Energy-Aware Path Planning by Autonomous Underwater Vehicle in Underwater Wireless Sensor Networks for Safer Maritime Transportation

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Received 21 April 2024 | Accepted 2 August 2024 | Early Access 20 August 2024

Abstract

Throughout history, maritime transportation has been preferred for international and intercontinental trade thanks to its lower cost than other transportation ways, which have a risk of ship accidents. To avoid these risks, underwater wireless sensor networks can be used as a robust and safe solution by monitoring maritime environment where energy resources are critical. Energy constraints must be solved to enable continuous data collection and communication for environmental monitoring and surveillance so they can last. Their energy limitations and battery replacement difficulties can be addressed with a path planning approach.This paper considers the energy-aware path planning problem with autonomous underwater vehicles by five commonly used approaches, namely, Ant Colony Optimization-based Approach, Particle Swarm Optimization-based Approach, Teaching Learning-based Optimization-based Approach, Genetic Algorithm-based Approach, Grey Wolf Optimizer-based Approach. Simulations show that the system converges faster and performs better with genetic algorithm than the others. This paper also considers the case where direct traveling paths between some node pairs should be avoided due to several reasons including underwater flows, too narrow places for travel, and other risks like changing temperature and pressure. To tackle this case, we propose a modified genetic algorithm, the Safety-Aware Genetic Algorithm-based Approach, that blocks the direct paths between those nodes. In this scenario, the Safety-Aware Genetic Algorithm-based approach provides just a 3% longer path than the Genetic Algorithm-based approach which is the best approach among all these approaches. This shows that the Safety-Aware Genetic Algorithm-based approach performs very robustly. With our proposed robust and energy-efficient path-planning algorithms, the data gathered by sensors can be collected very quickly with much less energy, which enables the monitoring system to respond faster for ship accidents. It also reduces total energy consumption of sensors by communicating them closely and so extends the network lifetime.

Keywords

Atificial Intelligence, Autonomous Underwater Vehicle, Energy-aware Path Planning, Maritime Commerce, Maritime Industry, Maritime Operations, Optimization Algorithm, Ship Management Systems, Safe Sailing Planning, Underwater Wireless Sensor Networks, Water Monitoring.

DOI: 10.9781/ijimai.2024.08.003

I. Introduction

There has been a close relationship between maritime and trade throughout history. Therefore, the most important reason for this is that the majority of international trade and especially intercontinental transportation is carried out using maritime transportation [1]. The most important factor in this is that sea transport is 3.5 times cheaper than railways, 7 times cheaper than road transport, and 22 times cheaper than air transport. This cost advantage causes the importance and volume of maritime transportation to increase day by day [2]. According to data from the International Chamber of Shipping (ICS), 90% of world trade is carried out by sea today [3]. For this reason, the report of the United Nations Conference on Trade and Development predicts that world maritime trade will grow at an annual growth rate of 3.8% between 2018 and 2023 [4]. The increase in world maritime trade causes intense maritime traffic and the inevitable result of this is the increase in the risk of maritime accidents. Historical data shows that these accidents generally occur on the busiest routes [5].

Increasing both the volume and value of the cargo transported over time further magnifies the damage caused by accidents in maritime transportation. It is not possible to define the cost of loss of life occurring during these accidents in monetary terms [6]. For example, the ship accident and the transportation blockage in the Suez Canal [7]–[9] caused severe economic consequences in the global supply chains

Please cite this article as:
T. Acarer. Energy-Aware Path Planning by Autonomous Underwater Vehicle in Underwater Wireless Sensor Networks for Safer Maritime Transportation, International Journal of Interactive Multimedia and Artificial Intelligence, vol. 8, no. 7, pp. 15-27, 2024, http://dx.doi.org/10.9781/ijimai.2024.08.003

like its impacts on the transportation costs of the Chinese fleet in the shipping network [10]. A case study [11] provides a scenario analysis explanation for observed outcomes in a retrospective analysis using constrained Suez Canal case material. The findings can be utilized to diagnose backward risk sources for accident investigation and estimate forward risk for restricted waterway accident prevention to prevent similar incidents like the Suez Canal blockage. If such risks can be observed and detected very quickly with low energy consumption and little system maintenance, then precautions can be taken earlier to avoid such accidents which may have devastating consequences.

The developments experienced in the industry in recent years are evident in many sectoral areas. These developments lead to major changes in conventional structures today, and in particular, they greatly change the way work is done and the functions of employees [12]. These changes significantly affect the activities of maritime enterprises and the management of ships, as in many sectors. As a result of these developments, it has become possible to obtain a lot of data that is of great importance for the management and safe navigation of ships traveling in international waters in recent years. In particular, data regarding sea conditions are among the primary elements of safe navigation. Marine data are not only related to the sea surface; today, seabed data are as important as above-water information. For this purpose, instantaneous collection of seabed movements and data on the sea floor and timely transmission to relevant maritime organizations is of great importance for safe sea navigation. In addition, these data are necessary for safe route planning of maritime businesses and navigational routes of ships. It is also extremely important to take precautions.

In recent years, the great opportunities provided in data transmission and communication systems, in addition to ship systems, have reached dimensions that easily allow monitoring of data on the seabed as well as the sea surface from long distances and intervening when necessary. Since the target of maritime communication is the communication between the units needed by the maritime vehicles, it can be defined as communication between ships and other ships, land units, and aircraft [13].

A. Motivation

The importance of underwater wireless sensor networks (UWSNs) [14] is evident in ocean data collection, resource exploration, and navigation due to rapid development. The concept of intelligent ocean underwater Internet of Things (IoT) has been proposed recently [15], with numerous applications. Various underwater sensor nodes feed environmental data to a data processing center. In harsh marine settings, these battery-operated nodes require expensive and complicated battery replacement. Energy efficiency is essential for improving UWSN performance and reliability due to limited energy and short lifetime [16].

By proposing a robust, energy-efficient AI-based metaheuristic algorithm for path planning in UWSN, the data gathered by sensors can be collected very quickly by consuming much less energy, which enables faster response of the monitoring system in case of any risks of ship accidents. It also reduces the total energy consumption of sensors by communicating them at a closer point. It so extends the network lifetime of UWSN, which monitors the underwater environment to avoid ship accidents.

In this paper, we consider a 3D energy-aware path planning problem with autonomous underwater vehicle that visits multiple sensor nodes. This paper also considers a case (broader than obstacle avoidance) where direct traveling paths between some node pairs should be avoided due to several reasons including obstacles, underwater flows, too narrow places for travel, and other risks like changing temperature and pressure.

B. Our Contributions

Our main contributions can be summarized as follows:

- This work provides a comparative study of the five commonly used metaheuristic-based approaches (Ant Colony Optimization-based Approach, Particle Swarm Optimization-based Approach, Teaching Learning Based Optimization-based Algorithm, Genetic Algorithm-based Approach, Grey Wolf Optimizer-based Approach) for 3D path planning problem by an AUV for data collection problems in UWSN.
- We also consider the traveling limitations between some of the sensor pairs such as obstacles between sensors, pressure, water flows, and changing temperature.
- We propose a modified version of the genetic algorithm, Safety-Aware Genetic Algorithm (SAGA)-based Approach, under the traveling limitations through the links between some sensor pairs by modifying the distance-based cost matrix for the path planning problem.

C. Organization

The rest of this paper is organized as follows. Section II provides related literature. Section III provides the system model and defines the problem. Section IV tackles the 3D path planning problem as a traveling salesman problem and proposes several algorithms: Ant Colony Optimization-based Approach, Particle Swarm Optimization-based Approach, Teaching Learning Based Optimization-based Algorithm, Genetic Algorithm-based Approach, Grey Wolf Optimizer-based Approach. In Section V, we propose a novel approach, Safety-Aware Genetic Algorithm-based Approach, by considering the problem with some limitations between some of the sensor pairs. In Section VI, we evaluate performances of the proposed algorithms. Section VII concludes the paper and provides future directions.

II. Related Work

This section considers the related literature for the path planning problem in UWSN.

There have been numerous attempts to resolve this problem. First, a significant portion of the energy used by UWSNs is usually attributed to data transmission. The collected sensor data is aggregated and reduced using data compression and optimization algorithms to reduce transmission data and energy consumption [17]. Second, the energy efficiency of UWSNs can also be increased with the use of smart node placement and routing strategies. Based on the uneven distance and energy expenditure between sensor nodes, optimal deployment and routing techniques can decrease energy consumption and increase network lifetime.

However, even with these methods, changing the battery is still necessary when it runs out. Thus, to charge underwater sensors, energy transfer technologies accomplish long-term monitoring and data transmission while avoiding the difficulty of regular battery replacement. DeMauro et al. [18] created a rechargeable lithium-ion battery module specifically for underwater applications to combat high water pressure and short circuit. Autonomous underwater vehicles (AUVs) are required to help with charging due to the limited transmission distance of energy, and route planning for AUVs is required.

An AUV is a self-propelled submersible that can be used for moderate tasks without human intervention. Underwater resource research, underwater environmental monitoring, and marine safety have all made extensive use of the AUV, which is regarded as an affordable and secure tool for seabed inquiry, search, identification, and rescue [19], [20]. The difficulty of losing data from its successive nodes arises from the AUV's limited power carrying capacity, which also limits its charging area. This makes it challenging to guarantee the AUV's practicality in cases for larger detecting region, particularly in marine conditions.

A plan to create magnetically charged cars for wireless rechargeable sensor networks (WRSNs) was put forth [21]. UWSNs are often used in a three-dimensional framework, in contrast to ground-based wireless rechargeable sensor networks, and their transmission power increases significantly with underwater distance.

Communication protocol design can conserve energy due to battery limits. Lee et al. compared energy-efficient UWSN MAC techniques depending on network topology [22]. A work [23] examines energy-efficient and dependable UWSN MAC and routing techniques. Another work [24] creates a packet-sending mechanism to eliminate redundancy and increase channel quality. A hybrid-coding-aware routing system for underwater acoustic sensor networks (UASNs) by Su et al. [25] reduces transmission overhead and ensures reliability.

Underwater sensor networks benefit from clustering's energy efficiency, data aggregation, resource management, and lifespan [26]. It divides the network into clusters, each with a cluster head (CH) that aggregates and relays information from individual nodes, eliminating redundant transfers [27]. This saves energy and bandwidth in underwater areas with restricted communication resources [28].

Sun et al. [29] developed a clustering-based communication protocol that lowered sensor node energy usage. A topology management approach for underwater sonar detection networks (USDNs) by Jin et al. can improve coverage performance and extend network lifetime with guaranteed coverage and connection [30]. A work [31] developed a virtual force-based distributed node deployment strategy to improve UWSN network coverage. Another work [32] builds a network topology control model including underwater aspects like robustness, energy consumption balance, and topology to extend UWSN lifetime and optimize data delivery.

Data collection, charging, and more are conceivable with autonomous underwater vehicles. AUVs gather data. AUVs with sensors can gather data on geology underwater, water conditions, marine life. A work [33] tested AUV-assisted communication, where the AUV collects energy-saving data as a mobile node. Another work [34] suggested using AUVs to collect data and plan pathways with K-means [35].

Underwater networking and communication require AUVs. Stationary or mobile sensors can provide data to a central station or other AUVs. Smooth communication and real-time underwater operation monitoring and control are possible. A field-deployable three-phase wireless charging system by Kan et al. [36] charges AUVs quickly, efficiently, and conveniently. To speed up AUV battery life, Ramos et al. [37] used dynamic system theory for navigation in 0–100 m ocean depths.

Autonomous docking and battery charging AUVs are being developed. This lets them run for long periods without human assistance. AUV batteries and sensor nodes charge when docked. Avoiding retrieval and recharge makes them more independent and efficient.

Energy efficiency is improved via AUV path design. To save electricity and increase network lifetime, Cheng et al. worldwide design the AUV's path, avoid underwater obstacles, and analyze its energy consumption model using kinematic and dynamical models [38]. Kumar et al. [39] propose a hybrid subsea AUV exploration method that greatly reduces their range. The work [40] sectors the exploring region into numerous smaller sections with data-receiving points. Path planning saves AUV energy while collecting data. A rechargeable UWSN path planning method [41] increases network lifetime.

To solve UWSN energy shortages and battery replacement difficulties, the work [42] proposes a path planning and energy-saving technique for charging underwater sensor nodes using AUVs. A genetic algorithm determines the optimal AUV path, while many AUVs charging the sensor network nodes maximize network size and transmission reliability. The outcomes of the simulation demonstrate that the AUV path planning scheme converges more quickly than conventional algorithms and increases the lifetime of UWSNs while energy balancing following node density and network size. In high-density networks, the proposed path planning technique lowers the energy consumption of exploratory AUVs by 15% per AUV.

A work [43] considers a path planning problem of unmanned aerial vehicle (UAV) from one point to another point by avoiding obstacles between them and it presents a comparative study of genetic algorithm, simulated annealing, grey wolf optimizer, and an improved version of grey wolf optimizer algorithm. However, it tackles a problem like the shortest path problem while our paper considers a problem like a traveling salesman problem (TSP).

Another research [44] tackles a path planning problem of AUV from one point to another point by considering ocean currents. It tackles the problem for both cases without obstacles between them and with obstacles between them. It presents a comparative study of A* [45], rapidly exploring random tree (RRT) [46], [47], genetic algorithm, particle swarm optimization, and an improved version of particle swarm optimization algorithm. However, it tackles a problem like the shortest path problem in an ocean environment with ocean currents while our paper considers a problem like a TSP.

A study [48] considers a motion planning problem of an autonomous ground vehicle from one point to another point by avoiding obstacles between them and it presents a comparative study of the probabilistic roadmap (PRM) [49], RRT, and the proposed algorithm, Optimistic Motion Planning using Recursive Sub-Sampling. The investigated problem is a 2D motion planning problem which differs from our TSP-type path planning problem.

Another work [50] proposes a new optimal path planning method for long-term autonomous underwater vehicle operations in areas where ocean currents change over time. These currents may surpass the AUV's top speed and momentarily reveal obstructions. Paths require both geographical and temporal characterisation, in contrast to the majority of other path design methodologies. This method allows for a trade-off between mission duration and energy requirements by utilising ocean currents to limit energy usage and achieve mission objectives. By using a parallel swarm search, the proposed method reduces the susceptibility to large local minima on the complex cost surface. The efficiency of the optimisation strategies is evaluated computationally and empirically using the Starbug AUV on a validated ocean model of Brisbane's Moreton Bay.

In another research [51], the genetic algorithm, grey wolf optimizer algorithm and nearest neighbour algorithm have been applied to solve this problem. It is shown that the nearest neighbour algorithm shows much quicker (nearly 30 times quicker) performance than the genetic algorithm and grey wolf optimizer algorithmn. On the other hand, the genetic algorithm exhibits better performance than the nearest neighbour algorithm while grey wolf optimizer algorithm demonstrates the worst performance among all them.

This present paper considers a 3D energy-aware path planning problem with autonomous underwater vehicle that visits multiple nodes. Then, it applies the five most commonly used metaheuristic-based approaches, namely, Ant Colony Optimization-based Approach, Particle Swarm Optimization-based Approach, Teaching Learning-based Optimization-based Approach, Genetic Algorithm-based Approach, Grey Wolf Optimizer-based Approach. This paper also considers a case (broader than obstacle avoidance) where direct traveling paths between some node pairs should be avoided due to several reasons including obstacles, underwater flows, too narrow places for the travel, and other risks like changing temperature and pressure.

Table I provides a brief comparison of the energy-aware path planning approaches in the closely related literature.

TABLE I. Brief Comparison of the Energy-aware Path Planning Approaches

Included Features	Underwater	3D	Multiple Point visit	Obstacle Avoidance
Ding *et al.* [43]	no	no	no	yes
Zeng *et al.* [44]	yes	no	no	yes
Kenye *et al.* [48]	no	no	no	yes
Witt *et al.* [50]	no	no	no	no
Gul *et al.* [51]	yes	yes	yes	no
This work	yes	yes	yes	yes

III. System Model and Problem Definition

This paper considers the energy-aware path planning problem with an AUV to visit sensors underwater. This section presents a motivating scenario and formulates the problem based on this motivation. First, we consider the system model of the UWSN. Then, we define the energy-aware path planning problem more precisely.

A. System Model

The network model is shown in Fig. 1. Every sensor node is connected to an underwater acoustics link, which transmits data to SINK nodes. Starting at a charge station (CS), the magnetic resonance coupling AUV charges each sensor node before making its way back to the CS for a charge and rest. It functions as a mobile sink to gather data.

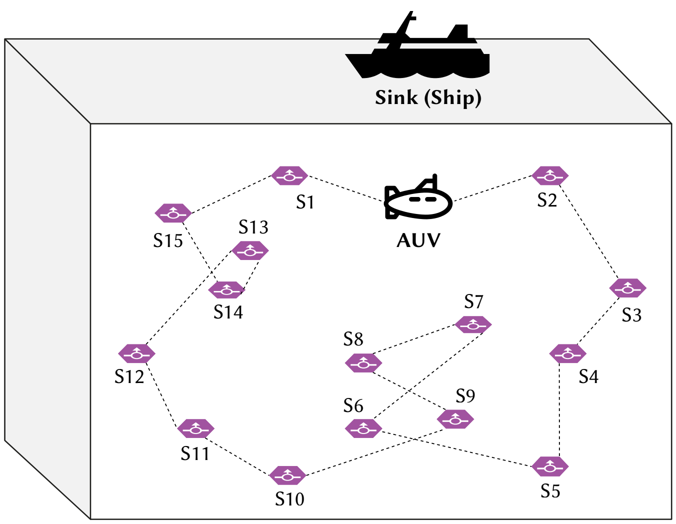

Fig. 1. The system model of the UWSN where the AUV collects data from all the fifteen sensors (N1, N2, ..., N15) which monitor the sea for anomaly/risk detection to avoid ship accidents. After aggregating all the gathered data, this is sent to the data sink which collects all the data to evaluate them.

One important problem in UWSNs is the energy consumption balance of underwater sensors. In several studies [34, 35, 36], AUVs have been used to collect underwater data to solve the problem of unequal energy use. The AUV moves and visits each sensor node by a predefined plan to balance each node's energy consumption.

B. Problem Definition

The energy-aware path planning problem via AUV can be categorized as a traveling salesman problem (TSP) [52]–[54]. The two main methods for resolving the TSP are the intelligent evolutionary algorithm and the classical search algorithm. Examples of the former include the greedy algorithm, the artificial potential field technique, and the quick progress algorithm. The latter includes methods like the ant colony algorithm, particle swarm optimization approach, teaching learning-based optimization algorithm, grey wolf optimizer algorithm, and genetic algorithm.

The most prominent NP-hard optimization problem is the TSP [53], [54]. TSP finds a route for a salesman that starts from home, visits a collection of locations, and returns to the original place with the minimum trip distance with each city visited once [56].

In a TSP problem with m sensor nodes, let cij denote the node distance from node i to node j. Let xij denote a binary variable that takes the value of 1 if node j is visited just after node i. Otherwise, it takes the value of 0. In this case, the energy-aware path planning problem can be considered as an NP-hard TSP as follows [55]:

Problem 1. *Minimizing the following cost function:*

$$\min_{x_{ij}} \sum_{j=1}^{m} \sum_{i=1}^{m} c_{ij}\, x_{ij} \tag{1}$$

where

$$\begin{aligned} \sum_{i=1}^{m} x_{ij} &= 1, j = 1, \dots, m \\ \sum_{j=1}^{m} x_{ij} &= 1, i = 1, \dots, m \\ \sum_{i \in K} \sum_{j \in K} x_{ij} &\leq |K| - 1, \forall K \subset \{1, \dots, m\} \end{aligned}$$

IV. Proposed Energy-Aware Path Planning (EAPP) Approaches

In this section, we tackle the energy-aware path planning problem of AUV which includes the distance between each pair of sensor nodes.

We present the following algorithms by tackling the EAPP problem as a TSP problem: Ant Colony Optimization-based Approach, Particle Swarm Optimization-based Approach, Teaching Learning based Optimization-based Algorithm, Genetic Algorithm-based Approach, Grey Wolf Optimizer-based Approach.

A. Ant Colony Optimization (ACO)-Based Approach

ACO has many inherent limitations, despite its strong performance in discrete problem solutions. Despite having great stability, it has several disadvantages when working with large amounts of data in terms of convergence speed and results in correctness [59].

We tackle the EAPP problem as a TSP and propose a 3D path planning solution based on the ACO [57], [58].

B. Particle Swarm Optimization (PSO) Algorithm-Based Approach

PSO has been popular with researchers for its ability to hybridize, specialize, and exhibit novel emergent behaviors in various application areas. PSO's main benefit is tweaking fewer parameters. PSO finds the optimal particle interaction solution but converges slowly to the global optimum in high-dimensional search space. It performs poorly on large, complex datasets. PSO rarely finds the global optimum solution in multidimensional situations. Local optima traps and particle velocity variations confine trials to a sub-plain of the search hyper-plain [62], [63].

We tackle the EAPP problem as a TSP and propose a 3D path planning solution based on the PSO [60], [61].

C. Teaching Learning Based Optimization (TLBO)-Based Algorithm

TLBO solves large global optimum optimization problems with a sophisticated metaheuristic method. Several TLBO variations have been proposed to improve local optima avoidance and convergence speed [65].

We tackle the EAPP problem as a TSP and propose a 3D path planning solution based on the TLBO-based Algorithm [64].

D. Grey Wolf Optimizer (GWO)-Based Approach

GWO is easier to implement than PSO and GA. On the other hand, it has the drawbacks of poor convergence speed, low solution precision, and local optimum tendency.

We tackle the EAPP problem as a TSP and propose a 3D path planning solution based on the GWO algorithm [66].

E. Genetic Algorithm (GA)-Based Approach

We tackle the EAPP problem as a TSP and propose a 3D path planning solution based on the Genetic Algorithm [67],[68].

The basic principle of genetic algorithms is to solve complex optimization problems by imitating biological evolution. The first steps in applying a genetic algorithm to tackle TSP issues are identifying the individuals of the TSP solution and initializing the population. Every member of the population is rated according to a fitness function, and the most fit individuals are selected for genetic processes including selection, crossover, and mutation. The genetic algorithm's termination criterion is the maximum number of iterations selected. Furthermore, the individual fitness for this work is the total route size or the total AUV energy consumption. By summing up the distances of all the sensing nodes, equation (2) may be utilized to determine the fitness of each individual in this circumstance.

$$Fitness = \sum_{t=1}^{N-1} \frac{1}{\sqrt{(x_l - x_{l-1})^2 + (y_l - y_{l-1})^2 + (z_l - z_{l-1})^2}} \tag{2}$$

where N denotes the number of nodes; (x_l, y_l, z_l) denotes the 3D position of node l.

V. Safety-Aware Genetic Algorithm (SAGA)-Based Approach

In this section, we consider the energy-aware path planning problem by also considering the limitations that emerge between some of the sensor pairs. The obstacles between sensors can block direct traveling from one sensor to the other. Changing pressure, water flows and changing temperature can be other reasons for the AUV not prefer to travel from one sensor to the other sensor directly. In this case, the AUV will visit some other sensor/s between those two sensors.

We propose a modified version of the genetic algorithm, the Safety-Aware Genetic Algorithm (SAGA)-based Approach, for the 3D path planning problem with small obstacles that emerge between some of the sensor pairs.

In the SAGA approach, we do not modify the standard GA itself; however, we transform the distance cost matrix by replacing the cost of the unavailable path between some nodes with a very large number of M to avoid preferring those paths during path planning.

Fig. 2 shows the flow diagram of SAGA, which exhibits its difference from GA.

Before applying the genetic algorithm, the distance cost matrix obtained for n nodes can be written as

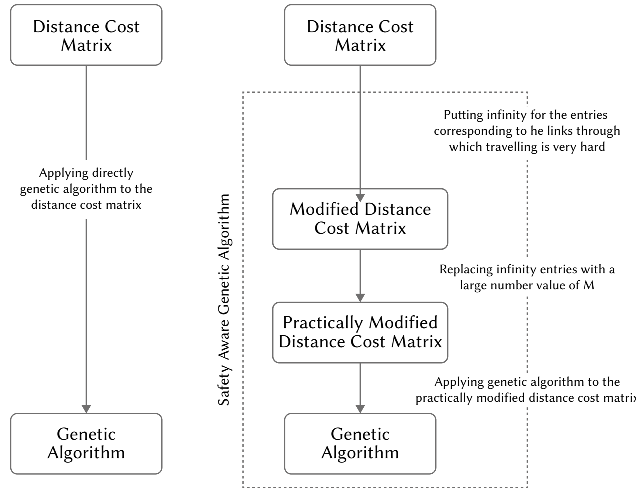

Fig. 2. The flow charts of GA (left one) and SAGA (right one), which exhibits the difference of SAGA from GA.

$$D = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1(n-1)} & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2(n-1)} & d_{2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ d_{(n-1)1} & d_{(n-1)2} & \dots & d_{(n-1)(n-1)} & d_{(n-1)n} \\ d_{n1} & d_{n2} & \dots & d_{n(n-1)} & d_{nn} \end{bmatrix} \tag{3}$$

Due to several reasons including underwater flows, too narrow places for the UAV's travel, and other risks like changing temperature and pressure, direct traveling paths between some node pairs should be avoided in some cases. In such cases, if we consider blockage between node $(n-1)$ and node n such that traveling from node $(n-1)$ to node n is not possible, then their distance can be modified as $d_{(n-1)n} = \infty$.

By replacing all $d_{(n-1)n}$ entries $(d_{12}, d_{23}, \dots, d_{(n-1)n})$ with ∞ such that $d_{(n-1)n} = \infty$, the modified distance cost matrix D_{mod} obtained before applying the genetic algorithm for n nodes can be written as

$$D_{mod} = \begin{bmatrix} d_{11} & \infty & \dots & d_{1(n-1)} & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2(n-1)} & d_{2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ d_{(n-1)1} & d_{(n-1)2} & \dots & d_{(n-1)(n-1)} & \infty \\ d_{n1} & d_{n2} & \dots & d_{n(n-1)} & d_{nn} \end{bmatrix} \tag{4}$$

Giving a very large number M instead of ∞ can be more practical for the implementation. M can be chosen as the square of the maximum distance between two nodes in the matrix.

By replacing all ∞ with M such that $d_{(n-1)n} = M$, the practically modified distance cost matrix D_{mod}^{prac} obtained before applying genetic algorithm for n nodes can be written as

$$D_{mod}^{prac} = \begin{bmatrix} d_{11} & \mathbf{M} & \dots & d_{1(n-1)} & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2(n-1)} & d_{2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ d_{(n-1)1} & d_{(n-1)2} & \dots & d_{(n-1)(n-1)} & \mathbf{M} \\ d_{n1} & d_{n2} & \dots & d_{n(n-1)} & d_{nn} \end{bmatrix} \tag{5}$$

By considering the practically modified distance cost matrix D_{mod}^{prac} instead of the distance cost matrix D, we apply the 3D genetic algorithm, which brings safety-awareness about each link between node i and node $i+1$. Hence, we propose the SAGA-based Approach, for the 3D energy-aware path planning problem.

To sum up the implementation of SAGA, we applied the GA in the 3D path planning problem with the difference that we modified the distance cost matrix before applying the GA, which brings safety awareness to GA and converts it into SAGA.

VI. Numerical Results

In this section, we evaluate the performance of the algorithms for the 3D energy-aware path planning problem of AUV which includes the distance between each pair of sensor nodes. For the simulations, we formed a 500 m × 500 m × 500 m space by locating sensor nodes randomly (The related works choose similar range of dimension length and distances).

In the first subsection, we consider a scenario with an AUV and 50 nodes by considering no limits in links that block traveling directly between some node pairs. In the second subsection, we consider a scenario with an AUV and 100 nodes by considering no limits in links that block traveling directly between some node pairs. In the last subsection, we consider two separate scenarios with an AUV and 50 nodes and with an AUV and 100 nodes by considering limits in some links that block traveling directly between some node pairs.

A. 50-Node Scenario

In this subsection, we will consider a scenario with 50 nodes and a single AUV. Fig. 3 illustrates the locations of the 50 nodes in the 500 m × 500 m × 500 m space.

Locations of the 50 nodes are given as { (440, 20, 472), (500, 57, 325), (283, 289, 65), (292, 309, 106), (55, 147, 388), (452, 20, 45), (236, 381, 178), (423, 9, 16), (157, 461, 36), (75, 28, 450), (141, 72, 153), (290, 354, 346), (2, 213, 111), (146, 175, 125), (156, 207, 283), (447,261, 360), (106, 139, 228),(448, 482, 170),(426, 110, 221), (487, 279, 21), (257,240, 184), (323, 160, 225), (139, 20, 384), (294, 106, 400), (412, 353, 409), (437, 60, 12), (239, 5, 27), (256, 270, 219), (317, 388, 242), (207, 297, 388), (167,154, 441), (148, 463, 94), (185, 103, 278), (270, 445, 26), (346, 261, 303), (387,232, 380), (397, 414, 211),(29, 368, 61), (150, 118, 369), (205, 65, 489), (116,350, 124), (223, 359, 458),(458, 201, 137), (13, 98, 242), (338, 186, 18), (58, 445, 314), (428, 152, 166),(212, 156, 281), (208, 330, 93),(100, 333, 420) }

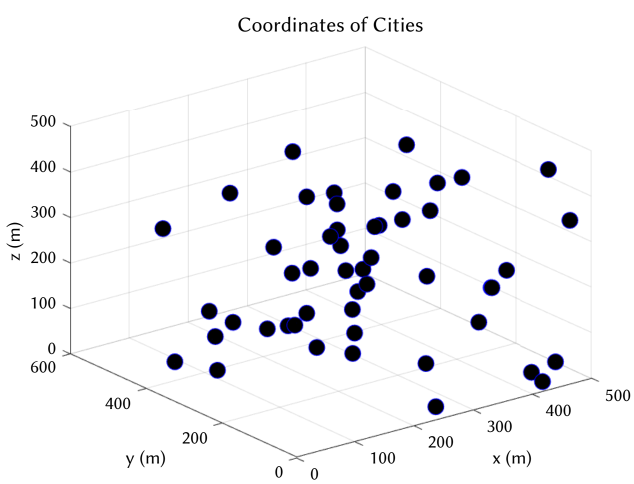

Fig. 3. The coordinates of the sensor nodes to be visited by the AUV.

By considering different subsets of these parameters, we evaluate the performance of the following algorithms by tackling the EAPP problem as a TSP problem: Ant Colony Optimization (ACO)-based Approach, Particle Swarm Optimization (PSO)-based Approach, Teaching Learning Based Optimization (TLBO)-based Algorithm, Genetic Algorithm (GA)-based Approach, Grey Wolf Optimizer (GWO)-based Approach.

In the following subsubsections, we present the solutions achieved by ACO-based Approach, PSO-based Approach, TLBO-based Algorithm, GA-based Approach, and GWO-based Approach as a result of 1000 iterations.

1. ACO-Based Approach

In this subsubsection, we present an ACO-based solution for the 3D TSP problem.

Fig. 4 exhibits ACO's achieved path planning solution in 1000 iterations for visiting the 50 nodes in Fig. 3.

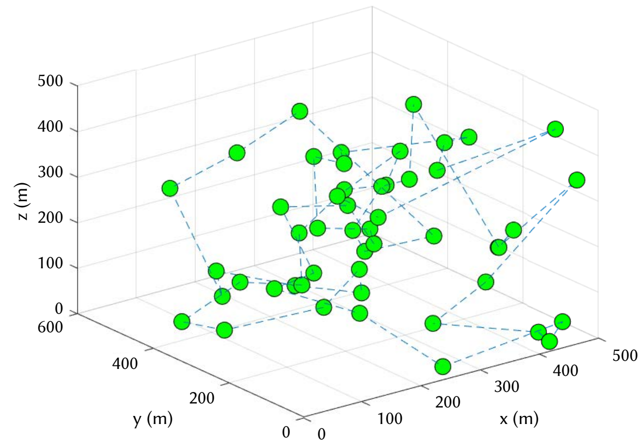

Fig. 4. The achieved path planning solution for visiting the 100 nodes by AUV with ACO in 1000 iterations.

2. PSO-Based Approach

In this subsubsection, we present a PSO-based solution for the 3D TSP problem.

Fig. 5 exhibits the PSO's achieved path planning solution in 1000 iterations for visiting the 50 nodes in Fig. 3.

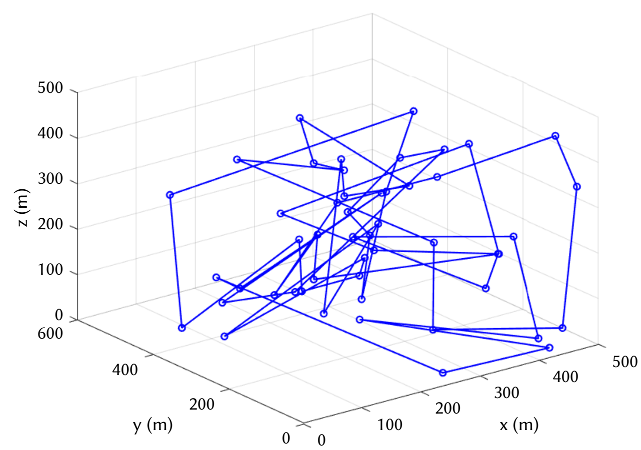

Fig. 5. The achieved path planning solution for visiting the 100 nodes by AUV with PSO in 1000 iterations.

3. TLBO-Based Algorithm

In this subsubsection, we present a TLBO-based solution for the 3D TSP problem.

Fig. 6 exhibits the TLBO's achieved path planning solution in 1000 iterations for visiting the 50 nodes in Fig. 3.

4. GWO-Based Approach

In this subsubsection, we present a GWO-based solution for the 3D TSP problem.

Fig. 7 exhibits the GWO's achieved path planning solution in 1000 iterations for visiting the 50 nodes in Fig. 3.

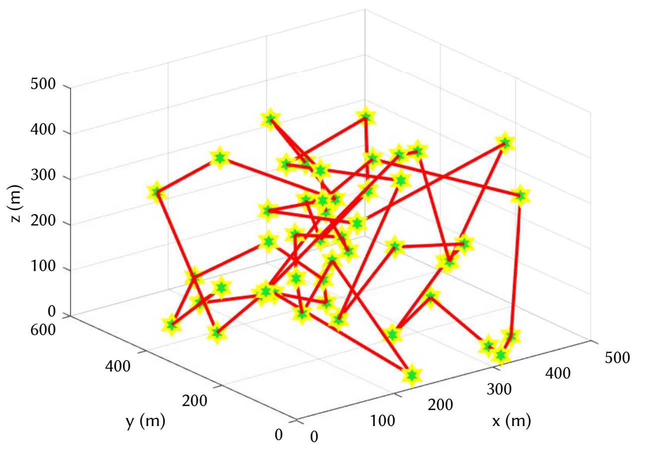

Fig. 6. The achieved path planning solution for visiting the 100 nodes by AUV with TLBO in 1000 iterations.

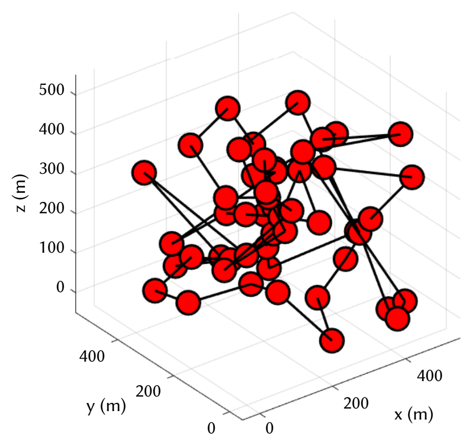

Fig. 7. The achieved path planning solution for visiting the 100 nodes by AUV with GWO in 1000 iterations.

5. GA-Based Approach

In this subsubsection, we present a GA-based solution for the 3D TSP problem.

Fig. 8 exhibits the GA's achieved path planning solution in 1000 iterations for visiting the 50 nodes in Fig. 3.

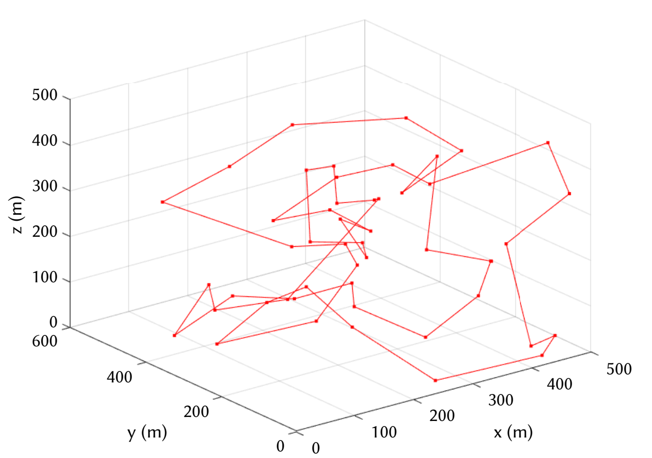

Fig. 8. The achieved path planning solution for visiting the 100 nodes by AUV with GA in 1000 iterations.

6. Comparison and Discussion

Considering the general trend, the GA-based Approach shows better performance than the ACO-based Approach, PSO-based Approach, TLBO-based Approach, and GWO-based Approach.

Fig. 9 shows the total traveled distance by AUV with different algorithms (the ACO-based Approach, PSO-based Approach, TLBO-based Approach, GWO-based Approach, and GA-based Approach) for visiting the 50 nodes, which are located initially as given in Fig. 3.

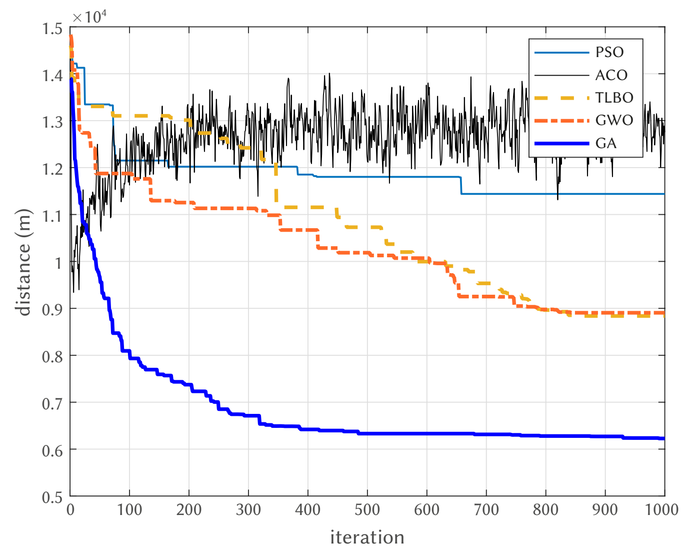

Fig. 9. The achieved path lengths for visiting the 100 nodes by all the algorithms (the ACO-based Approach, PSO-based Approach, TLBO-based Approach, GWO-based Approach, and GA-based Approach) in 1000 iterations.

From Fig. 9, we can make the following observations on the performance of the algorithms for the 50-node scenario. The ACO-based approach achieves better in less number of iterations such that its performance becomes worse with the increasing number of iterations after achieving its minimum. Although the PSO-based approach achieves better with an increasing number of iterations, it achieves better than just the ACO-based approach for 1000 iterations. Although the GWO-based approach converges faster than TLBO-based approach, both achieve almost the same performance for 1000 iterations, which is considerably better than the ACO-based approach and PSO-based approach. The GA-based approach not only achieves much better than all of ACO-based Approach, PSO-based Approach, TLBO-based Approach, GWO-based Approach but also converges faster than PSO-based Approach, TLBO-based Approach, GWO-based Approach (Only ACO-based approach converges to minimum very fast.)

From Table II, we can make the following observations. At the beginning (in the first iteration), all the algorithms except the GA-based approach have similar performance with at most 2.5% difference (366 m difference between ACO-based approach and GWO-based approach) while the GA-based approach achieves 4.0% difference better than ACO-based approach. In iteration 100, the TLBO-based approach achieves the worst performance while the GA-based approach achieves considerably better than the other approaches (3534 m, namely, 30.4% less than the ACO-based approach which is the second best). In iteration 300, the ACO-based approach achieves the worst performance while the GA-based approach achieves considerably better than the other approaches (4418 m, namely, 39.7% less than the GWO-based approach which is the second best). In addition, PSO and TLBO-based approaches achieve closely to each other in iteration 300. In iteration 600, the ACO-based approach achieves the worst performance while the GA-based approach achieves considerably

TABLE II. Total Distance for Visiting the 50 Nodes By the Algorithms (the ACO-Based Approach, PSO-Based Approach, TLBO-Based Approach, GWO-Based Approach, and GA-Based Approach) With Respect to Iteration Number (Note That Iteration 1 Is Considered as the Beginning Instead of Iteration 0)

Iteration	1	100	200	300	400	500	600	700	800	900	1000
ACO	14468	11628	12683	13214	12748	12130	13177	12652	12936	12981	12502
PSO	14787	12150	12019	12019	11851	11802	11802	11439	11439	11439	11439
TLBO	14603	13103	13012	12421	11153	10729	10069	9533	8963	8906	8906
GWO	14834	11874	11254	11130	10669	10186	9996	9251	8977	8837	8837
GA	13889	8094	7374	6712	6420	6330	6330	6314	6279	6271	6227

better than the other approaches (3666 m, namely, 36.7% less than the GWO-based approach which is the second best). In addition, GWO and TLBO-based approaches achieve very closely to each other in iteration 600 (just 0.73% difference). In iteration 1000, the ACO-based approach achieves the worst performance while the GA-based approach achieves considerably better than the other approaches (2610 m, namely, 29.5% less than the GWO-based approach which is the second best). In addition, GWO and TLBO-based approaches achieve very closely to each other in iteration 1000 (just 0.77% difference), which is much better than the ACO-based approach and PSO-based approach.

B. 100-Node Scenario

In this subsection, we will consider a scenario with 100 nodes and a single AUV. Fig. 10 illustrates the locations of the 100 nodes in the 500 m × 500 m × 500 m space.

Locations of the 100 nodes are given as { (408, 82, 323), (453, 398, 190), (64, 156, 406), (457, 265, 267), (317, 83, 176), (49, 301, 470), (140, 132, 438), (274, 328, 276), (479, 345, 312), (483, 375, 294), (79, 226, 104), (486, 42, 151), (479, 115, 236), (243, 457, 116), (401, 77, 423), (71, 413, 98), (211, 270, 113), (458, 499, 86), (397, 40, 114), (480, 222, 218), (328, 54, 156), (18, 481, 462), (425, 3, 216), (467, 388, 93), (340, 409, 453), (379, 435, 490), (372, 43, 220), (197, 200, 56), (328, 130, 130), (86, 401, 205), (354, 216, 298), (16, 456, 132), (139, 91, 302), (24, 132, 356), (49, 73, 111), (412, 69, 59), (348, 435, 149), (159, 290, 160), (476, 275, 213), (18, 73, 254), (220, 427, 43), (191, 312, 132), (383, 176, 401), (398, 257, 15), (94, 201, 465), (245, 38, 366), (223, 120, 245), (324, 62, 290), (355, 92, 119), (378, 120, 230), (139, 209, 482), (340, 25, 274), (328, 452, 261), (82, 473, 116), (60, 246, 245), (250, 245, 313), (480 169, 340), (171, 451, 198), (293, 185, 184), (112, 56, 494), (376, 391, 19), (128, 195, 443), (253, 121, 457), (350, 202, 399), (446, 49, 50), (480, 66, 131), (274, 472, 168), (70, 479, 340), (75, 288, 69), (129, 30, 361), (421, 118, 54), (128, 177, 327), (408, 411, 248), (122, 8, 390), (465, 22, 358), (175, 85, 452), (99, 325, 446), (126, 366, 168), (309, 324, 350), (237, 226, 99), (176, 274, 16), (416, 149, 373), (293, 373, 251), (275, 95, 240), (459, 344, 453), (143, 92, 305), (379, 185, 309), (377, 313, 430), (191, 391, 403), (284, 41, 289), (38, 465, 92), (27, 388, 120), (266, 244, 444), (390, 218, 15), (468, 224, 245), (65, 154, 84), (285, 255, 490), (235, 256, 357), (6, 409, 251), (169, 398, 236)}.

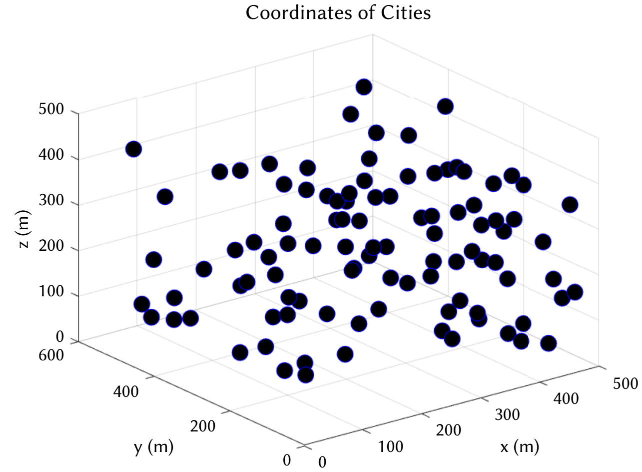

Fig. 10. The coordinates of the 100 sensor nodes to be visited by the AUV.

By considering different subsets of these parameters, we evaluate the performance of the following algorithms by tackling the EAPP problem as a TSP problem: Ant Colony Optimization (ACO)-based Approach, Particle Swarm Optimization (PSO)-based Approach, Teaching Learning Based Optimization (TLBO)-based Algorithm, Genetic Algorithm (GA)-based Approach, Grey Wolf Optimizer (GWO)-based Approach.

In the following subsubsections, we present the solutions achieved by ACO-based Approach, PSO-based Approach, TLBO-based Algorithm, GA-based Approach, and GWO-based Approach as a result of 1000 iterations.

1. ACO-Based Approach

In this subsubsection, we present an ACO-based solution for the 3D TSP problem.

Fig. 11 exhibits ACO's achieved path planning solution in 1000 iterations for visiting the 100 nodes in Fig. 10.

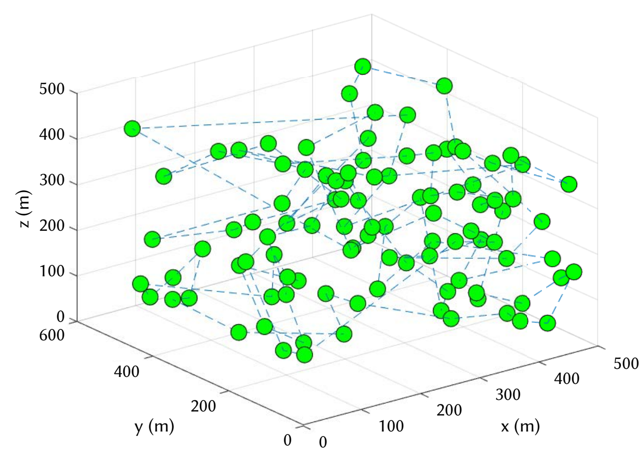

Fig. 11. The achieved path planning solution for visiting the 100 nodes by AUV with ACO in 1000 iterations.

2. PSO-Based Approach

In this subsubsection, we present a PSO-based solution for the 3D TSP problem.

Fig.12 exhibits the PSO's achieved path planning solution in 1000 iterations for visiting the 100 nodes in Fig. 10.

3. TLBO-Based Algorithm

In this subsubsection, we present a TLBO-based solution for the 3D TSP problem.

Fig. 13 exhibits the TLBO's achieved path planning solution in 1000 iterations for visiting the 100 nodes in Fig. 10.

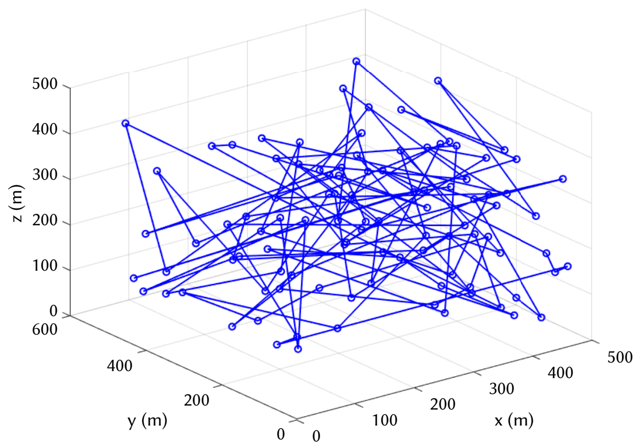

Fig. 12. The achieved path planning solution for visiting the 100 nodes by AUV with PSO in 1000 iterations.

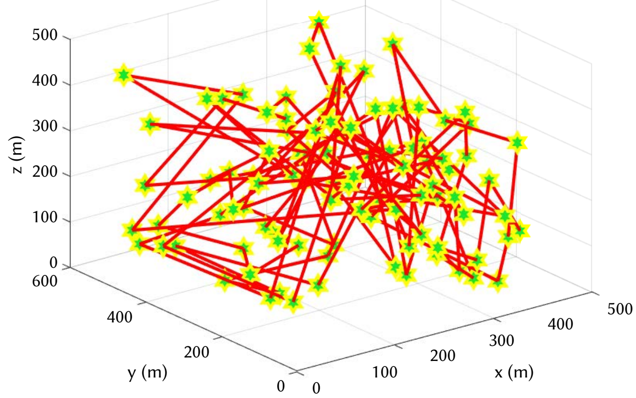

Fig. 13. The achieved path planning solution for visiting the 100 nodes by AUV with TLBO in 1000 iterations.

4. GWO-Based Approach

In this subsubsection, we present a GWO-based solution for the 3D TSP problem.

Fig. 14 exhibits the GWO's achieved path planning solution in 1000 iterations for visiting the 100 nodes in Fig. 10.

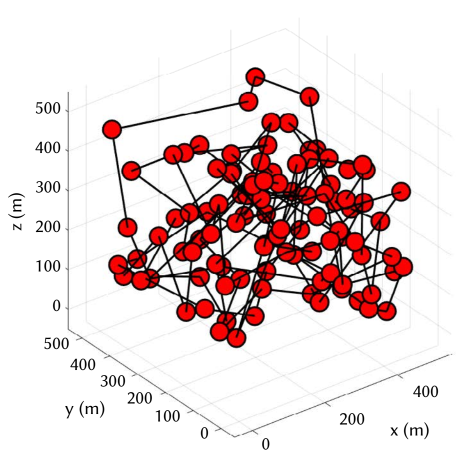

Fig. 14. The achieved path planning solution for visiting the 100 nodes by AUV with GWO in 1000 iterations.

5. GA-Based Approach

In this subsubsection, we present a GA-based solution for the 3D TSP problem. Fig. 15 exhibits the GA's achieved path planning solution in 1000 iterations for visiting the 100 nodes in Fig. 10.

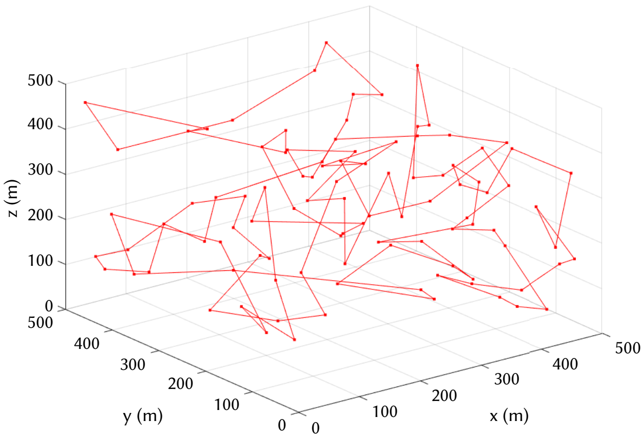

Fig. 15. The achieved path planning solution for visiting the 100 nodes by AUV with GA in 1000 iterations.

6. Comparison and Discussion

Considering the general trend, the GA-based Approach shows better performance than the ACO-based Approach, PSO-based Approach, TLBO-based Approach, and GWO-based Approach.

Fig. 16 shows total traveled distance by AUV with different algorithms (ACO-based Approach, PSO-based Approach, TLBO-based Approach, GWO-based Approach, and GA-based Approach) for visiting the 100 nodes, which are located as given in Fig. 10.

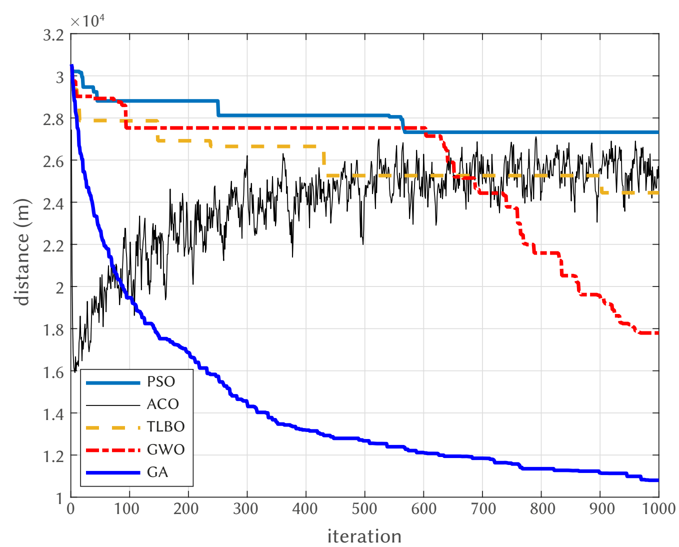

Fig. 16. The achieved path lengths for visiting the 100 nodes by all the algorithms (the ACO-based Approach, PSO-based Approach, TLBO-based Approach, GWO-based Approach, and GA-based Approach) in 1000 iterations.

From Fig. 16, we can make the following observations on the performance of the algorithms for the 100-node scenario. Although the PSO-based approach achieves better with an increasing number of iterations, it achieves worse than all the other approaches for 1000 iterations. The ACO-based approach achieves better in less number of iterations such that its performance becomes worse with the increasing number of iterations after achieving its minimum. The GWO-based

TABLE III. Total Distance for Visiting the 100 Nodes By the Algorithms (ACO-Based Approach, PSO-Based Approach, TLBO-Based Approach, GWO-Based Approach, and GA-Based Approach) With Respect to Iteration Number (Note That Iteration 1 Is Considered as the Beginning Instead of Iteration 0)

Iteration	1	100	200	300	400	500	600	700	800	900	1000
ACO	27446	20564	21526	26213	24262	24379	13177	12652	12936	12981	12502
PSO	30230	28808	28808	28120	28120	28120	27323	27323	27323	27323	27323
TLBO	29366	27864	26917	26649	26649	25264	25264	25264	25264	25264	24448
GWO	30418	27525	27525	27525	27525	27525	27525	24432	21589	19529	17794
GA	30549	19471	16861	14455	13182	12676	12120	11848	11351	11159	10803

approach converges almost as fast as the TLBO-based approach in the first 600 iterations while it converges to its minimum faster than the TLBO-based approach. The TLBO-based approach achieves almost the same as the ACO-based approach whereas the GWO-based approach achieves considerably better than all of the TLBO-based approach, the ACO-based approach and PSO-based approach. The GA-based approach not only achieves much better than all of the ACO-based Approach, PSO-based Approach, TLBO-based Approach, GWO-based Approach but also converges faster than PSO-based Approach, TLBO-based Approach, GWO-based Approach (Only ACO-based approach converges to its minimum very fast.) Considering all these, increasing the number of nodes from 50 to 100 nodes makes a considerable difference in some of these algorithms, especially the PSO-based approach and TLBO-approach.

From Table III, we can make the following observations. At the beginning (in the first iteration), all of the algorithms except the GA-based approach have similar performance with at most 2.5% difference (366 m difference between ACO-based approach and GWO-based approach) while the GA-based approach achieves 4.0% difference better than ACO-based approach. In iteration 100, the TLBO-based approach achieves the worst performance while the GA-based approach achieves considerably better than the other approaches (3534 m, namely, 30.4% less than the ACO-based approach which is the second best). In iteration 300, the ACO-based approach achieves the worst performance while the GA-based approach achieves considerably better than the other approaches (4418 m, namely, 39.7% less than the GWO-based approach which is the second best). In addition, PSO and TLBO-based approaches achieve closely to each other in iteration 300. In iteration 600, the ACO-based approach achieves the worst performance while the GA-based approach achieves considerably better than the other approaches (3666 m, namely, 36.7% less than the GWO-based approach which is the second best). In addition, GWO and TLBO-based approaches achieve very closely to each other in iteration 600 (just 0.73% difference). In iteration 1000, the ACO-based approach achieves the worst performance while the GA-based approach achieves considerably better than the other approaches (2610 m, namely, 29.5% less than the GWO-based approach which is the second best). In addition, GWO and TLBO-based approaches achieve very closely to each other in iteration 1000 (just 0.77%difference), which is much better than the ACO-based approach and PSO-based approach.

C. Safety-Awareness in 50-Node Scenario and 100-Node Scenario

In this subsection, we evaluate the performance of the Safety-Aware Genetic Algorithm (SAGA)-based solution for the 3D TSP problem under the limitation where visiting node i just after node $i-1$ has an extreme distance cost so impossible to visit.

1. Safety-Aware Genetic Algorithm (SAGA)-Based Approach

In this subsubsection, we observe the Safety-Aware Genetic Algorithm (SAGA)-based solution for the 3D TSP problem. Fig. 17 exhibits the SAGA's achieved path planning solution in 1000 iterations for visiting the 50 nodes in Fig. 3.

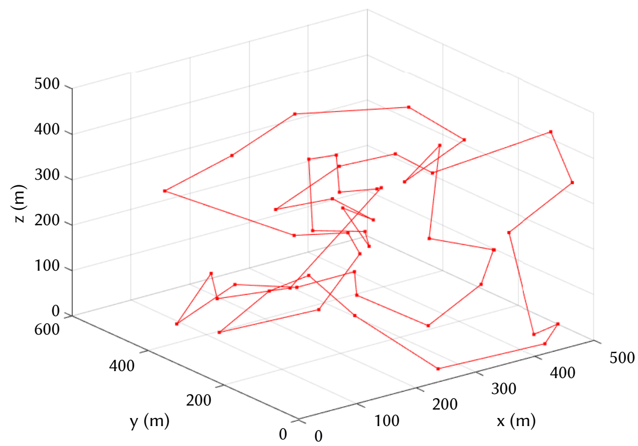

Fig. 17. The achieved path planning solution for visiting the 50 nodes by AUV with SAGA in 1000 iterations under limitations.

Fig. 18 exhibits the SAGA's achieved path planning solution in 1000 iterations for visiting the 100 nodes in Fig. 10.

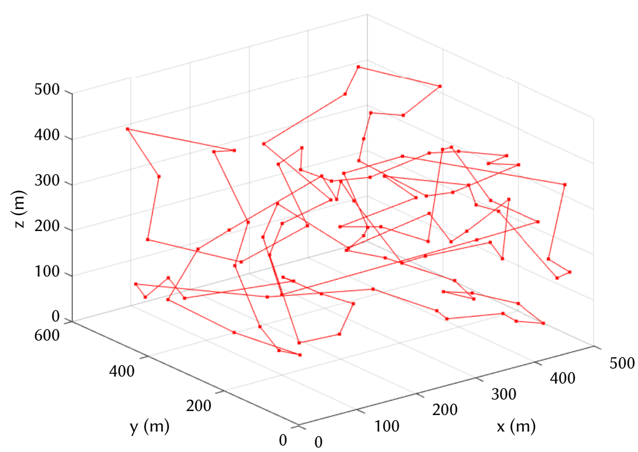

Fig. 18. The achieved path planning solution for visiting the 100 nodes by AUV with SAGA in 1000 iterations under limitations.

2. Comparison and Discussion

Considering the general trend, the GA-based Approach shows better performance than SAGA-based Approach. Fig. 19 shows the total traveled distance by AUV with GA-based Approach and SAGA-based Approach under the 50-node scenario in Fig. 3 and the 100-node scenario in Fig. 10.

From Fig. 19, we can make the following observations on the performance of the GA-based Approach and SAGA-based Approach under the 50-node scenario and the 100-node scenario. Under the 50-node scenario, the GA-based Approach and SAGA-based Approach achieve almost the same performance with just a slight difference.

TABLE IV. Total Distance for Visiting the Nodes By the GA-Based Approach and the SAGA-Based Approach Under 50-Node Scenario and 100-Node Scenario With Respect to Iteration Number (Note That Iteration 1 Is Considered as the Beginning Instead of Iteration 0)

Iteration	1	100	200	300	400	500	600	700	800	900	1000
GA with 50 node	13889	8094	7374	6712	6420	6330	6330	6314	6279	6271	6227
SAGA with 50 node	14999	8604	7392	7197	6964	6738	6558	6524	6491	6491	6404
GA with 100 node	30549	19471	16861	14455	13182	12676	12120	11848	11351	11159	10803
SAGA with 100 node	31356	19108	15030	13402	12713	12278	11907	11419	11321	11123	10996

Similarly, under the 100-node scenario, the GA-based Approach and SAGA-based Approach achieve almost the same performance with just a slight difference.

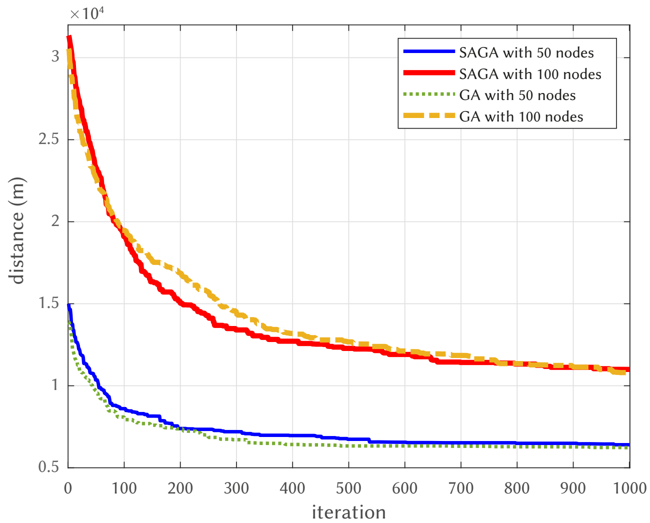

Fig. 19. Total distance for visiting the nodes by the GA-based Approach and the SAGA-based Approach under 50-node scenario and 100-node scenario in 1000 iterations.

From Table IV, we can make the following observations. Under the 50-node scenario, the GA-based Approach and SAGA-based Approach achieve almost the same performance with just a slight difference. In iteration 1000, the difference between the GA-based approach and the SAGA-based approach becomes very subtle (177 m, namely, 2.76% less than the SAGA-based approach). Similarly, under the 100-node scenario, the GA-based Approach and SAGA-based Approach achieve almost the same performance with just a slight difference. Just between iterations 100 and 400, the difference increases. However, after iteration 500, the difference decreases again. In iteration 1000, the difference between the GA-based approach and the SAGA-based approach becomes very subtle (193 m, namely, 1.76% less than the SAGA-based approach).

In iteration 1000, the difference between the GA-based approach and the SAGA-based approach becomes very subtle (193 m, namely, 1.76% less than the SAGA-based approach).

VII. Conclusions

Because there is a growing need for ocean exploration these days, research is focusing on longer range and greater exploration ranges. In this research, we present an efficient path-planning approach using an autonomous underwater vehicle with limited battery power for charging the underwater wireless sensor network (UWSN) and theoretically analyze its total energy usage. Due to the limited energy supply of the UWSN, we tackle the problem from the charging perspective. Several AUVs are a good approach to charge the UWSN to extend the exploration network. Furthermore, the charging efficiency and the range of exploration can be significantly increased by selecting suitable dive sites and designing a path that considers the node's location and data flow.

Data collection problems with autonomous underwater vehicles (AUV) can be handled by the following AI-based algorithms; Ant Colony Optimization-based Approach, Particle Swarm Optimization-based Approach, Teaching Learning-based Optimization-based Algorithm, Genetic Algorithm-based Approach, Grey Wolf Optimizer-based Approach. Simulations demonstrate that the AUV route planning system finds a better solution and converges more quickly than previous algorithms by using a genetic algorithm-based approach.

Different from the related literature, this work also considers the scenario where it is better not to use direct travel paths between specific pairs of nodes because of several reasons, such as flows below the surface, places too small for UAV movement, and extra hazards like electromagnetic waves. We propose a modified genetic algorithm-based approach, the Safety-Aware Genetic Algorithm (SAGA)-based Approach that introduces a very high cost for using the direct paths linking those nodes to tackle this more difficult scenario; thus, these direct paths will not be preferred during the path planning. In this scenario, the SAGA-based approach provides just a 3%longer path than the path provided by the GA-based approach. This shows that the SAGA-based approach performs very robustly for scenarios where it is better not to use direct travel paths between specific pairs of nodes for several reasons.

In the future, we can consider more complicated scenarios where the distance cost matrix can be defined instead of considering direct blockage in the links between the nodes through which direct traveling is very challenging because of the several reasons.

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