

Article

Modified Ant Colony Optimization to Improve Energy Consumption of Cruiser Boundary Tour with Internet of Underwater Things

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Abstract: The Internet of Underwater Things (IoUT) holds significant promise for developing a smart ocean. In recent years, there has been swift progress in data collection methods using autonomous underwater vehicles (AUVs) within underwater acoustic sensor networks (UASNs). One of the key challenges in the IoUT is improving both the energy consumption (EC) of underwater vehicles and the value of information (VoI) necessary for completing missions while gathering sensing data. In this paper, a hybrid optimization technique is proposed based on boundary tour modified ant colony optimization (BTMACO). The proposed optimization algorithm was developed to solve the challenging problem of determining the optimal path of an AUV visiting all sensor nodes with minimum energy consumption. The optimization algorithm specifies the best order in which to visit all the sensor nodes, while it also works to adjust the AUV's information-gathering locations according to the permissible data transmission range. Compared with the related works in the literature, the proposed method showed better performance, and it can find the best route through which to collect sensor information with minimum power consumption and a 6.9% better VoI.

Keywords: internet of underwater things (IoUT); autonomous underwater vehicle (AUV); value of information (VoI); energy efficiency; modified ant colony optimization (MACO) algorithm



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1. Introduction

With the increasing demand to discover, study, utilize, and explore the underwater world, underwater IoT technology has become necessary to satisfy these human goals [1]. To satisfy these purposes, the autonomous underwater vehicle (AUV) was developed to operate and navigate in underwater environments without the need for human control [2]. AUVs are used for many purposes, such as exploring underwater depths, research, rescue, underwater safety, and underwater equipment maintenance and repair [3]. While AUVs perform their tasks, they may have to navigate close to the seabed. In this case, AUVs can be affected by undesirable and rapidly changing hydrodynamic forces and moments due to the bottom effect. For this reason, AUVs should have good hydrodynamic performance. Therefore, these UAVs, in order to be able to position themselves in a very short time and

follow the determined trajectory, should perform these maneuvers quickly and with the lowest tracking error [4]. AUVs are supplied with different sensors, like sonar, cameras, pH sensors, fluorometers, magnetometers, and so on.

Whether the data collected by UAVs are on the sea surface or deep in the ocean, the data can be either stored within the UAV or transmitted to other station vehicles on the sea surface [2]. One traditional technique to transfer data between UAVs and sea-surface stations is to use cables as a communication link. However, this technique is limited in range and degree of motion freedom. Therefore, the remote transmission of data is required.

In underwater environments, radio signals are not suitable due to the limited range of radio frequencies. Instead, acoustic waves are leveraged in underwater communications since they can travel for longer distances [5]. However, compared with radio waves, acoustic waves have more latency and lower speed. Therefore, unique innovations and techniques have appeared in the operation and design of underwater IoT systems due to this essential difference in the communication medium.

Energy efficiency is one of the critical issues and challenging problems, especially for the application used in this study, where the UAV works to navigate deep in the ocean to collect data from the nodes and transmit them to the station on the sea surface due to the fact that underwater nodes are battery-operated and difficult to recharge. Moreover, acoustic transceivers consume significantly more power than radio transceivers [5]. However, the energy consumption resulting from the navigation of UAVs is significant and dominant. Therefore, the optimization of trajectory planning is the key to minimizing the energy consumption of AUVs during their navigation and tour deep in the ocean based on data collection approaches.

This study has addressed the problem of data collection by an underwater cruiser (AUV) and returning the data to a station ship on the sea surface. The scenario can be described as follows:

- The UAV starts its tour from the ship station, and it sinks deep into the ocean to visit many nodes distributed randomly in the volumetric space of the ocean.
- The nodes represent sensors devoted to recording real data in the ocean. These node sensors communicate the data to the underwater cruiser when the cruiser arrives within the prescribed or suitable distance from the node.
- The UAV tries to visit all the nodes and return to the surface ship station along the shortest (optimal) path.
- The power consumption due to the AUV's tour is of course directly related to the length of the navigation path.

Accordingly, to minimize power consumption, an optimization technique can be considered to generate the optimal path based on the configuration space of the node position. This optimal path has to be followed by an underwater cruiser such that it has to visit and collect data from all nodes and then go back to the station. In this study, the combination of boundary tour (BT) and modified ant colony optimization methods (BT-MACO) is proposed to save the battery life of the AUV by determining an optimal path for collecting information from all the sensor nodes. Thus, if the AUV's journey is completed in the shortest path and avoids time-consuming paths, then an improvement in the value of information (VoI) can be achieved.

The remainder of the paper is organized as follows: Section 2 summarizes previous related works. The proposed BT-MACO method is illustrated in detail in Section 3. Section 4 shows the simulation results. The paper ends with the conclusion in Section 5.

2. Related Works

Path planning for AUV in the IoUT environment plays a significant role in improving data collection, conserving energy, and increasing system reliability. Many approaches have been explored to improve AUV navigation, ranging from heuristics to nature-inspired algorithms. In the IoUT environment, AUV path planning encounters many challenges, including real-time adaptation, computational complexity, energy consumption, and fluctuations in the aquatic environment. This survey presents a review of ten research papers, arranged chronologically, focusing on the approaches and challenges they face.

In [6], the authors utilized evolutionary algorithms to optimize paths in complex environments while improving mobility; however, the biggest challenge lies in the real-time computational load. In [7], the authors explored energy-saving strategies to extend the mission duration of autonomous vehicles while maintaining the quality of data collection. The biggest challenge of this approach is to balance energy efficiency and data accuracy. In [8], the authors developed a full-coverage path planning algorithm to ensure the comprehensive scanning of underwater target areas, despite the difficulty in adapting to dynamic terrain. The authors in [9] presented a dynamic detection algorithm to adjust autonomous vehicle trajectories in real time, which improves energy efficiency; however, this technique faces the challenges of environmental fluctuations. The authors in [10] investigated sensor clustering protocols to optimize autonomous vehicle trajectories, reducing energy consumption and increasing network lifetime, but data accuracy is considered a limitation. The authors in [11] presented a path optimization framework using synchronous wireless information and power transmission (SWIPT) for autonomous vehicles, which achieves a balance between data collection and energy harvesting; nevertheless, achieving data accuracy while saving energy is a challenge. The authors in [12] proposed the use of neural networks inspired by nature to guide autonomous underwater vehicles during path planning in complex environments, which improves both coverage and navigation efficiency. The authors in [13] presented a heuristic method for optimizing autonomous marine vehicle (AMV) trajectories, including the integration of environmental data such as ocean currents to improve coordination and reduce mission time. In [14], the authors applied evolutionary algorithms to improve coverage and reduce energy consumption in aquatic environments while improving efficiency. However, the computational complexity remains a major challenge. In [15], the authors explored the use of pre-defined routing points for autonomous underwater vehicle navigation, which reduces navigation time and improves efficiency. In [16], the study presented the solution to the path planning problem of UAVs to be like the solution to the traveling salesman problem (TSP). The article proposed an improved genetic algorithm and a hybrid algorithm based on particle swarm optimization together with ant colony optimization. In [17], the researchers proposed two algorithms to solve the problem of path planning for UAVs. The proposed techniques have previously been used for solving the previous optimization problems of Close-Enough Traveling Salesman and traveling salesman. In [18], the authors presented the approach of the traveling salesman problem to generate robust and quick motions for Mine Countermeasures in the presence of uncertain marine environmental conditions (vehicle dynamics, complex bathymetry, and ocean currents). The method and challenges in each related work are summarized in Table 1.

Different from those of the previous works, the contributions of the method proposed in this paper are summarized as follows;

- A boundary tour optimization algorithm is proposed to solve AUV battery-based trajectory planning for collecting sensor node information with minimum time and the energy consumption required in 3D environments.

- We introduce a hybrid method by merging the MACO and BT algorithms in a novel way that allows AUVs to complete their journey with minimum time, minimum energy consumption, and maximum value of information.
- The proposed optimization algorithm is developed by introducing the boundary tour strategy to collect sensor information depending on the range of transmission between the AUV and sensor nodes.
- Different test scenarios are introduced to verify the effectiveness of the proposed method.

Table 1. Methods and challenges.

Paper	Method	Challenges
[6]	Evolutionary algorithms	High computational load in real time
[7]	Energy-saving strategies	Balancing energy efficiency and data accuracy
[8]	Full-coverage route planning	Adapting to dynamic terrain and sensor limitations
[9]	Dynamic detection algorithm	Underwater environmental fluctuations
[10]	Data collection protocols	Balancing energy efficiency and data accuracy
[11]	SWIPT-based path optimization	Balancing energy harvest with data transmission accuracy
[12]	Neural networks inspired by nature	Rapid environmental changes such as ocean currents
[13]	Heuristic path planning	Real-time environmental data integration
[14]	Evolutionary algorithms	Complexity of calculations, adaptation to real time
[15]	Point-based reasoning	Environmental changes such as ocean currents

3. Proposed Methodology

An underwater acoustic sensor network (UWASNs) is deployed within a 3D area comprising n sensor nodes SNs. The sensors positioned at well-known locations are tasked with monitoring events in the surrounding environment and recording signals for each event. The surface station (ship) has an AUV assistant who visits the sensor nodes, collects the sensing information from them, and then goes back to the surface station. The surface station in turn transmits the collected information to a data center via an antenna for further analysis, as shown in Figure 1. The sensor nodes can transmit acoustic signals, and the AUV can receive these signals within a specific transmission range. This paper describes a simulation of a hybrid inheritance expert system for collecting sensing event information in an AUV-based IoUT environment. The model focuses on generating a driveway that guides the AUV to move with minimum energy consumption between sensor nodes to gather information resulting from the marine environment. As a result, an efficient strategy for determining the order of nodes to visit with minimum time is developed to reduce the energy consumption of the AUV.

As illustrated in Figure 1, each sensor node (SN) situated in 3D space possesses specific coordinates. To gather information from the nodes, an AUV must traverse a route that visits each SN sequentially without repetition, ultimately returning to the starting point. For instance, the AUV could navigate along the path $SN_1 \rightarrow SN_2 \rightarrow SN_3 \rightarrow \dots \rightarrow SN_1$. The distance between any two sensor nodes can be easily calculated by using the following method [19] in Equation (1):

$$d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \quad (1)$$

where $d_{i,j}$ is the distance between the i th and j th sensor nodes having a location represented by x , y , and z . If $i = j$, $d_{i,j} = 0$. Moreover, the distances between sensor nodes can be depicted as a symmetric matrix of dimensions $n \times n$.

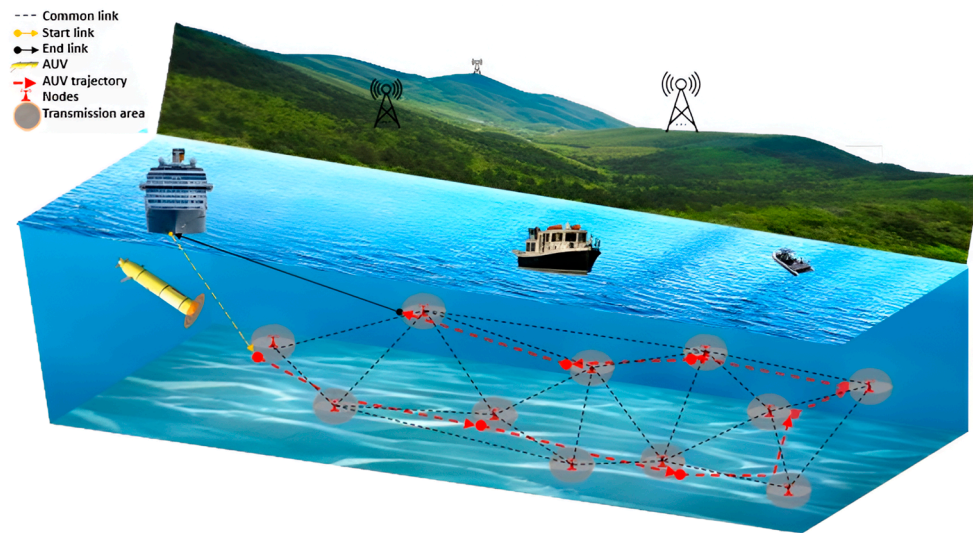


Figure 1. An illustration of the AUV trajectory to collect information from SNs.

3.1. Modified Ant Colony Optimization

Among the various techniques discussed in the literature, ant colony optimization (ACO) is widely utilized to determine the sequential order of paths based on the total path length [20]. The AUV in question can alter its course without needing to gather information from the precise locations of the sensor nodes thanks to the successful transmission area that exists between the AUV and the SNs. Therefore, to establish the path order, we initially implemented a modified version of ACO to determine the sequence in which the AUV should visit the sensor nodes, relying on the exact coordinates of the SNs. The modified ACO (MACO) proposed in this work starts with the initial pheromone matrix, and it can be calculated as follows [21]:

$$\tau_0 = \frac{10 \times Q}{n \times \left(\frac{1}{n} \sum_{i=1}^n \sum_{j=1}^n d_{i,j} \right)} \quad (2)$$

where n represents the number of sensors and Q represents constant pheromone updating.

In addition, the AUV journey starts from the mount point on the surface. We assume that the AUV's departure point from the ship is in the middle of the area to be surveyed. Hence, the first node represents the ship that the AUV starts its tour from this node or point. The second node is selected randomly as an integer within $[2, n]$. Then, the remaining nodes are selected consequently in a systematic way as follows [22]:

1. Select the current node cn (i.e., second node), which is the last node in the tour.
2. Calculate transition probabilities P by using

$$TP_{cn,j} = \begin{cases} (\tau_{cn,j})^{\alpha(It)} \times (\eta_{cn,j})^{\beta(It)} & j \in \text{unvisited nodes} \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

$$P = \frac{TP}{\sum TP} \quad (4)$$

where $TP_{cn,j}$ and P represents the transition value and transition probability from the cn to the j th node, where $j = 1, 2, 3, \dots, n$. The probabilities between the cn and the other remaining nodes are calculated according to unvisited nodes. $\tau_{cn,j}$ is a learning factor that denotes the value of the pheromone whenever there is a possibility of moving the AUV from the cn to the j th node. The pheromone value gives importance to a particular path by drawing on previous experiences gained during the previous search process.

Consequently, the pheromone level creates an indirect connection between ants and their reinforcement learning expressed in Equation (8). On the other hand, the heuristic factor η is a fixed quantity that remains constant throughout the AUV tour and is independent of the pheromone parameters. It indicates the willingness or attractiveness of the AUV to travel from the cn to the j th node. Mathematically, the heuristic value can be represented by the inverse distance value (i.e., $\eta_{cnj} = \frac{1}{d_{cn,j}}$). $\alpha(It)$ and $\beta(It)$ represent the pheromone exponential weight and the heuristic exponential weight. The calculations of these weights are given by Equation (5).

$$\alpha(It) = \beta(It) = 13.217 \times e^{-0.02 \times It} \quad (5)$$

Equation (5) possesses identical mathematical structures that are conceptually divergent. $\alpha(It)$ regulates the pheromone weighting, affecting the reinforcement process, whereas $\beta(It)$ regulates the heuristic weighting, affecting the utilization of past knowledge.

The Roulette Wheel selection method is used to pick the next sensor node with respect to the derived probability of visiting the selected node in the future. This process continues until the current tour T is constructed.

In addition to the aforementioned tour construction strategy, a new strategy is proposed to extend the exploration ability and overcome the stagnation problem of the algorithm in the search space. The proposed strategy focuses on swapping four randomly selected nodes Sn_i from the produced tour, where $Sn_1 \neq Sn_2 \neq Sn_3 \neq Sn_4 \neq 1$. The pair of tours $T1$ and $T2$ are produced as a result of swapping each two sensor nodes. Then, the best current tour can be represented as follows.

$$NT = \begin{cases} T & \text{if } C(T) < C(PT), \\ T1 & \text{if } C(T1) < C(PT) \text{ and } C(T1) < C(T), \\ T2 & \text{if } C(T2) < C(PT) \text{ and } C(T2) < C(T1) \text{ and } C(T2) < C(T), \\ PT & \text{otherwise.} \end{cases} \quad (6)$$

where NT and PT represent the best new tour and previous best tour, respectively. $C()$ denotes the cost function.

The pheromone decay rate $\rho(t)$ and the pheromone levels τ play crucial roles in enhancing the robustness and efficiency of the proposed MACO algorithm in finding high-quality solutions. Dynamically adjusting pheromone levels allows the algorithm to trade off exploration and exploitation ability. The decay rate is mathematically expressed as follows:

$$\rho(It) = \frac{\sqrt{2}}{3\pi^2} (1 - e^{-\frac{It}{MaxIt}}) \quad (7)$$

The formula includes an exponential growth factor which assures that $\rho(t)$ increases gradually over time. As iterations progress, the value of $\rho(t)$ increases non-linearly and approaches an asymptote. This means that $\rho(t)$ starts small to allow for more exploration in the early stages and grows over time to favor exploitation.

In addition, a new equation is developed to update pheromones based on dispersed previous pheromones and the baseline or initial level of pheromones, increasing the evaporation rate in order to adjust pheromone levels along the paths. The pheromone level of the paths is learned during the searching process and is given as follows:

$$\tau(It) = (1 - \rho(It))^2 \times \tau(It - 1) + \rho(It)^2 \times \tau_0 \quad (8)$$

where the decay component $(1 - \rho(It))^2 \times \tau(It - 1)$ represents the decay of existing pheromone levels, which becomes more pronounced as $\rho(It)$ increases. Moreover, the reinforcement component $\rho(It)^2 \times \tau_0$ adds a baseline level of the pheromones, ensuring

that even as pheromones decay, a minimum level is maintained, promoting some exploration. The suggested MACO algorithm is summarized in Algorithm 1.

Algorithm 1. Pseudo-code of MACO algorithm.

Begin

```

1:   $It = 1; nAnt = 25; n = SN$ ; Define sensors location  $Sn_i$  where
    $i = [1, \dots, n]$ ,  $Sn_i = [x_i, y_i, z_i] \in R^3$ ;
2:  Calculate the distance between Sensors nodes  $D = [d_1, d_2, \dots, d_n]$  using Equation (1);
3:  while  $It < MaxIt$  do
4:      Set Evaporation rate using Equation (7);
5:      for  $cn$  from 1 to  $nAnt$  do
6:          Evaluate  $Z(x_m^g | \forall m, m = 1, \dots, np)$  then find  $x_{best}^g$  and  $x_{worst}^g$ ;
7:          for  $j$  from 2 to  $n$  do
8:              Calculate the pheromone and the heuristic exponential
9:              weights using Equation (5);
10:             Construct the tour for  $ant^k$  randomly (start the ant at the ship location and
11:             randomly choose the next sensor);
12:             Calculate the transition probabilities  $P$  using
13:             Equations (3) and (4);
14:             Select next sensor node based on probabilities using
15:             RouletteWheel selection;
16:             Store the progressive construction of the current Tour in  $T$ ;
17:             end for
18:             Select four random sensor nodes from  $T$ , where  $Sn1 \neq Sn2 \neq Sn3 \neq Sn4$ 
19:              $\neq 1$ ;
20:             Construct a pair of Tours ( $T1$  and  $T2$ ) using the swap operation;
21:             Find fitness values for  $T$ ,  $T1$ , and  $T2$ ;
22:             end for
23:             Update the pheromone level using Equation (8);
24:              $It = It + 1$ ;
25:         end while

```

End

3.2. A Hybrid Boundary Tour

By assuming that the sensor nodes SNs are able to transmit their information in all directions within an r meter radius, we propose a novel approach to determine the critical points that the AUV can visit within the transmission and reception boundaries with minimal energy consumption, time, and cost, taking into account the priority of capturing the most important information. In addition to MACO, we propose a hybrid algorithm that tries to determine the best location for the AUV to start aggregating sensor information from sensor nodes based on the best constructed NT tour.

The proposed evolutionary algorithm first detects the locations that the AUV can visit by detecting the intersections of the NT . Detection is performed at the edges of the transmission range of the sensor nodes based on the angle of the AUV path between the connected sensors.

Each sensor node in the tour is represented by a 3D point; therefore, the k th point on the boundary of node transmission can be given by

$$P_k = \left(\lfloor r + (mb - 2r + 1) \cdot U \rfloor \mid k \in R^3 \right) \quad (9)$$

where mb and r represent the maximum bound of the search space and the radius transmission distance of the node. U denotes a uniform distribution within $[0, 1]$. These points represent positions along the lines determined by the center points and are randomly distributed within the bounds defined by the problem space. In this regard, a vector space direction (DV) between the j th node and the k th point is given by the vector direction rule as follows:

$$\overrightarrow{DV_p^j} = (x_p - x_j, y_p - y_j, z_p - z_j) \quad (10)$$

where x_j , y_j , and z_j represent the coordinates of the j th node.

Hence, the best location for the AUV to start aggregate information from sensor nodes can be calculated depending on Line Parametric rules $L(\delta)$ as follows [19]:

$$L(\delta) = (x_j + \delta(x_p - x_j), y_j + \delta(y_p - y_j), z_j + \delta(z_p - z_j)) \quad (11)$$

where δ is a control parameter that determines how far the sensor node is from its transmission range. When $\delta = 0$, the AUV can aggregate the node information exactly from the sensor node location. When $\delta = 1$, the AUV is at the boundary of node transmission. Therefore, when δ varies within $[0, 1]$, all coordinates between the sensor node and its transmission range along the vector direction can be traced, and this ensures that the AUV starts sensing information within the transmission range of the node. It should be noted that δ is dynamically changed depending on the maximum transmission range and sensor position. This dynamic change guarantees that the parameter is customized to the particular surroundings and environmental circumstances.

In such a setting, we assume that the x , y , and z coordinates represent the most likely locations for the j th sensor node to relay information. The 3D distance from the sensor node to its transmission range equals the radius r in meters and is given by

$$(x - x_j)^2 + (y - y_j)^2 + (z - z_j)^2 = r^2$$

Therefore,

$$\begin{aligned} ((x_j + \delta(x_p - x_j)) - x_j)^2 + ((y_j + \delta(y_p - y_j)) - y_j)^2 + ((z_j + \delta(z_p - z_j)) - z_j)^2 &= r^2 \\ \delta^2 [(x_p - x_j)^2 + (y_p - y_j)^2 + (z_p - z_j)^2] &= r^2 \\ \delta &= \frac{r}{\sqrt{(x_p - x_j)^2 + (y_p - y_j)^2 + (z_p - z_j)^2}} \end{aligned} \quad (12)$$

where $0 < \delta \leq 1$, and when $\delta > 1$, no data transfer exists, which guarantees that AUV starts receiving information inside the allowed transmission range.

The L coordinates represent the potential position in the space that the AUV can occupy, constrained by a transmission range from the center. This process tries for all nodes and then sufficiently learns based on the natural bound of each node, until it progressively reaches the best location for the AUV to sense information from all sensor nodes. Accordingly, a new tour can be constructed with the same sequence as the NT tour estimated by MACO. Therefore, a boundary tour (BT) estimation algorithm is proposed to optimize the path trajectory for the AUV to visit the nodes with minimum tour distance, which in turn affects AUV energy consumption.

For simplicity, we change the vector space direction participant in changing the direction of the line when the AUV sails from the i th node to the j th node. Hence, along with the aforementioned strategy, the proposed algorithm tries to construct a new tour NT randomly inherited from the best previously allocated coordinates and thus generates unexpected coordinates for the AUV. The inheritance process can be expressed as follows [23]:

$$L(\delta)_j^{g+1} = \begin{cases} L(\delta)_j^g & \text{if } U < 0.1, \\ NT_j^g & \text{otherwise.} \end{cases} \quad (13)$$

$$NT^{g+1} = \begin{cases} L(\delta)^{g+1} & \text{if } C(L(\delta)^{g+1}) < C(NT^g), \\ NT^g & \text{otherwise.} \end{cases} \quad (14)$$

where g represents the current iteration. The inheritance mechanism updates some direction in the tour balance exploration (new random directions) and exploitation (using the best previously allocated coordinates so far). In addition, the updated directions ensure diversity during the search trip. Thus, comparing the new tour $L(\delta)^{g+1}$ with the current best tour helps the algorithm to focus on improving their solutions progressively. Algorithm 2 summarizes the process of BT construction.

Algorithm 2. Pseudo-code of *boundary tour* (BT) algorithm.

Begin

```

1:   $g = 1; nAnt = 60; n = SN;$ 
2:  for  $m$  from 1 to  $nAnt$  do
3:    Calculate  $kth$  points  $P_k$  within the node bounds;
4:    Calculate direction vectors  $\vec{DV}_p$ ;
5:    Determine the best locations for the AUV using  $\delta$  and direction vectors;
6:    Determine  $C(L\delta)$ ;
7:  end for
8:  while  $g < Maxg$  do
9:    for  $m$  from 1 to  $nAnt$  do
10:   for  $j$  from 1 to  $n$  do
11:    Calculate  $P_k$  and  $\vec{DV}_p$  for each  $SN$  using Equations (9) and (10);
12:    Create new locations for the AUV using  $\delta$  and direction vectors;
13:    If  $U \leq 0.1$  then
14:      Create new locations for the AUV using  $\delta$  and direction vectors;
15:    else
16:      Use the best previous AUV location from the current population;
17:    end if
18:  end for
19:  If  $C(L(\delta)^{g+1}) < C(NT^g)$  then
20:     $NT^{g+1} = L(\delta)^{g+1};$ 
21:  else
22:     $NT^{g+1} = NT^g;$ 
23:  end if
24:  end for
25:   $g = g + 1;$ 
26: end while

```

End

3.3. Implementation Procedure

This sub-section briefly discusses the assumptions considered for AUVs along with marine environment-based sensor nodes. The steps required to find the efficient tour for the AUV to collect the node-recorded information within the allowed transmission area are also discussed.

3.3.1. AUVs and Sensor Nodes in the Marine Environment

To begin with, an advanced version of the ant colony optimization algorithm is developed to optimize the path planning of an AUV operating in a marine sensor network environment. The AUV needs to traverse through sensor nodes that are spread across different depths and regions in the underwater area. Each sensor node records specific environmental events and possesses a corresponding VoI based on the importance and relevance of the data captured. The behavior of the node is assumed to sense and record information and wait for the AUV to arrive to collect the recorded information optically. During the collection of information, we assume that the AUV can receive information within r meters far from the sensor node without collection delay. Thus, the optimization of the AUV's path and the appropriate dock location for data recording leads to energy conservation during its journey, as well as an increase in the VoI gathered from the sensor nodes. The MACO algorithm, which was originally meant to address path optimization problems by simulating the foraging behavior of ants, is altered with hybrid improvement optimization techniques for bettering the path and the most important dock location for the AUV.

3.3.2. AUV Searching Strategy

To optimize the performance of the AUV in selecting the shortest path and the best order in which to visit the SNs, MACO employed a unique approach that combines the inheritance principle with an advanced pheromone updating method. To this end, the inheritance strategy attempts to enhance the exploration ability of the algorithm by generating new members with characteristics related to the dominant members. In addition, the AUV can start to aggregate the nodes' information within r meters, thereby expanding MACO to find boundary tours, allowing the AUV to save energy during the trip. A local search is performed within the limited boundaries of each sensor, and new coordinates start to be explored, which in turn guides more members to the best AUV docking location. This will enable the AUV to avoid long-distance travel and save energy. Therefore, the BTMACO algorithm is proposed to find the best coordinates of the AUV so that the collection of recorded information from the sensor nodes can start optically with the lowest AUV energy consumption.

3.3.3. Performance Evaluation Metrics of the Model

Several key performance indicators are used to evaluate the effectiveness of the model.

Firstly, the path length measurement is used to assess the total distance traveled by the AUV when it starts its journey from the surface station up to visiting sensor nodes and then returns to the surface station (the ship). The surface station then forwards the gathered information to the central department for further analysis via an antenna. The path length evaluation formula is expressed as follows:

$$D = \sum_{i=1}^{SN} \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2 + (z_i - z_{i+1})^2} \quad (15)$$

On the other hand, the VoI is such an important metric to capture the full worth of data delivered at the surface station. The purpose of this is that the sensor nodes record information depending on the event that took place in their close proximity. Intuitively, we propose that each sensor has an event importance value as a heuristic, where with the sensor node having a high value, it means that very important information had been recorded, thus increasing the priority to visit this node to maximize the VoI. Thus, the process of information collection has sensor node-specific data, including node coordinates, time to transmit a packet, and node event importance. In addition, the time required for the AUV to reach the boundaries of the sensor nodes also affects the information collection

process. Collecting the information that has the highest importance would maximize the VoI, and it can be determined as follows [24]:

$$\text{VoI} = \beta \sum_{i=1}^n EI_i + (1 - \beta) \sum_{i=1}^n EI_i e^{-\sum_{q=i}^n \frac{t_{q \rightarrow q+1}}{\sigma}} \quad (16)$$

where β is the trade-off factor that contributes to balancing both the severity of the event and how quickly it decays over time. σ is a scaling factor indicating the level of sensitivity with timeliness. Moreover, t represents the time required for the AUV to sail from the q th node to the next node along with the time to transmit the packets and can be calculated as follows [24]:

$$\begin{aligned} t_{tra, q} &= \frac{h}{V} + \frac{D_q}{R} \\ t_{sail, q \rightarrow q+1} &= \frac{D_{q, q+1}}{VS} \\ t_{q \rightarrow q+1} &= t_{tra, q} + t_{sail, q \rightarrow q+1} \end{aligned} \quad (17)$$

where $t_{tra, q}$ represent the time required to send information from the q th sensor node to the AUV. $\frac{h}{V}$ denotes the propagation delay, and $\frac{D_q}{R}$ represent the data transmission time. $D_{q, q+1}$ is the desired distance for the AUV to sail from node boundary q to node boundary $q + 1$. VS denotes the static velocity of the AUV in meters/second (m/s).

The final measure is the overall energy consumption by the AUV during its journey. The total energy consumption for data collection depends on data transmission, data reception, and the energy consumed by the AUV during its journey, and this is calculated as follows:

$$EC = (P_{tra} + P_{rec}) \times t_{tra} + P_{mov} \times t_{mov} \quad (18)$$

where EC denotes the total energy consumption. P_{tra} , P_{rec} , and P_{mov} represent the power consumption for sending messages and receiving messages, and the power consumption during the movement of the AUV, respectively. t_{mov} denotes the time required for the AUV to complete its journey from the start node and return to the same node [25].

4. Results and Discussion

This section showcases the simulation outcomes to illustrate the effectiveness of the three trajectory planning algorithms aimed at energy conservation for AUVs. We study an IoUT environment that has a surface station positioned at the center of the search space, one AUV departing from the surface station, and n SNs. Two scenarios are evaluated in the examination, with the SNs positioned within a square area of $M \times M \times H$ meters. In the first scenario, 13 nodes are utilized, randomly placed within a $0.25 \text{ km} \times 0.25 \text{ km} \times 0.25 \text{ km}$ radius, with a transmission range of 480 m. In the second scenario, three nodes are arranged in a grid network, systematically located within a $0.6 \text{ km} \times 0.6 \text{ km} \times 0.6 \text{ km}$ radius and possessing a transmission range of 25 m. The battery-powered AUV is assumed to move at a constant velocity, with a power output of 100 watts (W), tasked with gathering data from all the SNs within the successful transmission range. Transmitting and receiving data entail a specific amount of energy; each sensor node utilizes 0.3 W for sending and 0.1 W for receiving. As the AUV reaches the boundary of an SN, the node promptly prepares samples of each data chunk, compiles them into a packet of length L ranging from 130 to 220 kbits, and transmits it to the AUV. All simulations were performed by using MATLAB R2021a on a PC with an Intel Core i7 CPU (1.80 GHz), a 1TB HDD Hard Disk, and 16 GB of RAM.

4.1. Trajectory Planning for AUV

In the first simulation test, we assess the effectiveness of the proposed algorithms within a 3D environment by utilizing 13 sensor nodes. These sensor nodes are randomly

and uniformly distributed within a square area measuring $0.25 \text{ km} \times 0.25 \text{ km} \times 0.25 \text{ km}$, with a surface station positioned at the center of the sea surface.

Figure 2 illustrates the trajectory planning processes of an AUV using three algorithms: boundary tour ACO (BTACO), boundary tour adaptive ACO (BTAACO), and boundary tour modified ACO (BTMACO). BTACO is a hybrid algorithm that combines traditional ACO with BT, whereas BTAACO is a hybrid algorithm that just uses adaptive parameters and lacks an inheritance method. The black dots in Figure 2 represent the sensor node locations, and the red dots represent the best location for the AUV to start collecting information from the sensor nodes. The sensor nodes send acoustic signals to the AUV within the transmission range marked with blue circles.

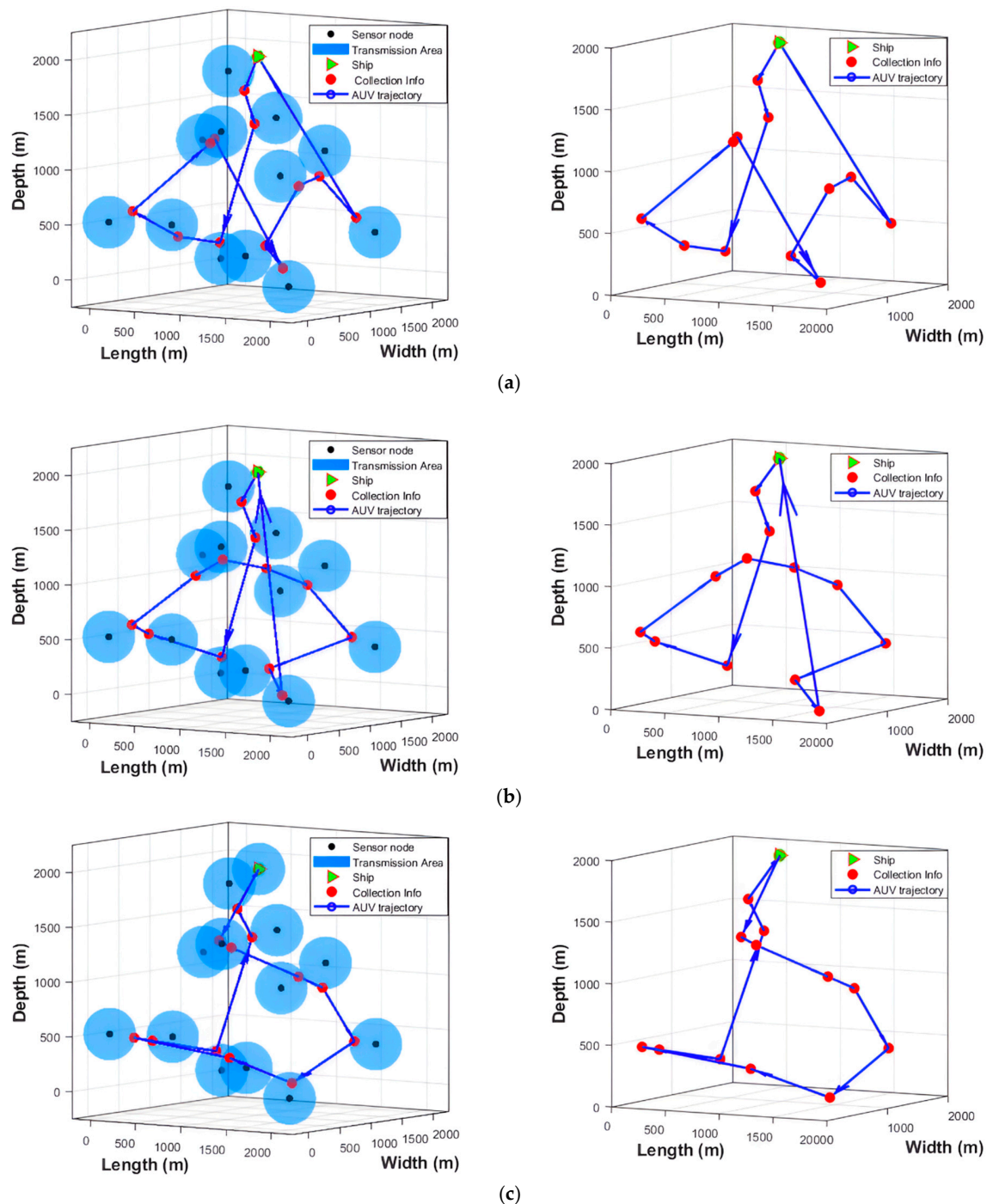


Figure 2. The optimal coverage path generated by three algorithms with 13 sensor nodes distributed within $0.25 \text{ km} \times 0.25 \text{ km} \times 0.25 \text{ km}$: (a) BTACO, (b) BTAACO, and (c) BTMACO.

As depicted in Figure 2a, the optimal tour generated by BTACO reveals that the sequence of sensor visits does not follow the nearest-neighbor approach, leading to a longer route for the AUV and consequently requiring more energy to complete its task of gathering information from the nodes. The shortcomings of this algorithm stem from its inability to adjust to the specific dynamics of the system, such as pheromone levels, among other factors. Conversely, the adaptive variant of ACO involves making modifications throughout the path selection process, influenced by dynamic elements such as the pheromone and heuristic exponential weights. This indicates that the algorithm possesses a level of flexibility, allowing it to alter its route according to real-time conditions to determine the optimal sequence of nodes to visit, ultimately conserving the energy of the AUV and extending its lifespan during navigation. As illustrated in Figure 2b, the AUV strategically avoids sensors located far from the starting point and in the midst of its route. Instead, it aims to visit neighboring sensors sequentially, which leads to the establishment of the shortest path and helps prevent excessive energy depletion of the AUV. This adaptive approach enhances its efficiency compared with the traditional BTACO in situations where the selection process is variable and energy management is essential.

Furthermore, it is important to highlight that the method proposed in this study demonstrated exceptional performance in selecting the shortest path when compared with the alternative method. As shown in Figure 2c, the AUV travels the shortest distances for several transitions between a certain node and the next one, in an area close to the desired sensor node and close to the boundaries of the next sensor node. These organized transitions allow the AUV to visit sensors to collect data with the least possible energy consumption, especially when the sensor network is expanded. Additionally, we notice that the trajectory that was constructed is established in a ring format, which indicates that the BTMACO algorithm established the main tour perfectly with the best order of sensor nodes, but since the data transmission areas are within certain limits and from all directions, it led to a slight increase in energy consumption compared with BTACO. On the other hand, with the increase in the search area and the number of sensors, the proposed method performed the best among its peers. This enhancement can be attributed to several factors: The revised approach advances performance by incorporating additional enhancements, such as the integration of more advanced trajectory planning techniques aimed at improving both energy efficiency and coverage. Modifications may involve hybrid methods, including the use of pheromone update learning to forecast optimal paths, along with innovative strategies for managing node visitation sequences. By inheriting a specific sensor network order from the leading member within the population, the system aims to explore a greater number of locations within the search space. Even with advancements in the processing phase, this ensures the optimal selection of the sensor visitation order, which has a significant impact on energy conservation, particularly when accounting for variables such as the distance between nodes, battery longevity, and data transmission.

To further assess the proposed model's performance against its competitors, we broadened the search space by incorporating additional sensor nodes. In this scenario, a grid network of 36 sensor nodes was established within a $0.6 \text{ km} \times 0.6 \text{ km} \times 0.6 \text{ km}$ area, with a surface station located at the center of the sea surface. As illustrated in Figure 3a, the BTACO method shows limitations, particularly as the network grid expands. It often converges to suboptimal solutions due to the static characteristics of its search process, frequently adhering to fixed routes and lacking the necessary adaptability for large, dynamic settings. Conversely, BAACO modifies its trajectory in response to current conditions, leading to greater improvements in efficiency; as depicted in Figure 3b, its trajectory demonstrates more consistency compared with BTACO. Although this flexibility enhances performance, BTACO still encounters difficulties when the network grid significantly increases, as it

does not inherently generate the best possible tour but instead adjusts the existing path based on prevailing conditions.

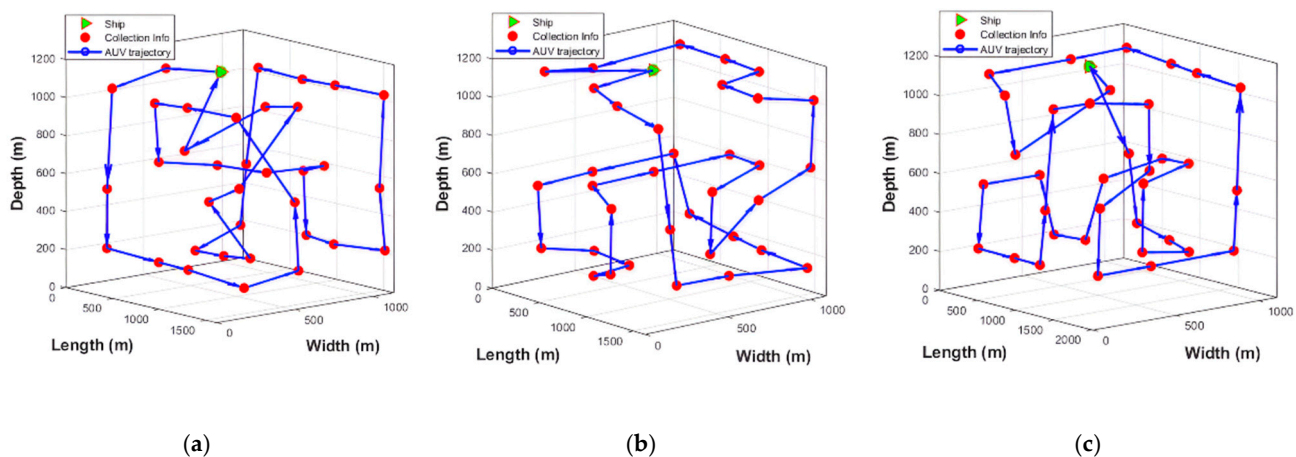


Figure 3. The optimal coverage path generated by the algorithm with 36 sensor nodes distributed within $0.6 \text{ km} \times 0.6 \text{ km} \times 0.6 \text{ km}$: (a) BTACO; (b) BTAACO; (c) BTMACO.

On the other hand, BTMACO represents a significant improvement, especially in larger networks with expanded search areas. This algorithm incorporates the dynamic restructuring of the tour during the search process and produces a smooth trajectory for the AUV, as shown in Figure 3c. As the network grid expands, the modified version (BTMACO) does not simply adapt to existing conditions but seeks to generate new tours dynamically throughout the exploration process. This restructuring allows the algorithm to find optimal paths wherein the travel distance is reduced along with the energy consumption being minimized for the AUV.

The performance differences among these methods become apparent as the search area expands and the network grid develops. In these kinds of situations, BTMACO shines, as it keeps changing its search approach. AUVs follow a dynamic path instead of following a fixed route or making only minor changes. This structured dynamism helps the modified version outperform its peers; it avoids the pitfalls of getting stuck in suboptimal paths (common in standard ACO) or overrelying on current network conditions (as in BTAACO). BTMACO achieves better results by seeking out new energy-efficient tours, even as the complexity of the network increases.

Figure 4 shows the rate of convergence for finding the path length with generation.

As shown in Figure 4, BTMACO seeks to explore the search space deeply as the smallest path length constricted in the first phase (MACO). This is because MACO dynamically updates the pheromone level and a new tour is generated depending on the dominant tour. In the second phase, the hybrid method (i.e., BT) explores the best locations of the transmission areas of the sensor nodes, which in turn leads to minimizing the energy consumption of the AUV by minimizing its journey length.

Another test applied to the proposed algorithm with different settings and objectives was conducted, and we found that the proposed BTMACO algorithm makes the AUV consume less energy among the competitors, about 11,509.6 kJ, which is less than the 11,759.6 kJ and 12,184.4 kJ consumed by the AUV when using the BTAACO and BTACO algorithms, respectively. Furthermore, when BTMACO is compared to its rivals, the VoI produced by it shows an effective value as BTMACO reaches the effective value. Although BTMACO requires a longer computation time (seconds) than other competitors, it makes the AUV achieve the target profit by reducing the time required to complete its journey while constructing the minimum tour distance, maximizing the VoI. Table 2 summarizes

the results of the three algorithms of the testing of four scenarios in the same situation. The best results were obtained for path length and VoI target scenarios with 13 and 36 sensor nodes, as indicated by bold red and bold yellow.

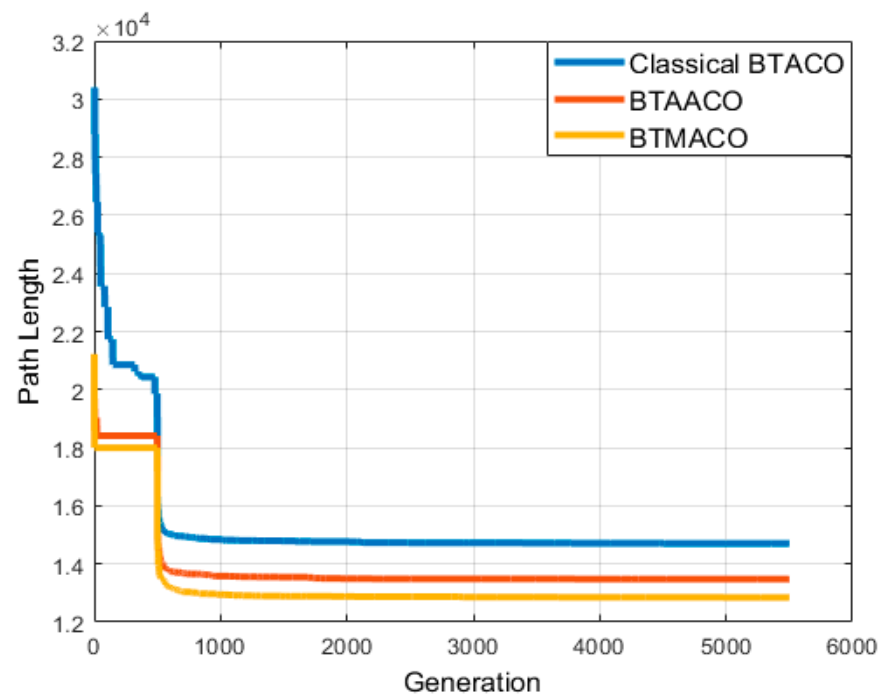


Figure 4. Performance of the three designed methods with generation.

Table 2. The simulation results of four scenarios.

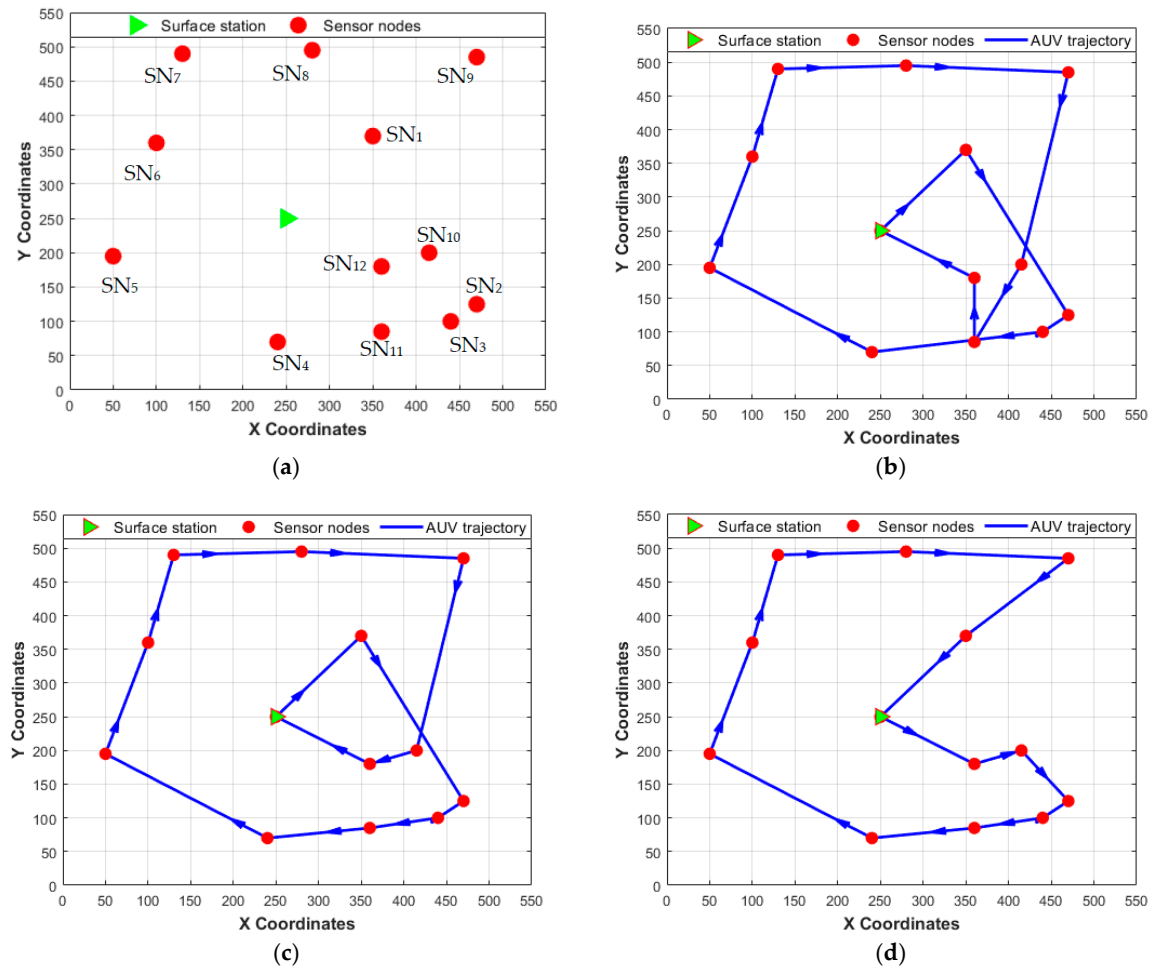
Objective	Distance					
Method	BTACO		BTAACO		BTMACO	
No. of nodes	13	36	13	36	13	36
D (m)	8671.9	14,705.5	8162.3	13,475.7	8488.2	12,847.7
VoI	28.2	79.2	28.4	79.3	28.3	79.4
EC (kJ)	2818.4	13,234.9	2652.7	12,128.1	2758.6	11,562.9
CT(s)	9.37	24	7.94	28.54	8.18	29.72
Objective	VoI					
Method	BTACO		BTAACO		BTMACO	
No. of nodes	13	36	13	36	13	36
D (m)	8730.6	13,538.3	8157.3	13,066.2	8574.1	12,788.5
VoI	28.2	79.3	28.4	79.3	28.3	79.4
EC (kJ)	2837.4	12,184.4	2651.1	11,759.6	2786.6	11,509.6
CT(s)	7.74	26.67	10.05	39.07	10.21	45.71

4.2. Trajectory Planning for AUV

To verify the effectiveness and performance of the proposed BTMACO for constructing the tour of the AUV, the proposed method was compared with previously published ones used in [24,26]. The two methods were engaged in the same situations, including sensor node locations, event importance, and data length, as shown in Table 3. In addition, the same factors were used in the two methods, with $SN = 12$, $\alpha = 600$, and $\beta = 0.5$. The comparison of the proposed method and previously published methods is presented in Figure 5.

Table 3. The sensor nodes' information.

SN_i	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 5$	$i = 6$	$i = 7$	$i = 8$	$i = 9$	$i = 10$	$i = 11$	$i = 12$
EI	1	2	2	4	6	4	3	6	7	6	7	7
L (Kbits)	150	190	160	190	220	220	130	180	150	190	190	150

**Figure 5.** Result of the constructed tour: (a) Sensor node deployment. (b) The resulting tour in [24]. (c) The resulting tour in [26]. (d) A tour built by using the suggested BTMACO.

A sensor network deployed over a surface area of 0.5 km by 0.5 km was considered, as illustrated in Figure 5a. The comparison of the methods presented in [24,26] with the proposed modified ACO method brings out several key points, especially with the focus on energy efficiency and the VoI. Both approaches presented in [24,26] used path-planning algorithms in their design to attain the highest VoI. Neither of these methods places a strong emphasis on energy efficiency when determining the order in which sensor nodes are visited. As shown in Figure 5b, the AUV creates a tour based on the method presented in [24], visiting SNs 1 to 4 first because they have low event importance and SNs 10, 11, and 12 at the end.

Similarly, the tour designed by the autonomous vehicle in [26] shows slight differences from that in [24], in line with the approach used in [24], as shown in Figure 5c. Moreover, the VoIs of both methodologies are about 49.8378 in [24] and 49.9909 in [26], indicating a moderate ability to capture relevant information during AUV operation. Nonetheless, these approaches do not place significant emphasis on energy efficiency when determining the sequence in which sensor nodes are accessed. Additionally, an excessive focus on the

VoI objective results in the AUV not attaining its optimal performance with minimal energy expenditure. In contrast, the proposed modified ACO method prioritizes energy-efficient trajectory planning by constructing the most effective order for visiting the sensor nodes; for instance, it recommends visiting sensors 12, 10, and 2 in a sequence that minimizes overall energy consumption, as depicted in Figure 5d. This represents a distinctive contribution when compared with the other two aforementioned methodologies. The proposed modified ACO creates a tour to visit some specific sensor nodes, e.g., sensors 12, 10, and 2, in a way that minimizes energy consumption. It is important to note that while trajectory planning directly affects energy efficiency, it does not directly degrade the VoI at this point. In this way, the present approach optimizes the AUV's journey by suggesting the most beneficial order in which to visit the sensor nodes in terms of the information collected while taking into account low energy consumption. Our method achieved a $\text{VoI} = 53.2663$, which is a significant enhancement over the two aforementioned competitors.

Figure 6 shows the VoI of the three competitors. This increase in the VoI by the proposed method is a consequence of the optimal sensor node visitation order and enhanced energy efficiency. This means that the energy efficiency of the AUV is maximized, and the order of the sensors visited is intelligently planned—it outperforms both competitors in terms of the VoI. The VoI obtained by the proposed method is improved by 6.9% and 6.8% compared with the methods presented in [24,26], respectively. This improvement reveals that the proposed modified ACO not only achieves energy conservation but also increases the VoI to the maximum value and thus outperforms its competitors.

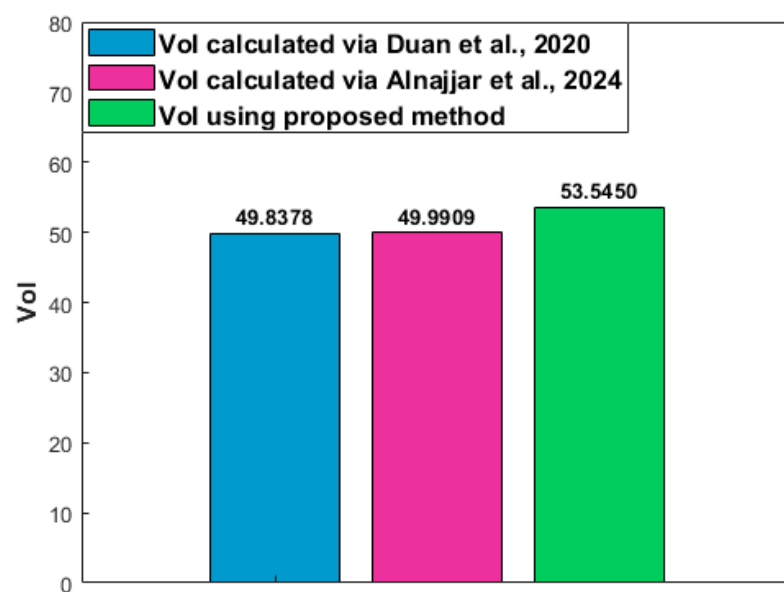


Figure 6. VoIs of the proposed method [24,26].

The proposed optimization algorithm or the navigation path of underwater cruisers can be improved by introducing recent intelligent techniques, neural network structures, and deep learning models [27–35]. Moreover, other optimization methods can be involved to enhance the navigation path of UAVs, such as the Bee algorithm, the Genetic Optimization Algorithm, Particle Swarm Optimization, the Butterfly Optimization Algorithm, and the Pelican Optimization Algorithm [36–40].

5. Conclusions

In this paper, a system based on the boundary tour optimization algorithm is designed to efficiently save AUV energy and reduce the path length required to collect sensing information. A boundary tour approach is used in combination with ACO to determine the

optimal AUV docking locations, which reduces the path length while the AUV sails among sensor nodes in an underwater environment. Depending on different testing scenarios, the proposed method has the ability to collect sensing information within the allowed transmission range. This is because the AUV detects the sensor nodes according to the restricted areas.

In the second phase of the construction tour, BTMACO explores different regions of the search space and continuously adapts the search progress by finding the optimal arrangement of sensor nodes. This is due to the flexibility of BTMACO by adapting the pheromone level, learning weights exponentially, and using the alternative addition strategy to store the best tour during the search trip. The result is a saving in the AUV's sailing time, which in turn also leads to saving energy consumption and increasing the VoI. The best results obtained based on different targets (distance or VoI) are the same: 12,788.5 m underwater cruising length, 79.4 VoI, and 11,509.6 kJ energy consumption. This indicates that the proposed method can provide the best order of sensor nodes that the AUV should visit even if different targets are used.

The main restriction of this work is the arrangement of sensor nodes, which might influence the scalability and general performance of the suggested approach in very dynamic or unevenly distributed network settings. Future studies in line with multi-objective optimization should investigate more flexible approaches for sensor node deployment to handle this difficulty. Moreover, future work will be to extend the sensor node network and classify nodes as clusters to test the transmitting of sensor node information between the closest node of the cluster and the AUV.

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