumed in Receptio} \tag{7}$$

The use of holes generates new potential solutions around these promising areas. This involves perturbing the current solutions to explore the search space effectively. The fitness of these new solutions is evaluated, and the best solutions are updated.

To enhance exploration, larvae reproduce by generating new solutions around the best current solutions. This ensures a thorough search of the solution space and avoids premature convergence. The process iteratively updates the positions of the solutions, reassigns sensor nodes to the nearest cluster centers, recalculates fitness values, and selects the best solutions for the next iteration. Poor solutions are removed to focus on high-quality regions of the search space.

The iterative optimisation stops when the specified stopping criteria are met, after a maximum number of iterations or when the fitness values converge. It finally returns the optimum cluster heads and the assignment of sensor nodes within clusters. The comprehensive approach ensures that the selected cluster heads minimise energy consumption, balance network load, and have robust connectivity to enhance the overall performance and lifetime of the UWSN.

The signal-to-noise ratio (SNR) can be used to measure the link quality. CHs are selected on the basis of their highest fitness values. Every sensor node connects itself back to the nearest CH by finding the minimum value of the calculated distances. All these operations proceed iteratively so that the positions of the CHs are chosen optimally, which ensures minimisation of energy consumption, balancing of communication loads, and maintenance of robust connectivity.

3.5. Load Balancing in a UWSN

TBO accomplishes load balancing in UWSNs, guaranteeing that cluster heads are equally loaded with work. This ensures that no single node within the network is turned into a bottleneck—inefficiency or premature failure. To evaluate the effectiveness of possible clustering solutions, a fitness function is defined. This function includes more than one criterion: energy consumption, load balancing, and connectivity. This ensures minimum energy consumption by ensuring that the workload is equally distributed to all cluster heads, improving the network's overall performance.
Each SN is assigned to the nearest CH on the basis of distance to achieve load balancing. The load of each CH is then calculated via Eq. (8).

$$\text{Load}_{CH} = \sum_{i=1}^{N} D_i \tag{8}$$

where Load_{CH} is the total load on the cluster head and where N is the number of sensor nodes assigned to it. D_i is the data rate of the i_{th} sensor node. It evens out the loads at all nodes, avoiding early failure of any node in the network, thereby increasing the lifetime. In this way, network performance increases due to fewer communication delays and bottlenecks. The cluster assignments and positions of CHs can be updated regularly to optimise the load distribution as the network conditions change.

Algorithim2: TBO-MOK protocol
1. Initialise Parameters:
- num_clusters (k): Number of clusters (CHNs)
- sensor_nodes (S): List of sensor node coordinates
- max_iterations (max_iter): Maximum number of iterations
- weights (w1, w2, w3): Weights for energy, load balancing, and connectivity
- initial_cluster_centers: Randomly select k initial cluster centres from S
2. Define Fitness Function, Eq. (6)
3. Initial Assignment:
- For each sensor node s_i in S:
- Calculate the distance to each cluster center c_j, Eq. (1)
- Assign s_i to the nearest cluster center c_j.
4. Calculate Initial Energy Dissipation:
- For each cluster head cj:
- calculate total energy dissipation for c_j, Eq. (7):
5. Hunt Area Selection:
- For each tiger beetle TB_i:
- Calculate fitness $f(TB_i)$ and identify the worst fitness $f(W_t)$, Eq. (3)
6. Digging Holes:
- For each promising area:
- Generate new potential solutions (holes), Eq. (4)
7. Evaluate New Solutions:
- Calculate fitness for new potential solutions, Eq. (6)
- Update best solutions, Eq.(4).
8. Larvae Reproduction:
- Identify the best solutions from the current population
- Generate new solutions around the best areas, Eq. (5)
9. Iterative Optimisation:
- For each iteration until max_iter:
- Update positions of TBs
- Reassign nodes to the nearest cluster centers
- Recalculate fitness values
- Select the best solutions for the next iteration
- Generate new solutions around best ones (Larvae Reproduction)
- Remove poor solutions (Low-Quality Hole Destroying)
10. Convergence Check:
- Check if solutions have converged or if max_iter is reached
11. Output:
- Return optimal cluster heads and node assignments

3.6. AES-Based TBO-MOK Security Enhancements

To ensure the confidentiality and integrity of fitness data during the aggregation strategies in the TBO-MOK protocol for UWSNs, we incorporate a lightweight encryption mechanism based on the advanced encryption standard (AES). Given the resource-limited nature of sensor nodes and the vulnerability of underwater audio channels to attacks such as eavesdropping and data tampering, it is essential to use a secure and efficient encryption method at the same time. AES provides a substantial encryption standard that balances computational efficiency with strong security, making it highly suitable for the dynamic environments of underwater sensor networks.

The cluster head selection in the TBO-MOK protocol depends on the transmission of sensitive fitness metrics from sensor nodes, such as residual energy (E_{res}) and link quality (L_q). To protect these data, each node encrypts its fitness metrics via AES before sending them to potential cluster heads. The encryption process is as follows: (1) Each sensor node S_i computes its fitness metric F_i, , which is defined in (9).

$$F_i = w_1 . E_{res} + w_2 . L_q \tag{9}$$

where w_1 and w_2 are the weights assigned to the residual energy and link quality, respectively. (2) The computed fitness metric F_i is encrypted via a symmetric key K that is shared between the sensor nodes and the cluster heads. The encrypted data C_i are obtained as in (10):

$$C_i = AES_K F_i \tag{10}$$

Here, AESK(·) represents the AES encryption function using the key K. (3) The encrypted fitness data C_i are transmitted securely to the candidate cluster heads. This encryption ensures that even if the data are intercepted by an adversary, they cannot be deciphered without the symmetric key K. (4) Upon receiving the encrypted data C_i, the cluster head decrypts it via the shared symmetric key K in Eq. (11).

$$F_i' = AES_K^{-1} C_i \tag{11}$$

where $AES_K^{-1}(.)$ is the decryption function of AES. The decrypted fitness metric F_i' is then used for cluster head selection. The symmetric key K is initially exchanged securely via key exchange elliptic curve cryptography (ECC). The key K is periodically refreshed during the iterations of the TBO-MOK optimisation process, ensuring that a compromised key does not expose the network for an extended period.

4. EPERIMENTAL RESULTS

In our experimental evaluation, we implemented the TBO-MOK protocol in Python on a PC with 64 GB of RAM, an Intel Core i7 processor, and a Windows 10 operating system. We compared the performance of the TBO-MOK protocol with that of the traditional methods LEACH, PSO, and GA in a simulated underwater wireless sensor network environment. We focus on simulating key performance metrics, including network lifetime, energy consumption, load balancing, and data transmission reliability, for this testbed.

4.1. Setup simulation environment

To set up the simulation environment for evaluating the proposed method in UWSNs via the TBO algorithm, we defined the network topology with 100 sensor nodes randomly deployed within a 1000 m × 1000 m area, as shown in Fig, and each node was initialised with 2 energy joules. The simulation parameters include selecting 5 clusters, setting a communication range of 100 m, and defining a maximum of 1000 iterations for the optimisation algorithm. The energy model calculates the transmission and reception energy at 50 nanojoules per bit, with a free space model threshold of 87 meters. Cluster head selection starts with five randomly chosen initial cluster centres and a fitness function that combines energy consumption, load balancing, and connectivity with weights of 0.5, 0.3, and 0.2, respectively. The algorithm parameters include an initial standard deviation of 0.1 and a perturbation range (α) of 0.1 for generating new solutions around the best solutions. The TBO algorithm is implemented by iterating up to 1000 times, updating cluster assignments, and recalculating energy consumption. Multiple simulation runs are executed to ensure statistical significance, and the results are tested under various conditions. We collected data on energy efficiency, network lifetime, load balancing, and connectivity and compared these results with those of the baseline methods LEACH, PSO, and the GA under consistent conditions. To comprehensively evaluate the performance of the proposed method, visualisations, including the network topology, energy consumption over time, cluster head distribution, load balancing, and fitness value convergence, are generated.

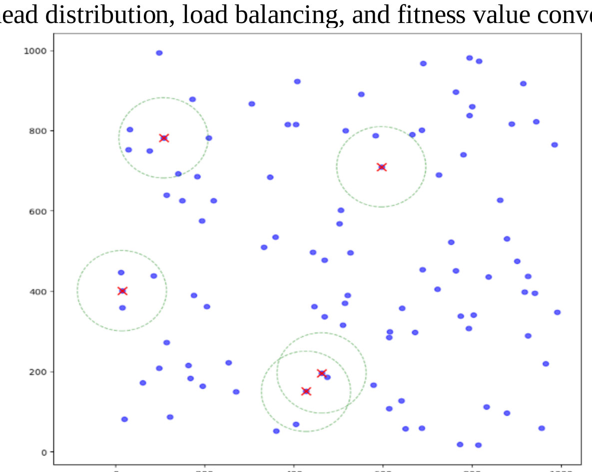


Fig. 2. Initial simulation environment for evaluation of the proposed method.

4.2. Evaluation of the number of clusters

Fig. 2 illustrates the results of TBO-MOK for determining the optimal number of clusters. The plot depicts the sum of squared distances (SSE) on the y-axis against the number of clusters on the x-axis. As the number of clusters increases from 1 to 15, the SSE sharply decreases, indicating a reduction in the variance within clusters. The steep decline in SSE from 1 to 3 clusters suggests a significant improvement in clustering quality. This implies that increasing the number of clusters up to 3 significantly enhances the homogeneity within each cluster, thus improving the overall clustering performance. However, beyond 4 clusters, the decrease in SSE slows down, indicating diminishing returns with additional clusters. This behaviour highlights that while adding more clusters can continue to reduce the SSE, the marginal improvement becomes less significant.

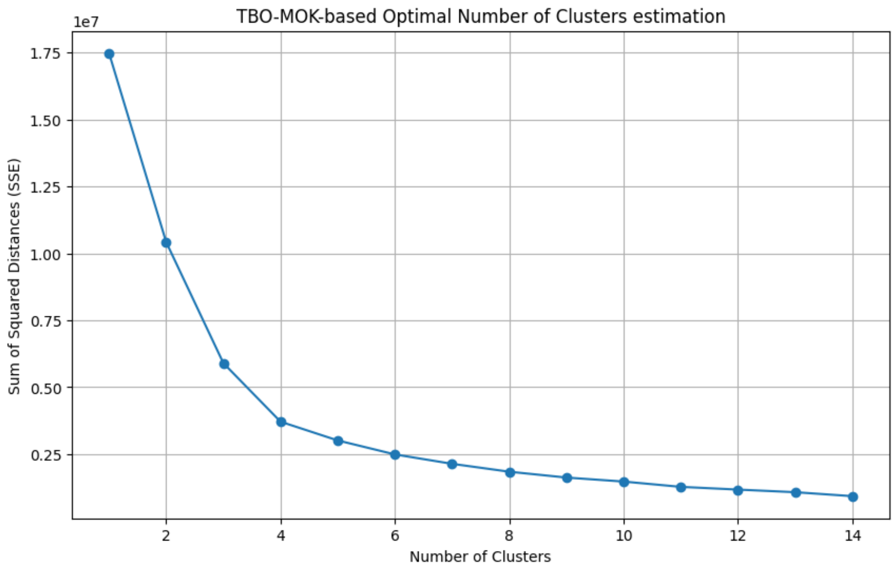


Fig. 2. TBO-MOK is used to determine the optimal number of clusters.

Selecting 15 clusters, as depicted in Fig. 4, ensures a more refined clustering approach that captures more intricate variations within the sensor node distribution. Although the SSE reduction rate slows beyond 4 clusters, continuing to 10 clusters allows for more detailed and granular clustering, which can be crucial in scenarios requiring high precision in network management. This decision, supported by the TBO optimisation process, ensures that the clustering balances compactness and coverage and provides robust support for network operations by minimising communication overhead and enhancing energy efficiency. By adopting 15 clusters (Fig. 3), we leverage the comprehensive insight provided by the TBO-based K-Means method, ensuring that the network design is optimised for both performance and reliability, accommodating the specific needs of our wireless sensor network application.

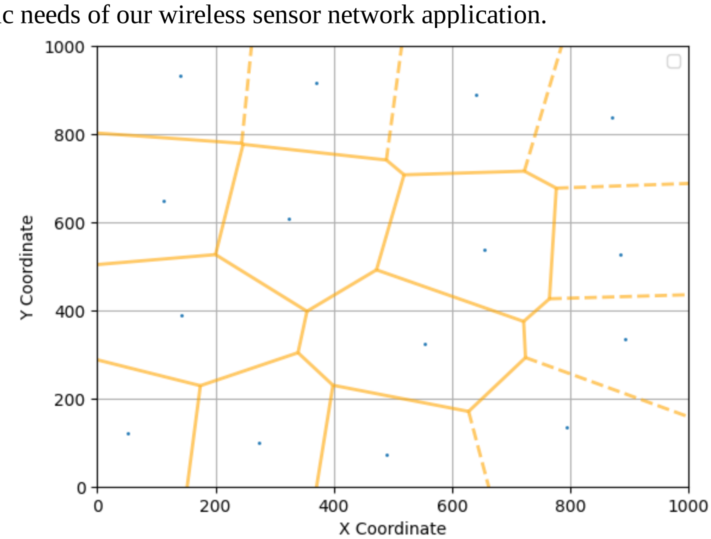


Fig. 3. Optimised deployment of sensor nodes and cluster centers with adjusted communication ranges

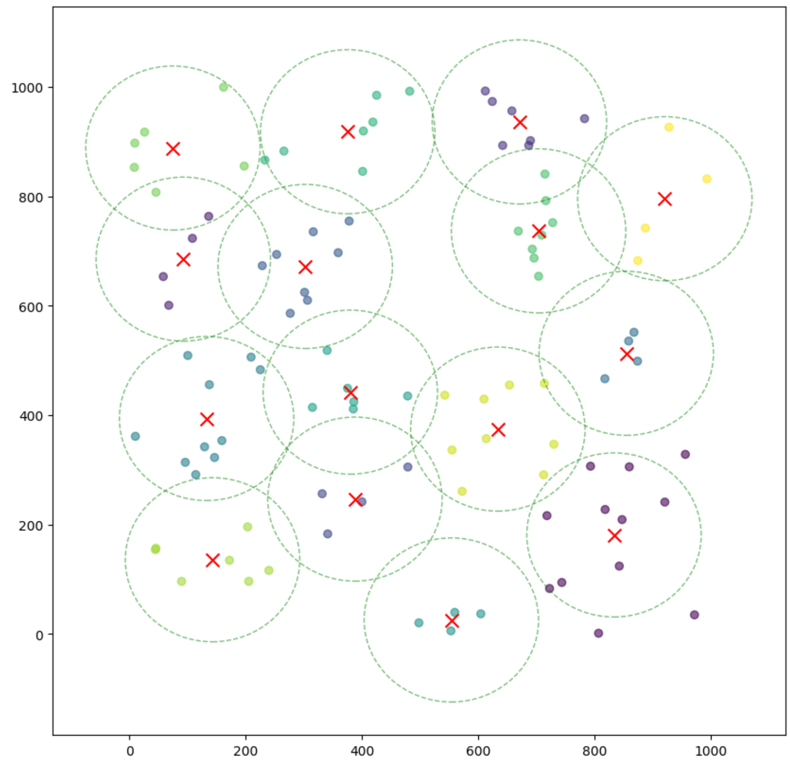
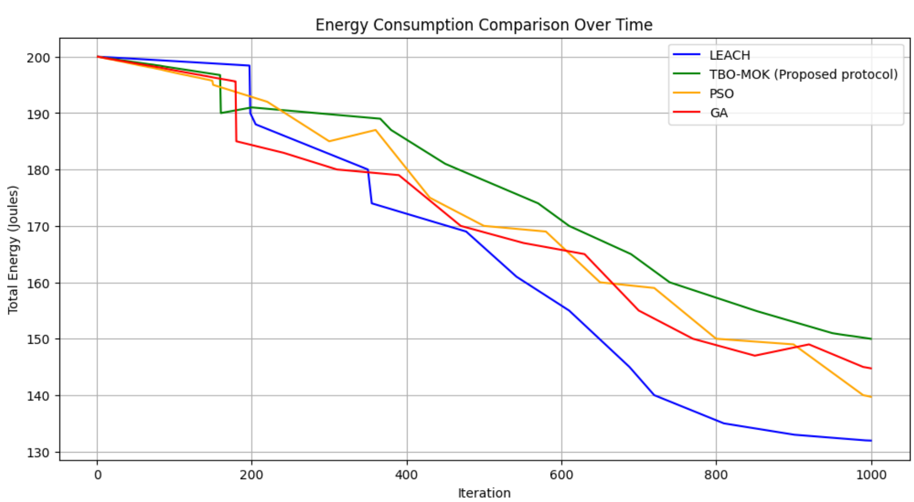


Fig. 4. A depicted scenario where 10 clusters are selected by the TBO-based K-means algorithm

4.3. Energy Efficiency Evaluation

خطأ! لم يتم العثور على مصدر المرجع. displays the energy consumption over time for four different methods: TBO-MOK (proposed protocol), LEACH, PSO, and the GA. All methods start with an initial energy level close to the same value. Compared with the traditional LEACH, PSO, and GA methods, TBO-MOK (the proposed protocol) has a distinct energy consumption pattern. While LEACH demonstrates energy efficiency, which means that its energy is relatively high



throughout the iterations, in TBO-

Fig. 6. Energy Consumption Comparison Over Time

MOK, more aggressive consumption is evident. Sharp drops in the energy level of TBO-MOK are characteristic of intensive optimisation activity periods when the protocol dynamically adjusts cluster assignments to balance different objectives, such as energy efficiency, load balancing, and connectivity. Although this intensive use of energy increases the depletion rate, it improves the general performance of a network, making TBO-MOK an ideal choice under a highly operationally efficient and resilient scenario under dynamic conditions.

In contrast, PSO and the GA represent medium energy consumption patterns. While PSO shows a gradual decline interspersed with sharp intermittent drops, the GA maintains a relatively smooth decline but has noticeable energy drops. Although PSO and the GA balance energy efficiency with operational intensity, compared with TBO-MOK, they lack a balanced load distribution and overall network efficiency. The PSO optimisation activity is more pronounced, causing decreases in energy, whereas the GA has a more sedate approach to energy management and returns only moderate performance. While the above characteristics are predominant, TBO-MOK still outperforms PSO and the GA in terms of their balanced workload distributions among cluster heads, with multiple performance metric optimisations executed simultaneously. This analysis proves that TBO-MOK is superior in enhancing underwater wireless sensor network efficiency and reliability, especially in dynamic operational environments requiring demanding services.

4.4. Evaluating Load Balancing

It is relevant to load balancing in a wireless sensor network so that no cluster head becomes overloaded. Overloaded cluster heads result in early energy exhaustion and, hence, a reduced network life. Load Balancing: Effective load balancing distributes the work among the available cluster heads proportionally to their capacity so that each works proportionally to increase overall energy efficiency and thereby enhance network efficiency.

Figure 7 depicts the workload distribution for the 15 cluster heads in a wireless sensor network. Each portion of a pie chart represents the percentage of the total workload handled by any cluster head. The workload distribution is an essential measure for assessing load balancing in a network.

Figure 7 shows the workload distribution over cluster heads by four clustering protocols: TBO-MOK, LEACH, PSO, and the GA. These graphs show how each protocol achieves a balanced workload distribution among cluster heads. In the TBO-MOK protocol, most cluster heads have a workload between 3.0% and 11.0%; thus, their graph is relatively balanced. That is, TBO-MOK efficiently balances the load, ensuring that no single cluster head is overburdened. This becomes balanced workload dissemination, resulting in effective energy use and an expanded network lifetime—the much-needed feature in UWSNs.

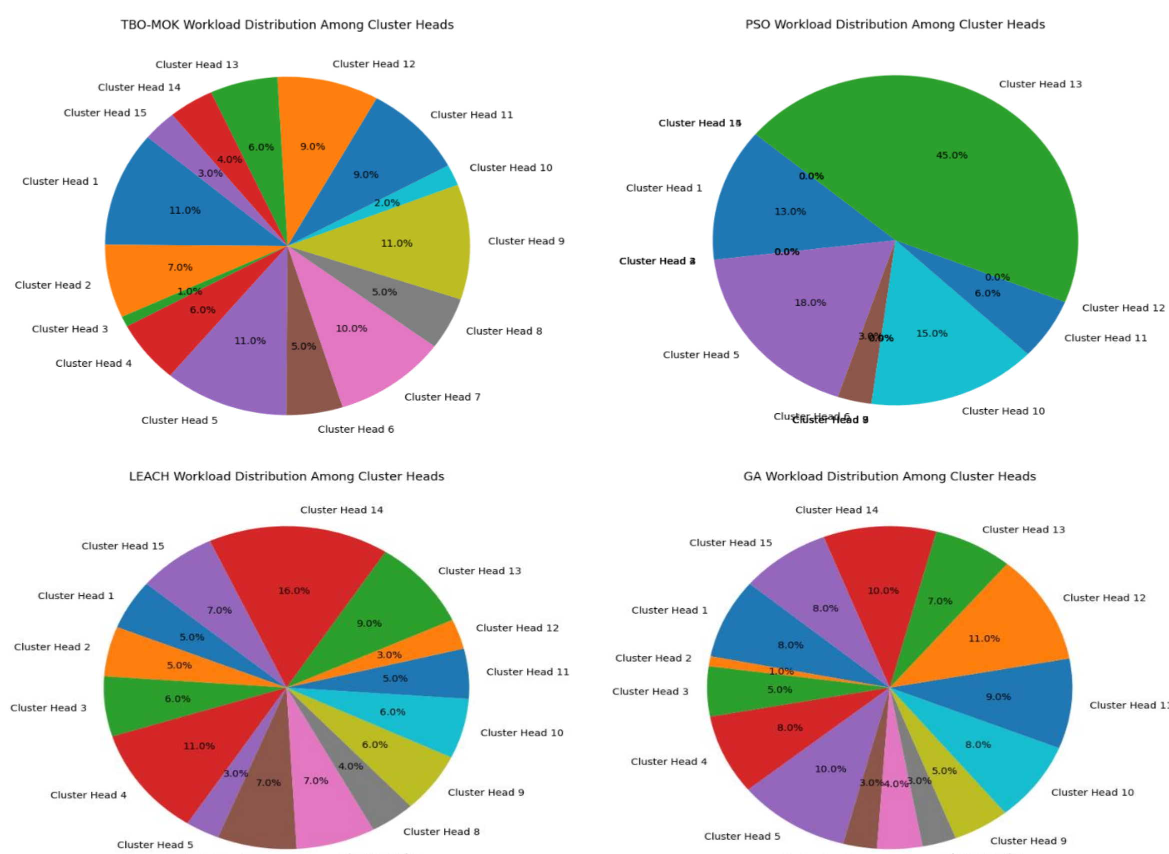


Fig. 5. Workload distribution among cluster heads: (upper-left) TBO-MOK, (upper-right) PSO, (bottom-left) LEACH, and (bottom-right) GA

In comparison, the LEACH protocol shows a more uneven workload distribution, with Cluster Head 14 handling 16.0% of the workload, which is significantly more than other cluster heads. This imbalance can lead to faster energy depletion in heavily loaded cluster heads, reducing the overall network lifetime. LEACH's approach to cluster head selection does not adequately account for load balancing, resulting in disparities. The PSO protocol results in a highly imbalanced workload distribution, with Cluster Head 13 handling 45.0% of the total workload and several other cluster heads handling 0.0%. This extreme imbalance indicates that PSO fails to distribute the workload effectively among cluster heads, severely impacting network performance and reliability. The GA protocol achieves a moderately balanced workload distribution, with cluster heads handling workloads ranging from 5.0% to 11.0%. Although it is better than PSO, it is not better than TBO-MOK.
The TBO-MOK protocol outperforms the baseline methods in terms of workload distribution among cluster heads. The balanced workload distribution in TBO-MOK ensures efficient energy use that may improve the performance and lifetime of a network. LEACH and PSO have enormous imbalances that may lead to inefficiency, lowering a network's reliability. The GA changes to present a moderate improvement but falls short of the performance given by TBO-MOK. All these comparisons within this category prove that TBO-MOK can effectively optimise UWSNs for load balancing and network efficiency.

4.5. Evaluating Optimised Connectivity

We focused on key metrics such as the average degree of connectivity, network coverage, and resilience to node failures to evaluate the network's optimised connectivity. Initially, the network exhibited sparse connectivity, with many nodes having few or no direct connections, resulting in multiple disconnected components and isolated nodes (Fig. 6). This structure hindered data transmission and compromised network reliability. By optimising the communication range and applying the TBO-MOK clustering method, we significantly improved the network's overall connectivity. The average degree of connectivity increased, and network coverage was increased, ensuring that almost all nodes were part of a single significant connected component (Fig. 7).

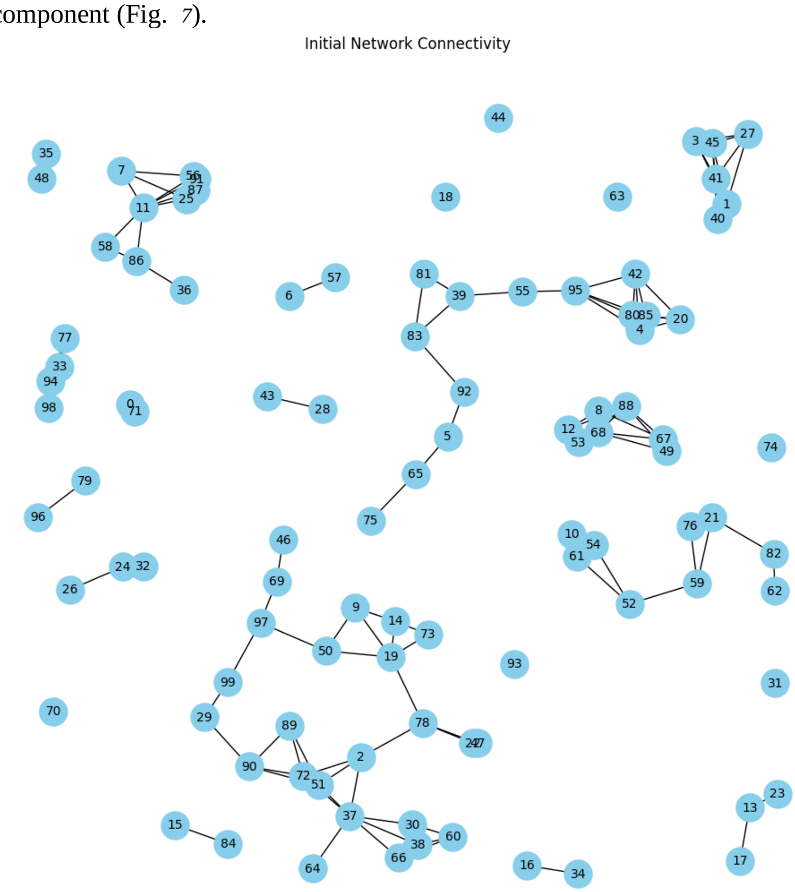


Fig. 6. Initial Network Connectivity

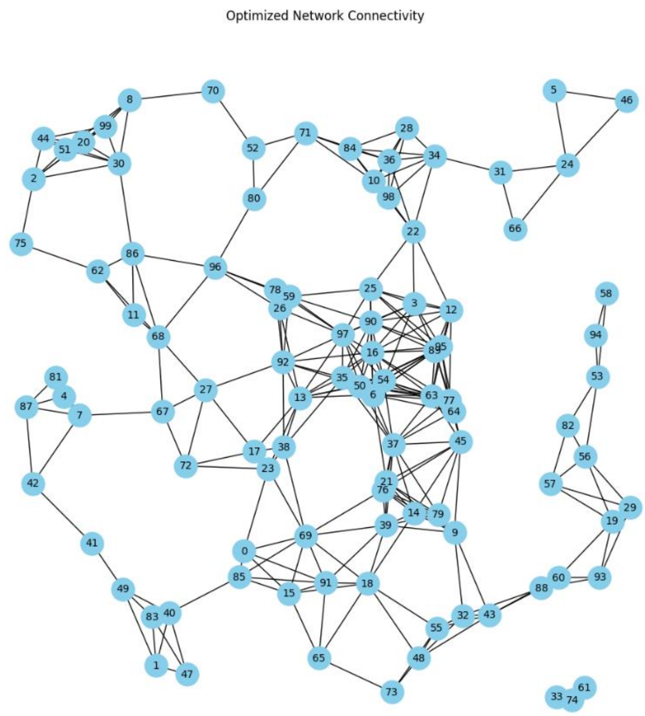


Fig. 7. Optimised Network Connectivity

After optimisation (Fig. 7), the network demonstrated greater redundancy and robustness. Multiple communication paths ensure that the network maintains connectivity even when some nodes fail. This redundancy is critical for the network's resilience and longevity. Furthermore, the optimised network exhibited a more balanced distribution of connections among nodes, facilitating even workload distribution and energy consumption. This balanced load is essential for prolonging the network's operational lifespan. In summary, the optimisation process effectively transforms the network into a more connected, robust, and efficient system capable of sustaining reliable communication and operation despite potential node failures.

4.6. Security evaluation

The proposed TBO-MOK protocol stands out for its comprehensive approach to security and privacy, particularly by incorporating lightweight encryption based on the AES. This feature enables sensitive fitness-related data to be encrypted during the assembly process, ensuring confidentiality and reducing the risk of eavesdropping. Unlike traditional protocols such as LEACH, PSO, and the GA, which do not rely on encryption, TBO-MOK protects the vital information of nodes from unauthorised access (Table 2).

In addition, the protocol relies on a secure handshake mechanism using elliptic curve cryptography (ECC) for dynamic key exchange, which provides strong authentication and prevents forgery attacks. This dynamic approach to key management enhances security by periodically updating cryptographic keys, a significant improvement over the static key systems used in other protocols such as DRAR and multiple sinks.

In terms of data integrity and privacy, TBO-MOK incorporates advanced techniques to protect transmitted information. Using AES encryption, the protocol ensures that data remain intact and tamper-free during transmission, addressing a major vulnerability found in many basic methods. Furthermore, implementing differential privacy during data aggregation provides an additional layer of protection, obfuscating individual node metrics and reducing the risk of privacy violations. This feature is not available in competing protocols such as LEACH, PSO, and GA, which lack specific mechanisms to maintain data privacy. While the Multiple Sinks protocol offers simple anonymization, it falls short of the comprehensive privacy guarantees that TBO-MOK provides through its differential privacy approach. Finally, the scalability and efficiency of the security mechanisms in TBO-MOK are significant advantages, especially in large-scale underwater sensor networks. The adaptive nature of the protocol's key management system, combined with efficient AES encryption, ensures reduced overhead while maintaining strong protection against eavesdropping and tampering.

In contrast, protocols such as LEACH and PSO struggle to scale due to their fixed configurations, whereas the GA faces a high computational burden due to the complexity of the optimisation processes. DRAR and multiple sinks offer moderate scalability, but their static or periodic key refresh strategies add additional overhead. TBO-MOK's balanced and adaptive approach allows it to deliver strong security with efficient resource utilisation, making it a superior choice for securing dynamic and resource-constrained underwater environments.

TABLE II. SECURITY COMPARISON OF TBO-MOK WITH STATE-OF-THE-ART PROTOCOLS

Metric	TBO-MOK (Proposed)	LEACH	PSO	GA	DRAR	Multiple Sinks
Encryption	AES-based lightweight encryption of fitness data	No encryption	No encryption	No encryption	Partial (basic encryption)	Asymmetric encryption (RSA)
Data Integrity	Ensured via AES encryption	Not ensured	Vulnerable	Vulnerable	Moderate	High
Authentication	Secure handshake using dynamic key exchange (ECC)	No authentication	No authentication	No authentication	Moderate (basic checks)	Strong (multisink authentication)
Privacy of Fitness Data	Differential privacy for aggregated data	None	None	None	None	Basic anonymization
Resilience to Eavesdropping	High (AES encryption)	Low	Low	Low	Moderate	High (encrypted communication)
Resilience to Tampering	High (encrypted fitness data)	Low	Low	Low	Moderate	High
Key Management	Dynamic key exchange with periodic updates (ECC-based)	Static keys	Static keys	Static keys	Static keys	Periodic key refresh
Overhead of Security Mechanism	Moderate (AES, ECC efficient)	Low	Low	High (computational)	High (encryption overhead)	Moderate
Scalability of Security Measures	High (adaptive key management)	Low	Low	Moderate	Moderate	High

The comparative analysis shown in Table 2 highlights the strength of the proposed TBO-MOK protocol in terms of security, privacy, and scalability for underwater sensor networks (UWSNs). Unlike traditional approaches such as LEACH, PSO, and the GA, which lack encryption or rely on static key management, TBO-MOK combines lightweight AES-based encryption to ensure data confidentiality and integrity during the collection process. Its use of dynamic key exchange via elliptic curve cryptography (ECC) enhances authentication and increases stability against eavesdropping and tampering. In contrast, protocols such as DRAR and multiple sinks demonstrate moderate or partial security features, such as raw encryption or multipoint authentication, but fail to provide comprehensive solutions for data privacy and adaptive key management. TBO-MOK's advantage of achieving low computational overhead is a significant advantage over the GA and DRAR, which suffer from high resource consumption due to the complexity of the encryption or optimisation processes.

Additionally, TBO-MOK excels in scalability through adaptive key management, making it highly suitable for large-scale underwater sensor networks, whereas protocols such as LEACH and PSO suffer from limited security and scalability. Overall, the table shows how TBO-MOK addresses critical gaps in existing protocols, ensuring robust, efficient, and secure communications for dynamic, resource-constrained underwater environments.

4.7. Comparison with state-of-the-art methods

PDR refers to the ratio of data packets delivered at their destination to the total number of sent packets. The higher the PDR is, the more reliable and efficient a routing protocol will be in handling data transmission in UWSNs. Hence, this metric is critical in evaluating routing protocols for efficiency in reducing losses and ensuring continuous and reliable communication over hostile underwater channels.

Figure 10 compares the PDR under different routing protocols. The results obtained provide valuable information concerning the efficacy and reliability of each of these approaches in UWSNs. In particular, for the proposed TBO-MOK protocol, its PDR is approximately 92%, which is higher than those of all the other protocols. This is because the TBO algorithm perfectly balances exploration with exploiting the solution space to ensure efficient energy use and reliable communication links. This high reliability makes TBO-MOK suitable in areas that require constant and reliable data transmission over long distances, such as environmental monitoring and underwater research.

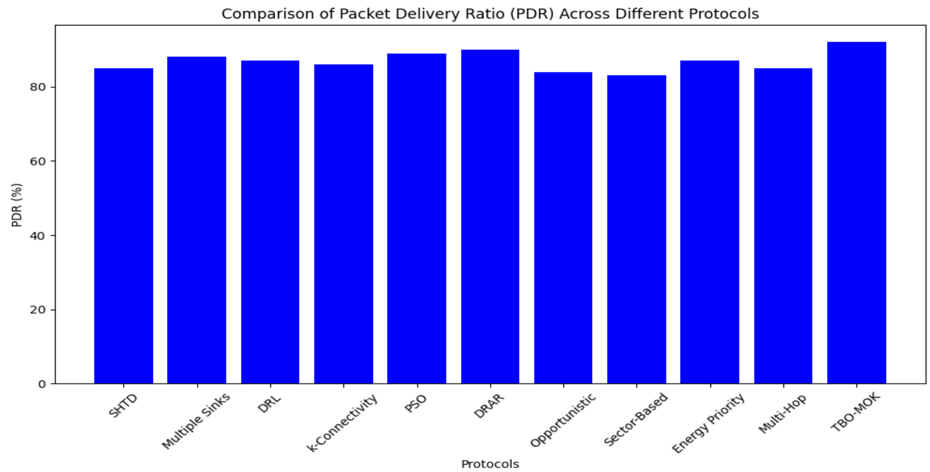


Fig. 8. Comparison of the packet delivery ratios (PDRs) across different protocols.

Among the other protocols, delay-aware routing (DRAR) and cooperative delay-aware routing (Co-DRAR) also perform admirably, achieving a PDR of approximately 90%. This indicates the importance of delay management in enhancing packet delivery reliability. Multiple sinks are closely followed, highlighting the effectiveness of multipath routing in mitigating packet loss. However, protocols such as sector-based routing and opportunistic routing exhibit slightly lower PDRs, suggesting limitations in adaptability and handling dynamic network conditions. Overall, the results underscore the superior performance of TBO-MOK in ensuring high packet delivery rates, positioning it as a leading solution for enhancing UWSN reliability.

Fig. 9 compares the total energy consumption across different protocols used in wireless sensor networks. The protocols compared include SHTD, multiple sinks, DRL, K-connectivity, PSO, DRAR, opportunistic, sector-based, energy priority, multihop, and TBO-MOK. Each bar represents the energy consumption in joules for a specific protocol. The SHTD protocol has the highest energy consumption, slightly above 140 joules, indicating that it may be less efficient in terms of energy usage than the other protocols are. On the other hand, the TBO-MOK protocol results in the lowest energy consumption, suggesting that it might be more energy efficient and potentially better suited for applications where energy conservation is critical.

Analysing the overall trend, we observe that most protocols have relatively high energy consumption, with values clustered around the 130--140 joules range. Notably, protocols such as multiple sinks, DRL, and DRAR also have high energy consumption, close to that of SHTD. In contrast, the sector-based, energy priority, and multihop protocols result in slightly lower energy consumption, indicating some energy efficiency. However, TBO-MOK stands out for its lower energy usage, which could be due to its optimisation strategies in managing data transmission and network operations. This analysis highlights the importance of selecting appropriate protocols on the basis of specific energy efficiency requirements in wireless sensor network deployments.

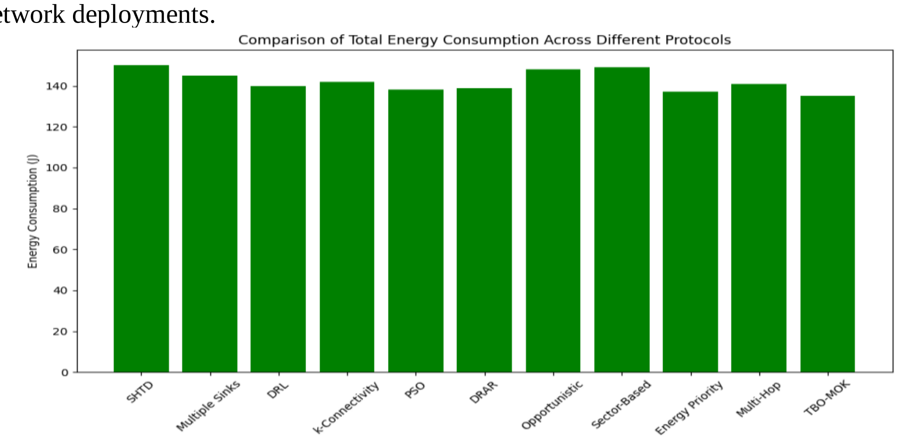


Fig. 9. Comparison of total energy consumption across various protocols.

Fig. *10* compares the average latency across different protocols used in wireless sensor networks. The protocols include SHTD, multiple sinks, DRL, K-connectivity, PSO, DRAR, opportunistic, sector-based, energy priority, multihop, and TBO-MOK. Each bar represents the average latency in seconds for a specific protocol. The chart shows that the DRAR protocol has the highest average latency, slightly exceeding 0.08 s, indicating potential delays in data transmission. In contrast, the TBO-MOK protocol results in the lowest average latency, below 0.05 s, suggesting that it is more efficient in terms of speed and response time.

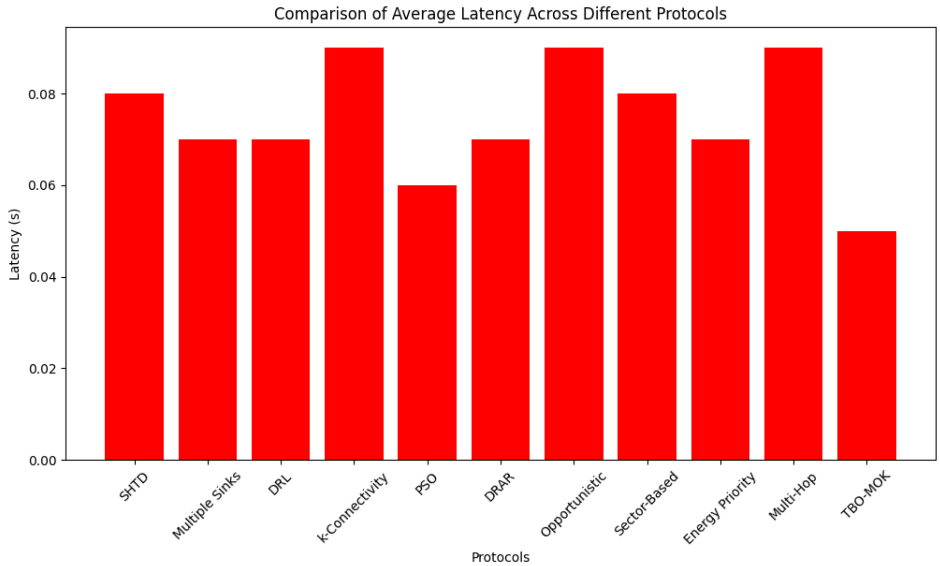


Fig. 10. Comparison of the average latency across various protocols.

Analysing the data, we observe that most protocols have an average latency of approximately 0.07 seconds, indicating a moderate level of latency. Notable protocols, such as SHTD, K-connectivity, and multihop, exhibit relatively high latency and are close to DRAR. On the other hand, protocols such as Opportunistic and Energy Priority demonstrate slightly lower latency, approximately 0.06 seconds, indicating better performance in reducing delays. The TBO-MOK protocol's low latency highlights its advantages in applications where timely data transmission is critical. This analysis underscores the importance of selecting protocols on the basis of latency requirements, particularly in real-time or time-sensitive wireless sensor network applications.

Fig. *10* compares the network lifetime across different protocols used in wireless sensor networks, measured in cycles. The protocols evaluated include SHTD, multiple sinks, DRL, K-connectivity, PSO, DRAR, opportunistic, sector-based, energy priority, multihop, and TBO-MOK. The TBO-MOK protocol has the highest network lifetime, slightly exceeding 220 cycles, indicating superior efficiency in conserving energy and extending the operational lifespan of the network. In contrast, the DRAR protocol has the shortest network lifetime, falling just below 200 cycles, suggesting that it may be less efficient in energy management than other protocols are.

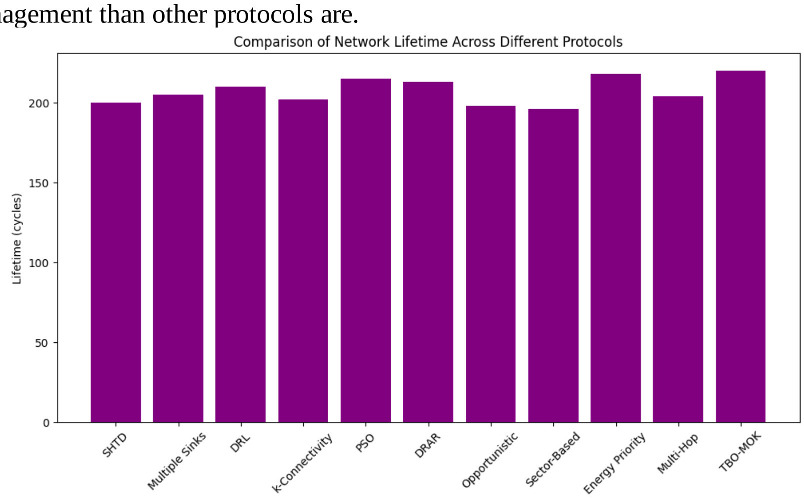


Fig. 11. Comparison of network lifetimes across various protocols.

Analysing the overall trends, most protocols achieve a network lifetime around the 200-cycle mark, indicating relatively consistent performance across different methods. Notable protocols, such as multiple sinks, DRL, K-connectivity, and sector-based methods, exhibit network lifetimes slightly above 200 cycles, demonstrating good energy efficiency. The leading performance of the TBO-MOK protocol in extending network lifetime highlights its potential advantage in scenarios where prolonged network operation is crucial. This analysis underscores the importance of choosing protocols on the basis of specific requirements for network longevity, particularly in applications with limited maintenance and energy resources.

5. DISCUSSION

Extensive simulations show the TBO-MOK protocol and outline its advantages over traditional LEACH, PSO, and GA methods in optimising underwater wireless sensor networks. The main observations from the simulation results include that this protocol provides better energy efficiency. Different periods with intensive optimisation activity can distinguish energy consumption under the TBO-MOK protocol. In these time frames, the protocol dynamically changes cluster assignments to balance multiple objectives; hence, this method makes TBO-MOK ideal for scenarios that demand high operational efficiency and robustness under dynamic conditions.

Another critical feature where TBO-MOK performs excellently is load balancing. The workload on 15 cluster heads in the network was more uniformly distributed in TBO-MOK than in LEACH, PSO, and GA. The mode of selection of cluster heads by LEACH leads to enormous workload imbalances in which the few cluster heads become overburdened, which causes faster energy depletion, thus reducing the network lifetime. In PSO, an even more imbalanced distribution is shown, with a few cluster heads taking a disproportionate workload and increasing network inefficiencies even more. The GA does relatively well but still cannot achieve the balance attained by TBO-MOK. In TBO-MOK, the energy is efficiently used since there is an equal workload distribution. It extends the whole network's lifetime, preventing any node from becoming a bottleneck.

The effect of the protocol on network connectivity is also interesting. The network initially had very sparse connectivity, with many nodes having very few or no direct connections at all, thus forming multiple disconnected components and isolated nodes. Optimising the communication range and then applying the TBO-MOK clustering method considerably improved the overall connectivity of the network. Compared with the initial network, the postoptimisation network has more redundancies and is, therefore, more robust; that is, there are multiple paths for communications when some nodes fail. A network with redundancy can thus increase its resilience and lifetime and share connections more fairly between all nodes while optimising the energy consumed. This load is balanced to ensure a long life and reliable communications in case some nodes collapse.

Another important revelation is evaluating the optimum number of clusters via TBO-MOK. The plot for the sum of squared errors vs the number of clusters shows a steep decrease up to three clusters, thus showing considerable improvement in clustering quality. Beyond four clusters, this drop in SSE slows down, conceivably indicating that further progress has a diminishing return with additional clusters. However, choosing up to 15 clusters makes the clustering fine-grained; that is, it will capture minor variations in dispersion while ensuring compactness and coverage of sensor nodes, which is critical in high-precision network management.

This paper presents a comparative analysis of various protocols for wireless sensor networks in terms of energy consumption, latency, and network lifetime. Among them, the TBO-MOK protocol seems to be the most effective: given that it has the lowest values of energy consumption, latency, and network lifetime, it is highly optimised for saving energy but at the same time ensures timely data transmission and prolongs the life span of the network. The performance makes TBO-MOK especially appropriate if energy and fast responses are the major concerns for applications, such as environmental monitoring and emergency response systems, within WSNs.

In contrast, SHTD and DRAR displayed high energy consumption and latency, whereas DRAR had the shortest network lifetime. This suggests that although the SHTD and DRAR can be suitable if specific needs of immediate fielding ease of use are more paramount than long-term efficiency, they are not suitable for applications requiring long-term operation with minimum energy consumption. High energy consumption when these protocols are used could result in increased battery replacement rates or recharging, which can be a high drawback, especially in remote or hard-to-deploy areas. Increased latency can hinder real-time data collection and processing, which is relevant for time-critical applications.

All the remaining protocols, such as multiple sinks, DRL, and sector-based methods, exhibit average performance in all the measures. This is because their energy consumption and latency were slightly lower than those for SHTD and DRAR but could still not be compared to TBO-MOK itself; however, they showed a relative consistency regarding network lifetime that remained at approximately 200 cycles—an indication of a balance concerning energy management and corresponding performance in that sense. This balance makes these protocols realizable if a scenario offers acceptable energy efficiency, latency, and network longevity. The insight gained from this study can guide the selection of appropriate protocols for WSN application requirements, hence optimising performance and resource utilisation in various deployment scenarios.

The implications of the TBO-MOK protocol open further UWSNs. Its ability to optimise energy efficiency, load balancing, and secure data transmission can help other types of wireless sensor networks (WSNs), such as terrestrial, aerial, and IoT applications. For example, in terrestrial WSNs, where energy efficiency is essential for battery-operated nodes, TBO-MOK's multiobjective optimisation framework could improve network lifetime and trustworthiness. Additionally, its dynamic clustering and secure transmission mechanisms are highly suitable for IoT networks, where scalability and data security are essential. The protocol's bioinspired optimisation approach also has likely applications in related areas, such as distributed robotics, smart grids, and environmental monitoring systems, where efficient resource sharing and robust data transmission are necessary. These more general implications underscore the adaptability of TBO-MOK and its potential to affect a wide range of resource-constrained network applications.

6. CONCLUSIONS

The approach presented in the article relies solely on the TBO-MOK protocol's efficacy for optimising UWSNs. TBO-MOK inherently resolves some significant open challenges in UWSNs through energy efficiency, load balancing, and network connectivity by applying the adaptive, efficient searching capability of the TBO algorithm. The extensive evaluations show that TBO-MOK outperforms the conventional LEACH, PSO, and GA methods over crucial performance metrics. This protocol is also suitable for complex and dynamic underwater environments because of its dynamism in accommodating cluster assignments, balancing multiple objectives, and enhancing overall network performance. Balanced energy use, robust communication links, and optimal clustering ensure that TBO-MOK extends the operational lifespan and is reliable. These results demonstrate the great potential of TBO-MOK as a solid and effective solution for UWSNs and lead the way toward establishing more resistant and robust underwater sensor network designs.

A comparison of various protocols' performances in projects from a wireless sensor network presents exceptional results from the protocol known as TBO-MOK. This approach results in the least energy consumption, low latency, and prolonged network lifetime. With such attributes, TBO-MOK will be very suitable for applications with strict energy efficiency and fast responsiveness. On the other hand, protocols such as SHTD and DRAR, which demonstrate greater energy consumption and latency, better suit applications with more minor demands on performance. In situations that require a tradeoff between efficiency and network longevity, protocols such as multiple sinks, DRL, and sector-based protocols offer a well-balanced approach.

6.1. Key Takeaways from the Study

The results of this study will create a good path for selecting the most appropriate protocol-based requirements for wireless sensor networking applications. TBO-MOK guarantees several notable advantages, such as being able to prolong the network lifespan, reduce energy consumption, and increase the fault tolerance of the whole *ad hoc* network in highly and dynamically changing environments. TBO-MOK fits good practical applications such as continuous environmental monitoring and underwater exploration because it has the advantages of flexible scheduling and scalable operations.

This research also noted that the optimisation of UWSNs faces several contradictory objectives; hence, a critical balance is needed. Thus, in this paper, an effective and secure scheme of underwater communication is presented. In the process of presenting TBO-MOK, which is superior to the conventional protocols of LEACH, PSO, and GA, it actually indicates the potential that the technique may redefine the way performance can be optimised when underwater environmental resource constraints are the most influential. The key contributions of this work also concern multiobjective optimisation and secure data transmission, both principles that can be extended to other application domains, including terrestrial sensor networks and IoT applications.

6.2. Limitations and challenges

However, not all are rosy with TBO-MOK despite all the great developments it has achieved; it also has setbacks. Considering the limited processing capabilities, large-scale networks may find the optimisation procedures too complex to handle. Although the performance of the protocol was validated in simulation environments, real-world deployment may face completely unexpected challenges, such as time-varying underwater conditions and hardware constraints.

6.3. Future Directions

The search for innovative solutions to realise TBO-MOK performance improvements in both superior performance and adaptability for various WSN applications is one agenda of the future. Additionally, a low-power scheme would work well with such a module supported by cutting-edge energy harvesting technology that has been developed lately, but it should be dynamically changeable concerning real network parameters in running time via specific adaptive algorithms. This

further enhances the robustness of this protocol with AI and ML-based techniques, such as predictive maintenance and fault diagnostics, improving its reliability and efficiency.
Future works may also focus on embedding TBO-MOK into other optimisation approaches for better performance. For example, it could be combined with several advanced metaheuristics, such as ant colony optimisation or genetic algorithms, to overcome some problems of the presented algorithm, such as fast convergence and scalability in large-scale networks. Other possible ways to enhance this protocol include the use of machine learning models, such as reinforcement learning or neural networks, which enable the protocol to adapt dynamically to changes in network conditions in real time.
Another avenue for exploration involves testing the protocol in more complex underwater environments, such as those characterised by varying depths, dynamic current patterns, or interference from marine life. Real-world deployments and field tests provide invaluable insights into the protocol's resilience and identify further opportunities for refinement.
This work lays the way for further development related to UWSNs to offer more reliable, efficient, and adaptive solutions to this particular class of communications over complex environments.

Conflicts Of Interest

The author's paper clearly states that no conflicts of interest exist in relation to the research or its publication.

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