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Maximizing Lifetime and Target Coverage in Dynamic Underwater Wireless Sensor Networks using an Enhanced Genetic Algorithm

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Abstract

Dynamic underwater wireless sensor networks (UWSNs) play a crucial role in marine monitoring and surveillance, but their performance is severely constrained by limited energy resources and harsh environmental dynamics. This paper studies the Maximum Lifetime Target Coverage (MLTC-UWSN) problem, which aims to prolong network lifetime while guaranteeing complete target coverage and connectivity under a probabilistic sensing model. We propose EGA-MLTC, an enhanced genetic algorithm that integrates improved crossover, mutation, and diversity-preserving mechanisms within a key-time scheduling framework, enabling effective extraction of disjoint sensor covers that adapt to sensor state variations. The proposed approach is evaluated against baseline metaheuristics, including Differential Evolution (DE) and Harmony Search (HMS), under diverse network scales, sensor densities, and environmental conditions. Simulation results show that EGA-MLTC consistently achieves longer operational lifetimes and more robust coverage than competing methods. These findings establish EGA-MLTC as a practical and scalable solution for efficient and reliable operation of dynamic UWSNs.

Keywords: Underwater wireless sensor network maximizing network lifetime evolutionary computation dynamic sensor network

1 Introduction

Underwater wireless sensor networks (UWSNs) are critical in monitoring aquatic environments, facilitating numerous applications such as marine biology research, disaster prevention, environmental monitoring, and military surveillance [1, 2]. These networks consist of sensor nodes that collect, process, and transmit data through underwater communication channels. However, due to the unique and challenging nature of the underwater environment, UWSNs face several critical constraints, including limited energy resources, unreliable communication links, and dynamic topologies influenced by water currents and other environmental factors [3, 4].

Among the key challenges, network lifetime optimization is one of the most pressing issues for UWSNs. Energy resources in sensor nodes are typically non-rechargeable, and once depleted, the network's operational capabilities are significantly diminished [5, 6]. Hence, efficient energy management is essential to maximize the operational period of the network, especially in dynamic underwater environments where node mobility, adds complexity to network maintenance. Furthermore, the majority of prior studies on UASNs have overlooked the dynamic nature of such networks. In real-world scenarios, sensor nodes can gradually fail, exhaust their energy resources, or become lost due to harsh and unpredictable changes in the underwater environment [7]. Simultaneously, the network must guarantee target coverage, ensuring that the sensor nodes continuously and reliably monitor the region or events of interest. Balancing the extension of network lifetime with the assurance of effective target coverage in such a dynamic setting is a non-trivial task [8, 9].

Due to the computational complexity of optimizing both network lifetime and target coverage, traditional optimization techniques often struggle to adapt to the dynamic nature of UWSNs [10–12]. In this context, metaheuristic algorithms offer a promising solution. These algorithms are well-suited to solving complex, large-scale optimization problems due to their flexibility and ability to explore vast solution spaces efficiently [13–15]. Metaheuristic techniques can provide near-optimal solutions for energy-efficient scheduling and dynamic resource allocation, helping to prolong network lifetime while ensuring consistent target coverage [16]. Metaheuristic algorithms, particularly evolutionary algorithms, have garnered significant attention from researchers for addressing various optimization challenges in wireless communications [17–20]. To tackle the problem of maximizing network lifetime in dynamic UWSNs while maintaining complete target coverage, we introduce EGA-MLTC, an enhanced genetic algorithm tailored to the MLTC-UWSN setting. Our framework partitions sensors into multiple disjoint covers and activates them sequentially (key-time scheduling) to reflect underwater dynamics; coverage is enforced under a probabilistic acoustic sensing model that incorporates distance-dependent attenuation and environment-driven uncertainty, and connectivity is maintained among active sensors. We evaluate EGA-MLTC against strong metaheuristic baselines, including DE, HMS, and MPHSA. To the end, our main contributions are summarized as follows:

- We formalize the *MLTC-UWSN* problem: maximize operational lifetime while guaranteeing complete target coverage and connectivity under a probabilistic sensing model (frequency-dependent attenuation) and realistic sensor state

dynamics (active, sleep, disconnected, dead). We introduce a *key-time* scheduling abstraction and cast cover construction as a set-cover–type search.

- We propose **EGA-MLTC**, an enhanced GA with (i) an improved crossover operator that preserves feasibility on permutation encodings, (ii) mutation for exploration, and (iii) diversity-preserving selection (including Hamming-distance–aware recombination) to avoid premature convergence and scale to large networks. Fitness is defined by the number of disjoint valid covers extractable from an individual.
- We conduct extensive simulations in 3D small- and large-scale settings, with uniform and Gaussian deployments, varying sensor-state transition probabilities and detection thresholds. Results show that **EGA-MLTC** consistently finds more disjoint covers per key-time and achieves longer lifetimes than DE, HMS, and MPHSA, while meeting coverage and connectivity constraints.

The paper is structured as follows: Section 2 discusses related literature, while Section 3 covers preliminaries and formulation for the MLTC-UWSN problem, and Section 4 introduces the proposed algorithm. Section 5 presents experimental results and analysis. Finally, Section 6 draws the conclusions and potential future direction.

2 Related Works

This section presents the related work on maximizing network lifetime in dynamic UWSNs while ensuring target coverage. While energy-efficient target coverage has been extensively studied in terrestrial wireless sensor networks (TWSNs) [8, 21], research in this area for UWSNs is still scarce, although UWSNs hold great promise for underwater applications such as marine habitat observation, disaster detection, pipeline monitoring, etc.

Regarding maximizing network lifetime in TWSNs while meeting target coverage, in [22], this article addresses the target coverage problem in directional sensor networks, aiming to maximize network lifetime while meeting the coverage quality requirements of each target. In this context, directional sensors are capable of rotating freely around their centers, and targets can demand varying levels of coverage quality. They analyzed the inherent relationship between sensor orientation and the targets within their sensing range. Building on this, we developed a heuristic algorithm for the maximum cover sets to effectively solve the target coverage problem. In [23], the authors introduce the maximum coverage sets scheduling problem in WSNs, which aims to determine an optimal scheduling strategy for coverage sets to extend network-lifetime. To address this problem, they first proposed a greedy algorithm. Building on this, they develop an approximation algorithm. They also provided a theoretical analysis to validate the effectiveness of these algorithms. However, the problem is formulated under simplified assumptions, such as a binary sensing coverage model and homogeneous sensor nodes, without considering more realistic scenarios. Consequently, their model has limited applicability in practical deployments. Katti in [24], introduced an energy-efficient target coverage algorithm designed to form both joint and disjoint

cover sets for effective target monitoring. To conserve sensor node energy, the algorithm identifies optimal paths between the sink and sensor nodes, as well as between cover sets and the sink. It also keeps track of the number of targets monitored by each sensor and their remaining energy, enabling the selection of optimal paths that contribute to extending the network's lifetime. The authors in [25] presented an efficient approach for computing the maximum lifetime target coverage. The core idea of our method focuses on identifying targets covered by the fewest sensor nodes. Building on this strategy, they also introduce an algorithm that extends network lifetime by forming subsets of sensor nodes, ensuring continuous monitoring of all targets. In [26], the authors focused on extending the lifetime of wireless sensor networks (WSNs). They proposed an enhanced genetic algorithm-based scheduling approach that ensures complete coverage of target points while also maintaining connectivity between the active sensor nodes and the base station for reliable data transmission.

With respect to prolonging the network lifetime of UWSNs while guaranteeing target coverage, the study presented in [27] appears to be the most closely related to our work. In contrast to traditional TWSN models, their approach takes into account not only sensor inactivity due to energy depletion over time, but also potential sensor failures resulting from the dynamic and often harsh conditions of the underwater environment. Despite its contributions, this study still has certain limitations. Firstly, the sensing model is based on a Boolean representation, which limits its applicability in real-world scenarios. Secondly, although the problem is set in an underwater context, it does not incorporate important environmental parameters such as depth, current velocity, and salinity. Lastly, the proposed multi-population harmony search algorithm has its own drawbacks that merit further investigation. Therefore, there remains considerable room for improvement in this line of research.

From an algorithmic standpoint, evolutionary algorithms (EAs) have demonstrated remarkable success in addressing the inherent complexity of wireless sensor network (WSN) optimization problems, particularly where traditional optimization techniques fail to cope with dynamic environments and combinatorial search spaces, as discussed in [17, 28] and reference therein. For example, Vu et al. [20] applied multi-objective Harmony Search to strike a balance between minimizing deployment cost and maximizing coverage, showing that metaheuristics can effectively handle trade-offs in resource-constrained networks. Similarly, Luong et al. [9] introduced a metaheuristic framework for device-target association optimization, leveraging evolutionary search to enhance connectivity in large-scale IoT sensor networks. Recent advances in differential evolution have further reinforced the versatility of EAs: Huang et al. [29] developed an adaptive DE for multimodal optimization in WSNs, while Bu et al. [30] proposed a multi-strategy DE with adaptive hash clustering that significantly improved robustness and solution diversity. These contributions consistently highlight the superior adaptability of EAs in scenarios with high dimensionality, uncertainty, and dynamic constraints. Building upon this body of research, we address the challenge of prolonging the network lifetime of underwater wireless sensor networks (UWSNs) while ensuring complete target coverage—formulated as the MLTC-UWSN problem. This problem is of both theoretical and practical importance, yet it remains intrinsically difficult due to the complexities of real underwater environments, such as variable

temperature, depth, salinity, and acoustic noise, as well as the diverse operational states of sensor nodes (active, sleep, disconnected, or failed). To this end, we advance the algorithmic frontier by developing four metaheuristic approaches, with particular emphasis on an enhanced Genetic Algorithm (EGA). By incorporating improved crossover and mutation operators together with diversity-preserving mechanisms, our EGA-MLTC mitigates premature convergence and achieves superior scalability compared to DE, HMS and MPHSA. In doing so, our work extends the state of the art in evolutionary algorithm–driven optimization for dynamic UWSNs, providing a solid foundation for both future theoretical exploration and practical deployment.

3 Preliminaries and Problem Formulation

3.1 Preliminaries

3.1.1 The probabilistic sensing coverage model

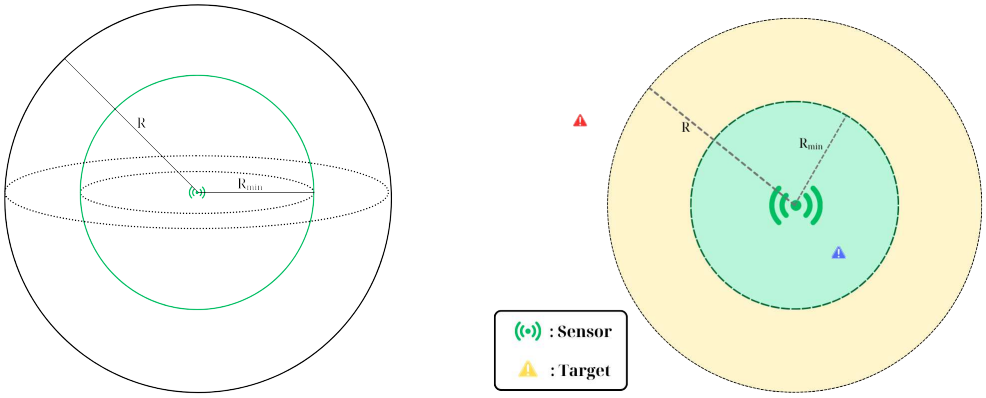
Unlike the Boolean sensing model as adopted in [14], the sensing behavior in underwater sensor networks is inherently uncertain. In such environments, sensors may fail to detect targets even when they are within the nominal sensing range due to various external factors, including temperature fluctuations, water pressure, depth, and ambient noise. To better reflect these real-world conditions and enhance the applicability of our study, we adopt a probabilistic sensing model, where the probability that a sensor detects a given target is defined as follows:

$$\mathsf{Pr}(S,O) = \begin{cases} 1, & \text{if } d(S,O) \leq R_{\min}, \\ \frac{1}{\left(\frac{d(S,O)}{R_{\min}}\right)^{1.5} \times 10^{0.2\alpha(f)(d-R_{\min})}}, & \text{if } d(S,O) > R_{\min}, \end{cases} \tag{1}$$

where $d(S,O)$[km] denotes the distance between the sensor S and target O, R_{min} is the guaranteed sensing radius, and $\alpha(f)$ presents the absorption coefficient at frequency f [kHz] given in [31] by:

$$\alpha(f) = \frac{0.11f^2}{1+f^2} + \frac{44f^2}{4100+f} + 2.75 \cdot 10^{-4} f^2 + 0.003 \tag{2}$$

Figure 1 illustrates the considered probabilistic sensing model employed for underwater sensors. The probability of sensing decreases as the distance from the sensor increases. Due to the unique underwater conditions, efficient target detection relies on the use of acoustic waves. As acoustic waves propagate through water, they reflect or scatter upon encountering underwater targets. These reflections and scatterings generate acoustic echo signals, which are then captured by sensors. By analyzing the acquired signals, it is possible to determine the distance, shape, size, and properties of underwater targets. Signal processing algorithms are applied to filter noise, analyze received data, and localize these targets. A sensor node can detect a target when the target is within its sensing range. In a three-dimensional space, this means that a target can be monitored or covered by the sensor if it lies within the sensor's spherical



(a) The project in three dimensions (b) The project in two dimensions

Fig. 1: Illustration of coverage area from various perspective.

coverage, with the sensor positioned at the center. However, the propagation of the underwater acoustic wave is influenced by external factors, which causes the detection probability to decrease as the distance increases. To ensure reliable detection, we define a detection threshold, denoted as θ, that requires the sensor's detection probability to exceed θ for the target to be considered detected. Consequently, each sensor has a unique effective sensing radius R defined as

$$R = \max_{O}\{d(S,O) \mid \mathsf{Pr}(S,O) \geq \theta\}. \tag{3}$$

For a sensor network to function properly, the detection probability of each target in the network must be greater than or equal to θ. However, to achieve robust coverage in large-scale sensor networks, evaluating only the connectivity between individual sensors and targets is insufficient. Rather, it is essential to analyze the collective connectivity dynamics throughout the entire network, since a target can be detected by multiple sensors. Specifically, the detection probability of a subset of sensors $\mathcal{S} = \{s_1, s_2, \ldots, s_n\}$ to target O is formulated as follows

$$\mathsf{Pr}(\mathcal{S},O) = 1 - \prod_{s_i \in \mathcal{S}} \left(1 - \mathsf{Pr}(s_i,O)\right), \tag{4}$$

where $1 - \mathsf{Pr}(s_i,O)$ represents the unsuccessful detection probability of sensor s_i to target O.

3.1.2 Sensor statuses

Each sensor within the network operates autonomously and is influenced by both internal and external factors. Consequently, the operational status of each sensor can be classified into four primary states:

- **Active State**: The sensor is fully operational and ready to detect targets within its sensing range.
- **Sleep State**: The sensor deactivates its detection capabilities to conserve energy.
- **Disconnected State**: The sensor temporarily loses connectivity due to environmental conditions or communication failures but retains the potential to reconnect and resume operation within the sensor network.
- **Dead State**: The sensor is no longer functional, typically due to power depletion or irreversible external damage.

Notably, the active and sleep states are collectively referred to as the ***functional status***, while the disconnected and dead states are classified as the ***non-functional status***. In the dynamic and unpredictable environment of UWSNs, sensor nodes may switch between functional and non-functional states over time. To manage this variability, the entire monitoring period is divided into a sequence of time slots of fixed duration[1]. At the beginning of each time slot, an adaptive scheduling mechanism determines which subset of functional sensors should be activated to maintain full target coverage, while the remaining functional nodes are kept in sleep mode to conserve energy.

3.1.3 Energy model

Energy is a critical factor in addressing the challenges of UWSNs, where harsh environmental conditions and operational constraints significantly impact sensing, communication, and overall energy consumption. Efficient energy management and optimization are essential to maintaining network performance and prolonging sensor node lifespans—particularly important in underwater settings, where replacing or recharging batteries is often impractical or infeasible. A sensor's energy is defined as the total power it consumes to execute its core functions, including sensing (acquiring environmental data) and communication (transmitting information to other nodes or control units). This encompasses energy used for data processing, signal transmission, and sustaining operational readiness. Notably, the energy required for sensing is directly proportional to the sensing radius: covering a larger area demands higher energy expenditure. The energy consumed during sensing by sensor S is given as follows

$$E_s = \rho \cdot r_i^k \tag{5}$$

where k is pass-loss exponent, $k \in [2, 6]$ and ρ is a proportionality constant.

Furthermore, underwater environments introduce additional factors—such as signal attenuation, noise, and pressure variations—that further increase the energy required for accurate sensing and reliable communication. Additionally, energy consumption during communication depends on several factors, primarily transmission distance and environmental attenuation. The required energy increases with the communication distance between sensors and receiving devices. Since water is a more complex transmission medium than air, transmitting signals over long distances requires significantly more energy. Moreover, factors such as temperature, salinity,

[1] We assume that sensors do not change their status during one time slot

and water pressure affect signal attenuation, further impacting energy consumption. Communication energy consumption includes the energy used for transmitting and receiving information between nodes. Besides, sensors also consume energy during information processing and even in sleep mode, though the latter is negligible. Initially, each sensor s_i has an initial energy E_i. At a given time τ, suppose sensor s_i has residual energy E_{i_τ} and consumes a total amount of energy E_{c_τ}, which includes sensing energy E_{s_τ}, processing energy E_{p_τ}, transmission energy E_{t_τ}, and reception energy E_{r_τ}. Then, the residual energy E_{l_τ} of the sensor s_i after time τ is computed as:

$$E_{l_\tau} = E_{i_\tau} - E_{c_\tau}, \tag{6}$$

where

$$E_{c_\tau} = E_{s_\tau} + E_{p_\tau} + E_{t_\tau} + E_{r_\tau}. \tag{7}$$

3.2 Problem formulation

3.2.1 Maximizing UWSNs lifetime problem

We now formulate a coverage optimization problem to prolong the UWSN lifetime, which is referred to as the MLTC-UWSN problem and expressed as follows. Given M targets need to monitor $\mathcal{T} = \{T_1, \ldots, T_M\}$ and N acoustic water sensor nodes $\mathcal{S} = \{s_1, \ldots, s_N\}$ with constrained energy deployed randomly in the undersea environment of dimensions $L \times W \times D$. Each sensor has its sensing radius, and due to environmental effects, the sensing probability for each target depends on the distance d between the sensor and the target, the assured sensing radius $R_{\min}$ and the frequency f. The sensors can be in one of four states during specific time periods: active, sleep, disconnected, or dead, each with a certain probability. The objective of the problem is to schedule the activity of the sensors so that all targets are continuously observed while maximizing the network lifetime. Fig. 2 illustrates a toy example network comprising $N = 8$ sensors $\mathcal{S} = \{s_1, \ldots, s_8\}$ monitoring $M = 5$ targets $\mathcal{T} = \{T_1, \ldots, T_5\}$.

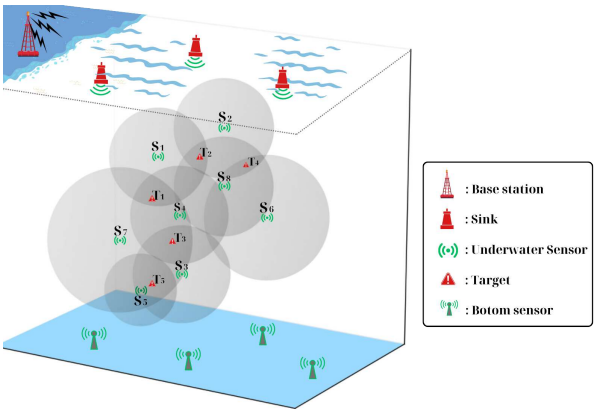


Fig. 2: Demonstration of the deployed model for the system.

The lifetime of a WSN, particularly in underwater environments, is defined as the continuous period during which the network remains operational—that is, from the moment it begins functioning until it can no longer guarantee complete monitoring of all designated targets. We consider the problem of maximizing the number of consecutive time slots, where in each time slot, the UWSN can monitor all the targets and stay connected. The mathematical formulation is as follows.

Input.

- W, D, L: The dimensions (width, depth, and length) of the UWSN deployment area.
- n, m: The number of sensors and targets in the UWSN.
- $s_{i_w}, s_{i_d}, s_{i_l}$: The coordinates of sensor s_i.
- $T_{i_w}, T_{i_d}, T_{i_l}$: The coordinates of target T_i.
- $R_{i_{\min}}$: The guaranteed sensing radius of sensor s_i.
- E_i: The initial energy of sensor s_i.
- θ: The required sensing probability threshold.

Output. The network lifetime T, and the state of each sensor (active, inactive, or dead) at every time slot $\tau = 1, \ldots, \mathsf{T}$.

Constraints. At each time slot, the network must satisfy:

- **Sensing requirement:** The cumulative sensing probability for each target, provided by the active sensors, must be no less than θ.
- **Connectivity requirement:** The active sensors must form a connected communication graph.

In this context, for further design of a mechanism, we introduce the concept of **cover**. A cover is defined as a set of sensors that are active, connected, and can monitor all the targets, each with a probability not less than θ. That is, each sensor in the cover can transmit information to every other sensor in the set—either directly or through multi-hop paths using other sensors within the same cover. Hence, the network is considered alive at a given time if at least one valid cover can be identified. And the work of such a UWSN scheduling mechanism is to define which cover to operate at the beginning of each time slot.

3.3 Maximizing UWSN lifetime by finding cover for each key-time

Due to the dynamic nature of the problem, we propose a method based on the definition of **key-time**, which is a sequence of consecutive time slots. At the beginning of each key-time, we identify disjoint covers among the operational sensors in the network. During a key-time, each cover is activated in turn, while the others remain in sleep mode. When one sensor in the active cover becomes non-functional, the next cover of the key-time is activated. A key-time ends when all covers have been exhausted, and a new key-time begins with an updated scheduling decision. This process continues

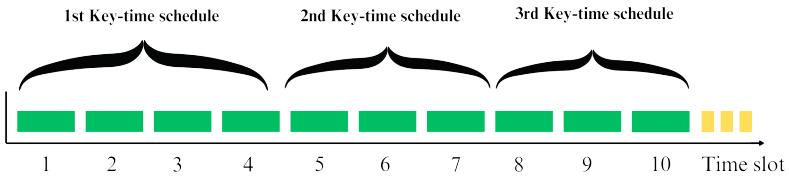


Fig. 3: Key-time schedule

until no valid cover can be found to ensure complete target coverage, which marks the end of the network's lifetime.

Assume that at the t-th key-time ($t = 1, 2, \ldots$), the sets of functional sensors, disconnected sensors, reconnected sensors, and dead sensors are denoted as $\mathcal{S}^{(t)}, \mathcal{F}^{(t)}, \mathcal{R}^{(t)}, \mathcal{D}^{(t)} \subseteq \mathcal{S}$, respectively. At the first key-time, we initialize $\mathcal{S}^{(1)} = \mathcal{S}$ and $\mathcal{F}^{(1)} = \mathcal{R}^{(1)} = \mathcal{D}^{(1)} = \varnothing$. At the next key-time, some sensors may become non-functional due to external factors or depleted batteries, and thus

$$\mathcal{S}^{(t+1)} = \left(\mathcal{S}^{(t)} \cup \mathcal{R}^{(t)}\right) \setminus \left(\mathcal{F}^{(t)} \cup \mathcal{D}^{(t)}\right). \tag{8}$$

In the considered system, the primary objective is to maximize the duration during which all monitored targets remain covered. Specifically, within each key-time, assuming uniform energy consumption rates across sensors, we aim to identify as many disjoint sets of active sensors (covers) as possible. Each cover corresponds to a set of sensors that can simultaneously monitor all targets. Within $\mathcal{S}^{(t)}$, suppose we can identify $K^{(t)}$ disjoint covers $C_1^{(t)}, C_2^{(t)}, \ldots, C_{K^{(t)}}^{(t)}$ that satisfy:

- $C_j^{(t)} \subseteq \mathcal{S}^{(t)}$ for all j
- $C_i^{(t)} \cap C_j^{(t)} = \varnothing$ for all $i \neq j$
- For every target T_m ($m = 1, \ldots, M$) and cover $C_j^{(t)}$, we have $\mathsf{Pr}(C_j^{(t)}, T_m) \geq \theta$
- The sensors within each $C_j^{(t)}$ form a connected subgraph.

The objective at the beginning of each key-time t is to maximize $K^{(t)}$. When $\max K^{(t)} = 0$, the network is considered non-functional. If the active time (in slots) of cover $C_j^{(t)}$ is $\tau_j^{(t)}$, determined by the minimum residual lifetime of its sensors, then the duration of key-time t is

$$\tau^{(t)} = \sum_{j=1}^{K^{(t)}} \tau_j^{(t)}. \tag{9}$$

The overall lifetime of the UWSN is

$$\mathsf{L} = \sum_{t=1}^{T} \tau^{(t)}, \tag{10}$$

where T is the last key-time before the network becomes non-functional.

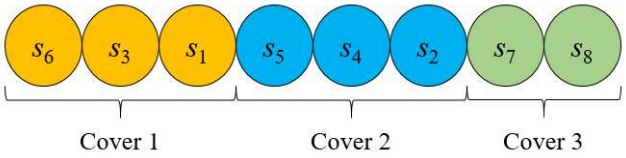


Fig. 4: An example of extracting 3 disjoint cover from an individual

4 Proposed Algorithms for Finding Covers

By finding the optimal number of disjoint covers, the probability of sustained lifetime is increased. At any given point in time, a cover set of sensors is selected to be active with the aim of detecting all targets. The problem of determining the number of covers to extend the lifetime of a WSN can be reduced to the set covering problem, which is NP-complete [32]. Hence, we will propose metaheuristic algorithms for efficiently finding high-quality solutions to the problem. These algorithms are designed to find good, near-optimal solutions within a reasonable timeframe, which is essential for real-time or large-scale applications like underwater sensor networks [15, 33]. Furthermore, metaheuristics incorporate mechanisms to escape local optima, increasing the likelihood of finding better solutions in the highly multimodal search spaces typical of combinatorial problems.

4.1 Solution representation

In evolutionary algorithms, each individual represents a candidate solution to the problem. For our case, a solution is represented as a permutation of N integers, each corresponding to one sensor. Figure 4 illustrates an individual with $N = 8$ sensors divided into 3 disjoint covers. The fitness value measures the quality of an individual by evaluating the number of disjoint covers it can generate. At each key time t, we determine the set of active sensors $\mathcal{S}^{(t)}$. The relationship between sensors and targets can be modeled as a bipartite graph $\mathcal{G}^{(t)} = (\mathcal{S}^{(t)}, \mathcal{T}, \mathcal{E})$, where $\mathcal{S}^{(t)}$ and $\mathcal{T}$ represent the functional sensors at the beginning of key time t and the set of targets, respectively. If a sensor $s_i \in \mathcal{S}^{(t)}$ can detect a target $T_j \in \mathcal{T}$, then an edge (s_i, T_j) exists in $\mathcal{E}$. An example of such a bipartite graph is illustrated in Figure 5. The procedure for calculating the fitness value of an individual is summarized in Algorithm 1. The resulting fitness value depends on the number of disjoint covers found.

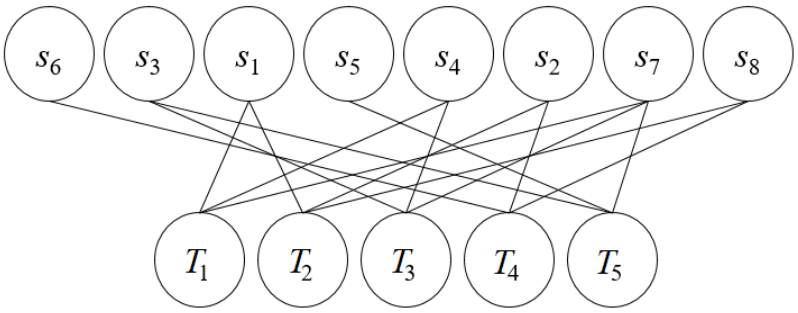


Fig. 5: Illustration of the bipartite graph

Algorithm 1: Evaluate fitness value

Input: An individual c, which is a permutation of $\{s_1, s_2, \ldots, s_n\}$.
Output: Fitness value f_c of the individual c.

Initialize: $k = 1$; $C_k^{(t)} = \varnothing$
for $i \leftarrow 1$ **to** n **do**
  $C_k^{(t)} \leftarrow C_k^{(t)} \cup \{c[i]\}$
  if $C_k^{(t)}$ *forms a valid cover* **then**
    $k \leftarrow k + 1$
    $C_k^{(t)} \leftarrow \varnothing$ `// Start a new cover`
  end
end
if $C_k^{(t)}$ *forms a valid cover* **then**
  return k
else
  return $k - 1$
end

4.2 Initialization

To ensure population diversity, we adopt a randomized initialization strategy. Each individual is generated as a random permutation of the N sensors, which guarantees that all sensors are represented exactly once in every solution. This approach not only provides a diverse set of starting individuals but also ensures that the generated solutions are valid candidates for the evolutionary process.

4.3 Evolutionary operators

The crossover operator used in this algorithm is modified from single-point crossover (SPC). The SPC is to generate a random number within the individual length range, and then intercept the first half of the father's individual and the second half of the mother's individual to cross-breed the children according to the generated random

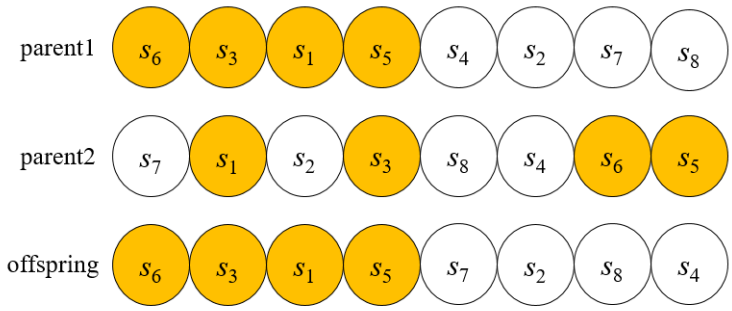


Fig. 6: Illustration of improved crossover operation

Algorithm 2: Improved crossover operator

Input: The parents individual
- *male* $p_1 = \{x_1, x_2, ..., x_n\}$
- *female* $p_2 = \{y_1, y_2, ..., y_n\}$

Output: The offspring individual $c = \{c_1, c_2, ..., c_n\}$

```
Initializing a blank list c
Randomly an integer number k, k = 1, n
for i ← 1 to k do
    Adding x_i to c
end
for j ← 1 to n do
    if y_i ∉ c then
        Adding y_i to c
    end
end
return c
```

number. However, due to the possibility of repetitions within the child individual, in this article, we suggest an improved crossover operation, described via Algorithm 2. Figure 6 visually illustrates the improved crossover process, guaranteeing a valid new individual. To improve the efficiency of the algorithm, in this article, we suggest using Hamming distance function. The Hamming distance between two individuals x and y of length n is defined as follows:

$$H(x,\, y) = \sum_{i=1}^{n} f_i(x,\, y), \text{ with } \begin{cases} f_i(x,\, y) = 1, \text{if } x_i \neq y_i; \\ f_i(x,\, y) = 0, \text{if } x_i = y_i. \end{cases} \tag{11}$$

The Hamming distance function quantifies the dissimilarity between two individuals, with a larger Hamming distance indicating greater differences. If two individuals have a small Hamming distance, crossing them is less likely to enhance the population, potentially causing premature convergence. Therefore, crossover occurs only when the

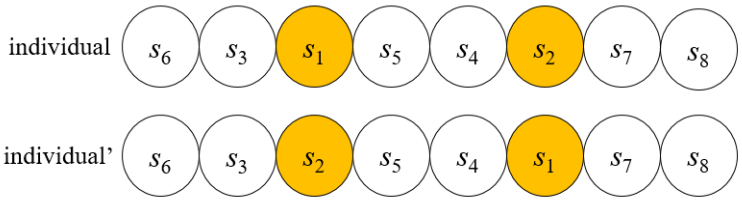


Fig. 7: An example illustrates RMS mutation operator on an individual

Algorithm 3: Mutation operator

Input: The individual $c = \{c_1, c_2, ..., c_n\}$
Output: The mutated individual $c' = \{c'_1, c'_2, ..., c'_n\}$

Choosing randomly 2 different integers *point1* and *point2* $\in$ [1, n]
$t \leftarrow c_{point1}$
$c_{point1} \leftarrow c_{point2}$
$c_{point2} \leftarrow t$
return c

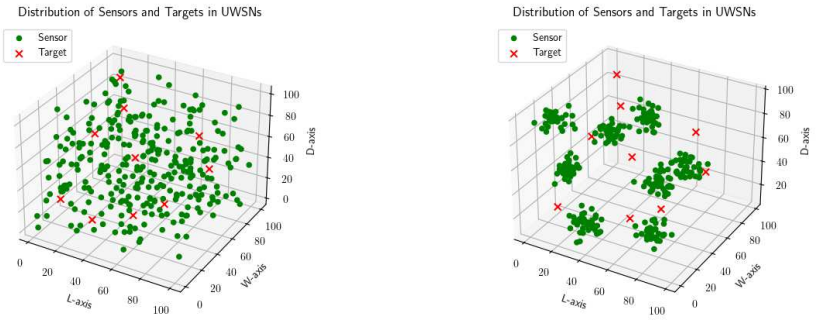
Hamming distance exceeds a specific threshold, set to $\frac{n}{10}$ in this paper. Mutation is another important operator that can increase the diversity of the population, thereby preventing premature convergence. Whether each individual x undergoes mutation is determined by its mutation rate p_x. In this paper, we choose a simple mutation method that swaps the positions of two genes in the individual. Details of the mutation method are shown in Algorithm 3 with an example of a gene mutation in Figure 7.

4.4 Selection

Each individual y in the population is evaluated and assigned a fitness f_y calculated using the fitness function presented in the previous section. A new individual obtained from the previous step is added to the population if its fitness value is better than the worst fitness value in the current population. The individual with the worst fitness value is then removed from the population.

5 Experimental Results

To prove the effectiveness of those proposed algorithms, we have conducted various experiments with different experimental scenarios to compare EGA-MLTC with three previous algorithms, the most close multipopulation harmony search MPHSA [27], a version of the differential evolution algorithm (DE) [29, 30] and a version of Hamorny search algorithm HMS [20, 34]. These compared metaheuristic algorithms have been proven to be effective and efficient in designing and operating wireless sensor networks in the related literature. Thorough evaluations and analyses were performed to give deep insight into the experimental results. All experiments were conducted on a



(a) Uniform distribution (b) Gaussian distribution

Fig. 8: Distribution of Sensors and Targets in UWSNs

machine with Intel Core i7-7820HQ @ 2.90GHz, 16 GB RAM and Window 10 OS. The code was written in Java.

5.1 Experimental settings

We simulated a total of 500 topologies, divided into two types of networks: **small-scale** and **large-scale**, each containing 250 topologies. Sensors were deployed in both network scales using a uniform distribution. During the experiments, we considered two environment sizes: a small-scale environment of $100 \times 100 \times 100$ and a large-scale environment of $500 \times 500 \times 500$. Sensor coordinates were initialized according to a uniform distribution, as illustrated in Figure 8a. Let (X, Y, Z) denote the position of a sensor, and (L, W, D) denote the length, width, and depth of the environment, respectively. Then, using a uniform distribution, the coordinates are generated as:

$$X \sim \mathcal{U}(0, L), \quad Y \sim \mathcal{U}(0, W), \quad Z \sim \mathcal{U}(0, D). \tag{12}$$

Additionally, to further assess the effectiveness of the algorithm, we conducted experiments using an alternative sampling distribution. Specifically, we employed the **make_blobs()** function, which generates isotropic Gaussian blobs for clustering, as illustrated in Figure 8b. In this experiment, the number of sensors was set to 300, the number of targets to 15, and the number of clusters to 8. Table 1 summarizes other parameters of the sensor networks for both environments.

In total, we choose datasets for two networks: a small-scale network, suitable for environments like lakes, and a large-scale network, such as seas or rivers. For each network, the number of sensors and targets is adjusted to reflect realistic scenarios.In particular, for the small-scale network, we select between 300 and 600 sensors, together with 10 to 20 targets. In contrast, the large-scale network involves a much larger number of nodes, with 500 to 1000 sensors and 20 to 50 targets. The sensing radius is adjusted according to the size of each network, and all sensors are uniformly distributed to ensure full coverage of the monitored area. Furthermore, each dataset is

Parameter	Small-scale	Large-scale
Number of sensors	100, 200, 300, 400, 500	600, 700, 800, 900, 1000
Number of targets	10, 15, 20, 25, 30	30, 35, 40, 45, 50
Sensing radius	$\mathcal{U}[40, 50]$	$\mathcal{U}[125, 150]$
Sensor distribution	Uniform, Gaussian	
P_f	0.001, 0.005	
P_r	0.001, 0.005	
P_d	0.0001, 0.0005	
Initial Energy	1000	10000

Table 1: Parameter settings for simulation of small-scale and large-scale UWSNs

simulated 10 times to obtain average values and to minimize variations caused by the stochastic nature of the meta-heuristic algorithm. Through extensive experiments, we determined the most suitable parameters for the proposed algorithm. Each algorithm was executed for at least 500 iterations to ensure convergence toward a sufficiently accurate and stable result. Moreover, an early-stopping criterion was introduced: if no improvement was observed after 100 consecutive iterations beyond the 500th iteration, the algorithm was terminated. This threshold was found to be sufficient based on extensive experimental evaluation, as further iterations beyond this point rarely improved the solution quality. In addition, the population size plays a crucial role in determining solution quality. When the number of sensors is large, the population must also be sufficiently large to maintain diversity and avoid premature convergence. Each algorithm is run for at least 500 iterations. This threshold was found to be sufficient, as shown in Figure 9, where the performance of the algorithm stabilizes and exhibits only marginal improvements beyond 500 iterations.

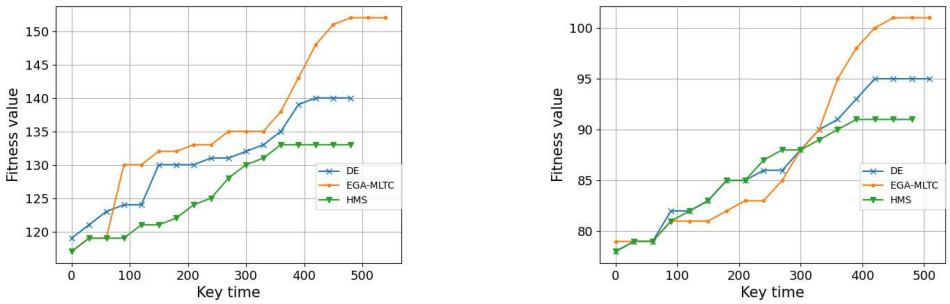
5.2 Experimental results

5.2.1 Evaluation of how the proposed algorithms perform under different parameters

Convergence analysis

Convergence reflects how quickly and effectively an algorithm approaches an optimal solution. Figure 9 presents a comparative analysis of the convergence performance among DE, EGA-MLTC, and HMS on both small- and large-scale datasets. The results indicate that the proposed EGA-MLTC algorithm demonstrates a superior capability in identifying high-quality solutions, although its convergence path varies with problem complexity. In the small-scale scenario (Figure 9a), EGA-MLTC exhibits dominant performance with a significantly faster convergence rate, rapidly achieving a higher fitness value than both DE and HMS, while the latter two algorithms show a slower progression and tend to stagnate at suboptimal solutions, suggesting they may be prone to premature convergence on local optima. In the more complex, large-scale scenario (Figure 9b), the convergence dynamics are notably different: during the initial search phase (approximately the first 350 key time units), HMS and DE display a faster initial improvement; however, EGA-MLTC showcases a robust ability to escape

local optima in the later stages, accelerating dramatically to eventually surpass its counterparts and attain the highest final fitness value. This behavior highlights its effectiveness in navigating vast and complex search spaces to locate superior solutions. In summary, across different network scales, EGA-MLTC consistently proves to be a more reliable optimization algorithm. While it may not always be the fastest in the initial phase of complex problems, its strength lies in its ability to avoid premature convergence and ultimately discover solutions of higher quality than the compared methods.



(a) 300 sensors – 20 targets

(b) 800 sensors – 40 targets

Fig. 9: Convergence comparison of DE, EGA-MLTC, and HMS algorithms in (a) a small-scale dataset and (b) a large-scale dataset. For clarity, only every 30th iteration is plotted.

Number of covers

The primary objective for maximizing network lifetime is to find the maximum possible number of disjoint sensor covers, as a higher number of covers directly translates to a longer operational lifespan for the network by allowing the system to cycle through them over time; therefore, an algorithm's effectiveness can be measured by its ability to find and maintain a large number of covers. Figure 10 illustrates the robustness of the solutions provided by each algorithm, plotting the number of available covers as a function of the network's operational key time τ, where a superior solution sustains a higher number of covers for an extended period. The results show a clear advantage for the proposed EGA-MLTC algorithm: while all algorithms identify a high number of covers initially, EGA-MLTC successfully maintains a higher count of active covers for a longer duration compared to its counterparts, sustaining at least three covers until key time $\tau = 28$, whereas the solutions from DE and HMS degrade more rapidly, dropping to the minimum of two covers at $\tau = 24$ and $\tau = 21$, respectively. This outcome demonstrates that the set of covers identified by EGA-MLTC is of higher quality, leading to a more graceful degradation of network capacity and, consequently, a longer effective lifetime, confirming that EGA-MLTC is the most effective algorithm based on this crucial metric.

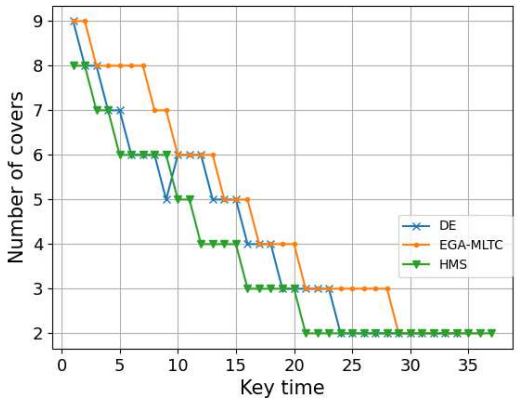


Fig. 10: Comparison of DE, EGA-MLTC, and HMS in a small-scale network based on the number of covers after each key time τ.

Energy consumption and stability

Energy consumption is a fundamental metric for evaluating the efficiency of network operations, and an effective scheduling algorithm must balance the quality of its solution (i.e., network lifetime) with the energy cost required to achieve it. Figure 11 presents the cumulative energy consumption of the three algorithms over their operational lifespan in a small-scale network. At first glance, the DE algorithm appears to be the most energy-efficient, as its curve remains the lowest, indicating the least total energy consumed; however, this interpretation is incomplete without considering the network lifetime achieved by each algorithm. As established in our previous analyses (e.g., Figure 10), the solution generated by EGA-MLTC results in a significantly longer network lifetime, and consequently, its higher total energy consumption is a natural and expected outcome of prolonged operational duration. This result highlights a critical trade-off: EGA-MLTC's advanced optimization strategy, which successfully identifies more robust and numerous sensor covers, incurs a higher energy expenditure per unit of time, yet this "investment" yields a disproportionately larger return in the form of extended network longevity. In contrast, while DE and HMS are more frugal in their immediate energy usage, their strategies lead to premature network failure, demonstrating that EGA-MLTC does not merely consume more energy, but rather utilizes it more effectively to fulfill the primary objective of maximizing the network's operational lifetime.

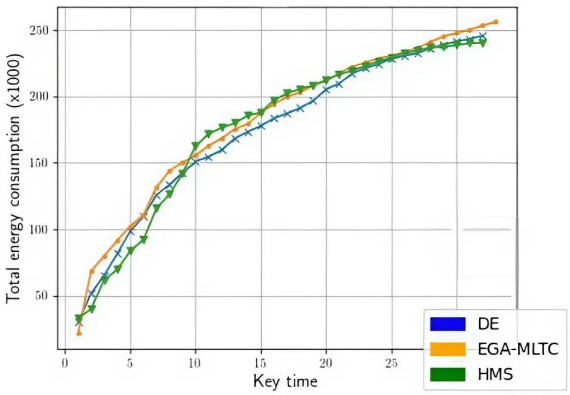
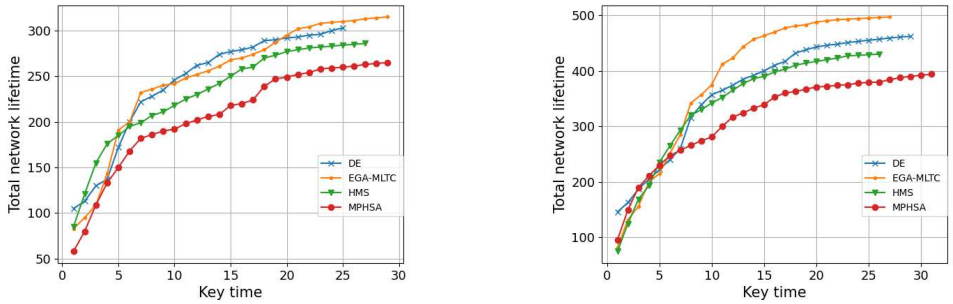


Fig. 11: Performance of DE, EGA-MLTC, and HMS algorithms in a small-scale network: energy consumption.

5.2.2 Comparison of the proposed algorithms with existing methods

Effect of the number of sensors

To evaluate the scalability and robustness of the proposed algorithm, we assessed its performance under varying sensor densities, progressively increasing the number of sensors from 100 to 500 while keeping the number of targets constant at 20. Figure 12 presents the total network lifetime achieved by each algorithm across these small-scale network scenarios, and the results consistently demonstrate the superior performance of EGA-MLTC across all tested configurations, as its curve consistently reaches the highest final network lifetime, indicating its effectiveness regardless of sensor density. More importantly, the analysis reveals the excellent scalability of the proposed algorithm: in scenarios with a lower number of sensors, such as in Figure 12a, EGA-MLTC's performance is competitive with DE, but as the network size and problem complexity increase (Figures 12c and 12d), the performance gap between EGA-MLTC and the other algorithms becomes significantly more pronounced, strongly suggesting that EGA-MLTC is more adept at navigating larger and more complex search spaces to discover higher-quality solutions. In contrast, while DE remains a strong competitor, it is consistently outperformed by EGA-MLTC as the network scales, and both HMS and MPHSA lag behind, with MPHSA showing the least effective performance in all cases, underscoring the robustness and superior scalability of EGA-MLTC and making it a highly suitable solution for optimizing network lifetime in sensor networks of varying scales.



(a) 100 sensors – 20 targets

(b) 200 sensors – 20 targets

(c) 400 sensors – 20 targets

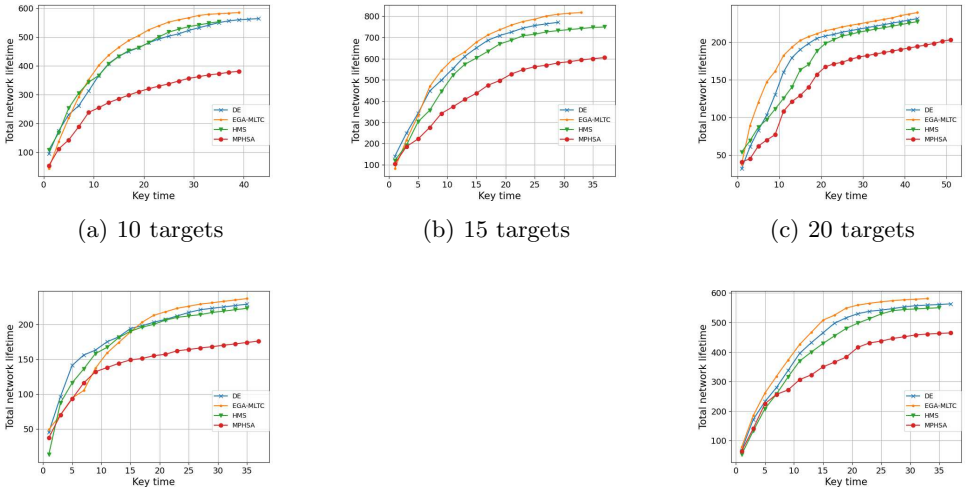
(d) 500 sensors – 20 targets

Fig. 12: Comparison of DE, EGA-MLTC, and HMS in small-scale networks with different numbers of sensors.

Effect of the number of targets

We further examined the robustness of the algorithms by evaluating their performance under an increasing number of coverage constraints, fixing the sensor count at 300 while varying the number of targets from 10 to 30, where a higher target count makes the problem more challenging as each cover must satisfy more stringent requirements, with the results summarized in Figure 13. The outcomes provide compelling evidence of the superiority and robustness of the proposed EGA-MLTC algorithm: across all five distinct scenarios, EGA-MLTC consistently achieves the longest total network lifetime, demonstrating its effectiveness regardless of the problem's constraint level. While the overall network lifetime naturally decreases as the number of targets increases due to the increased difficulty of forming valid covers, EGA-MLTC consistently maintains a significant performance margin over the other methods, highlighting its ability to effectively navigate the more constrained search space to find high-quality, long-lasting solutions. In contrast, while DE performs competitively, it is consistently surpassed by EGA-MLTC, particularly in finding the optimal long-term solution, and the performance of HMS and MPHSA remains significantly lower, further solidifying

the conclusion that EGA-MLTC is the most reliable and robust algorithm for this problem, especially as coverage demands become more rigorous.



(a) 10 targets (b) 15 targets (c) 20 targets

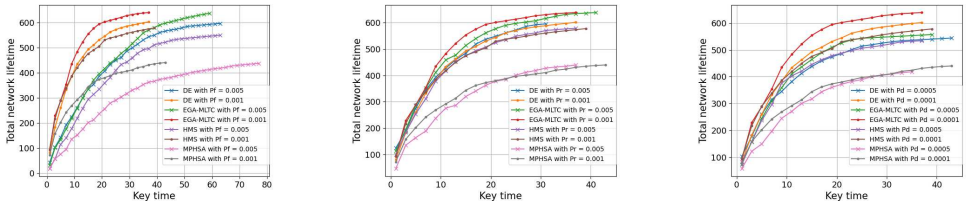
(d) 25 targets (e) 30 targets

Fig. 13: Network lifetime evaluation in a small-scale network with 300 sensors and varying numbers of targets.

Effect of sensor state probabilities

To simulate the dynamic and often unpredictable nature of underwater environments, we evaluated the algorithms' performance under varying sensor state transition probabilities, specifically analyzing the impact of the probability of sensor failure (P_f), the probability of reconnection (P_r), and the probability of permanent death (P_d), with the results illustrated in Figure 14. The results consistently highlight the robustness and superior adaptability of the proposed EGA-MLTC algorithm: as expected, higher failure and death probabilities (P_f, P_d) or a lower reconnection probability (P_r) led to a reduction in the overall network lifetime for all algorithms, yet across all tested scenarios, EGA-MLTC consistently achieved a longer network lifetime compared to the other methods. Notably, EGA-MLTC demonstrates remarkable resilience, maintaining a significant performance advantage under adverse conditions such as a higher probability of sensor failure (Figure 14a), indicating its ability to find effective coverage solutions even as the pool of functional sensors diminishes unpredictably. Furthermore, when conditions are more favorable, such as a higher probability of sensor reconnection (Figure 14b), EGA-MLTC proves more adept at capitalizing on these opportunities to extend the network's operational duration. This comprehensive analysis confirms that EGA-MLTC is not only effective but also robust, making it a reliable choice for

real-world UWSN deployments where the operational status of sensors is subject to constant environmental uncertainty.



(a) With P_f (b) With P_r (c) With P_d

Fig. 14: Comparison of DE, EGA-MLTC, HMS, and MPHSA in small-scale networks under different state probabilities.

Effect of threshold

The sensing probability threshold, θ, represents a critical quality-of-service (QoS) requirement, dictating the minimum acceptable coverage level for each target. We investigated the impact of this threshold on algorithm performance by comparing network lifetimes under two distinct settings, a standard requirement ($\theta = 0.8$) and a more stringent requirement ($\theta = 0.9$), with the results presented in Figure 15. As anticipated, increasing the threshold from 0.8 to 0.9 resulted in a shorter network lifetime for all evaluated algorithms, because a higher θ imposes stricter constraints on the formation of valid covers, making the optimization problem inherently more difficult. Despite the increased challenge, the proposed EGA-MLTC algorithm demonstrated clear superiority and robustness: under both standard and stringent QoS requirements, EGA-MLTC achieved the longest network lifetime, outperforming all competing methods, and while the performance of all algorithms degraded with the higher threshold, EGA-MLTC exhibited greater resilience, showing a less pronounced reduction in lifetime compared to the others. This consistent performance advantage across different thresholds further validates the effectiveness of EGA-MLTC as a reliable solution for real-world scenarios where coverage quality is a key operational parameter.

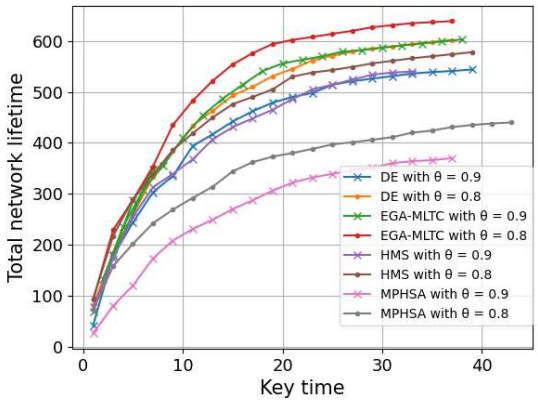
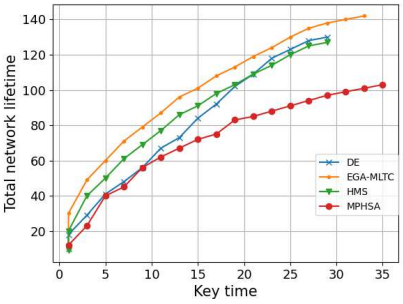


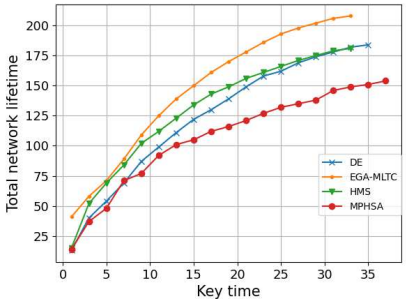
Fig. 15: Comparison of DE, EGA-MLTC, HMS, and MPHSA in a small-scale network with varying threshold θ.

Large-scale experiments

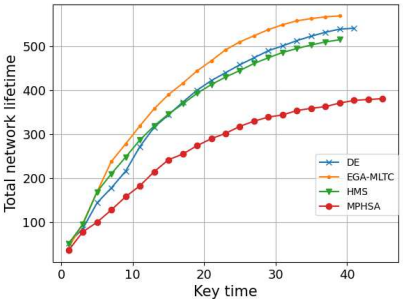
To conclusively validate the effectiveness of the proposed algorithm, we extended our evaluation to large-scale network scenarios, which more closely resemble real-world deployment conditions, designed to test the ultimate scalability and robustness of the algorithms when faced with a significantly larger number of sensors and targets, with the results illustrated in Figure 16 and Figure 17. Figure 16 examines the effect of increasing sensor density from 500 to 1000 sensors in large-scale networks, decisively reaffirming the conclusions drawn from the small-scale tests, as EGA-MLTC consistently outperforms all other algorithms; crucially, these large-scale results highlight the superior scalability of EGA-MLTC, where its performance advantage over competitors becomes even more significant as the number of sensors increases, demonstrating the algorithm's exceptional capability to efficiently explore vast and complex search spaces to identify optimal solutions. Similarly, Figure 17 evaluates the algorithms' robustness against an increasing number of targets from 20 to 50 within a large network of 1000 sensors, and once again, EGA-MLTC demonstrates its consistent superiority by achieving the longest network lifetime across all scenarios, proving the algorithm's robustness as it maintains effectiveness even when coverage constraints become more demanding in a high-density environment. In conclusion, the large-scale experiments provide definitive evidence that EGA-MLTC is not only superior in performance but also excels in scalability and robustness, and the findings from these challenging scenarios, combined with the comprehensive results from the small-scale tests, firmly establish EGA-MLTC as a practical, scalable, and highly effective solution for maximizing the operational lifetime of dynamic underwater wireless sensor networks.



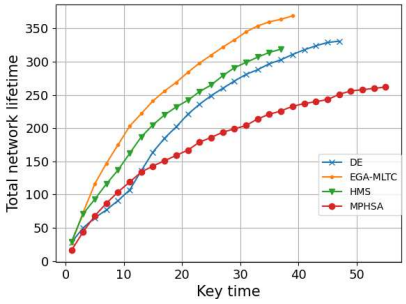
(a) 500 sensors – 20 targets



(b) 600 sensors – 20 targets

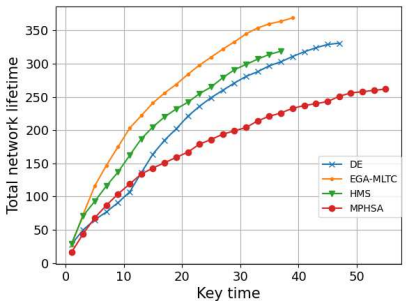


(c) 800 sensors – 20 targets

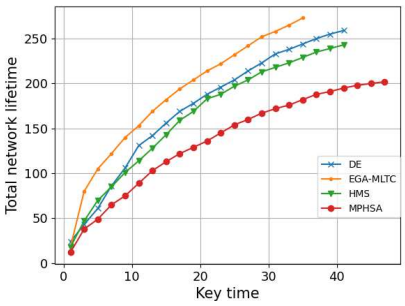


(d) 1000 sensors – 20 targets

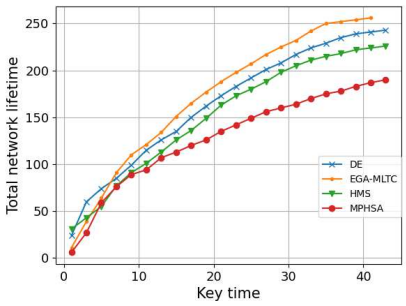
Fig. 16: Comparison of DE, EGA-MLTC, and HMS algorithms in large-scale networks with varying numbers of sensors.



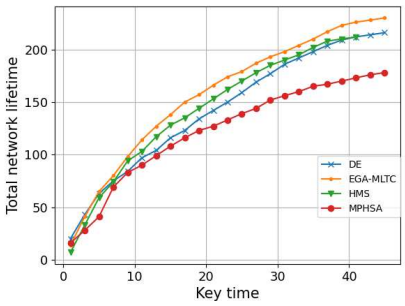
(a) 1000 sensors – 20 targets



(b) 1000 sensors – 30 targets



(c) 1000 sensors – 40 targets



(d) 1000 sensors – 50 targets

Fig. 17: Comparison of DE, EGA-MLTC, and HMS algorithms in large-scale networks with varying numbers of targets.

6 Conclusions

This paper addressed the MLTC-UWSN problem, which focuses on maximizing the operational lifetime of dynamic underwater wireless sensor networks while ensuring complete target coverage and connectivity. To solve this problem, we proposed EGA-MLTC, an enhanced genetic algorithm designed with improved crossover, mutation, and diversity-preserving mechanisms. The algorithm operates within a key-time scheduling framework, where sensors are partitioned into disjoint covers that are activated sequentially to account for environmental dynamics and sensor state changes. By extracting a greater number of valid covers, EGA-MLTC extends network lifetime while meeting both coverage and connectivity requirements. Through extensive experiments across small- and large-scale 3D networks, with varying numbers of sensors, targets, and environmental conditions, EGA-MLTC was compared against established metaheuristic baselines, namely DE and HMS. The results demonstrated that EGA-MLTC consistently outperformed the baselines by finding more disjoint covers and delivering longer overall network lifetimes. These findings confirm that carefully enhanced evolutionary strategies can effectively handle the combinatorial and dynamic challenges inherent in underwater sensing environments. Future work will extend this study in several directions. Potential avenues include the integration of more detailed underwater acoustic and energy models, distributed implementations of the algorithm that account for communication overhead, and exploration of adaptive mechanisms for handling mobile targets and variable coverage thresholds. Overall, EGA-MLTC provides a practical and scalable solution for lifetime-aware, coverage-guaranteeing operation in dynamic UWSNs.

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