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Energy-Efficient Multiple Autonomous Underwater Vehicle Path Planning Scheme in Underwater Sensor Networks

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Abstract: The issue of limited energy resources is crucial for underwater wireless sensor networks (UWSNs) because these networks operate in remote and harsh environments where access to power sources is limited. Overcoming the energy constraints is necessary to ensure the long-term functionality and sustainability of UWSN, enabling continuous data collection and communication for various applications such as environmental monitoring and surveillance. To solve the problems of limited energy and the difficulty of battery replacement in UWSN, a path planning and energy-saving scheme for charging underwater sensor nodes using AUVs (autonomous underwater vehicles) is proposed. Applying multiple AUVs to charge the sensing network nodes will maximize the size of the underwater sensing network as well as meet the transmission reliability, and the optimal path of AUVs is solved by using a genetic algorithm. Simulation results show that the AUV path planning scheme convergence is faster than that of conventional algorithms, and the lifetime of UWSN is prolonged while energy balancing according to the network size and node density. In high-density networks, the average energy consumption generated by AUVs for exploration is reduced by 15 percent for each additional AUV with our path planning.

Keywords: energy balancing; UWSN; multiple AUVs; optimization algorithm

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1. Introduction

It is well known that underwater sensor networks (UWSNs) [1] are playing an increasingly important role in the field of ocean data collection, ocean resource exploration, and assisted navigation with the accelerating speed of ocean development. In recent years, the concept of intelligent ocean underwater IoT (Internet of Things) has also been proposed [2], with a wider range of applications.

In UWSNs, underwater sensor nodes are distributed in different areas to detect environmental parameters and collect them in a data processing center (Sink). However, these nodes are usually battery-operated, and the batteries need to be replaced by expensive and difficult operations in harsh marine environmental conditions. UWSNs often face energy limitations and short lifetimes, making energy saving a key factor in improving their performance and reliability [3].

Numerous efforts have been made to solve this problem. Firstly, in underwater sensor networks, data transmission is usually a key factor in energy consumption in UWSNs. The collected sensor data is compressed and aggregated to reduce transmission data and energy consumption by using data compression and optimization techniques [4].

Secondly, reasonable node deployment and routing strategies can also help improve the energy efficiency of underwater sensor networks. Based on the uneven distance and energy consumption between sensor nodes, adopting the optimal deployment and routing scheme can minimize energy consumption and extend the lifetimes of the network [5].

However, in these methods, once the battery is used up, it still needs to be replaced. Therefore, it is necessary to charge the underwater sensor nodes through technologies such as energy transmission to avoid the trouble of frequent battery replacement and achieve long-term monitoring and data transmission [6]. To overcome high water pressure and short-circuit, DeMauro et al. [7] designed a rechargeable lithium-ion battery module for underwater use. Due to the limited distance of energy transmission, it is necessary to use autonomous underwater vehicles (AUVs) to assist in charging, and path planning for AUVs is necessary.

The AUV is a kind of unmanned underwater self-propelled submersible for moderate activities without control [8]. The AUV is considered an economical and safe tool for seabed investigation, search, identification, and rescue, and they have been widely used in the fields of underwater resource exploration, underwater environmental monitoring, and marine safety [9]. However, due to the limited power carried by the AUV, the charging area is also limited, making it difficult to ensure its practicality when the detection area is larger (especially in marine environments), which leads to the problem of losing data from its subsequent nodes.

Xie et al. [10] proposed a scheme to make magnetic charging cars to charge the sensors in wireless rechargeable sensor networks (WRSNs). Unlike ground-based wireless rechargeable sensor networks, UWSNs are usually applied in a 3D framework, and the transmitting power greatly enlarges with the distance underwater.

Inspired by this idea, considering the special underwater environment, we proposed an energy-efficient multi-AUV path planning scheme by using the genetic algorithm. We built a rechargeable underwater sensor network model with multiple AUVs to traverse and charge the sensing nodes to extend the subsea monitoring range and the sensor detection cycle. The scheme can minimize the navigation distance, expand the exploration range of the UWSN, and prolong the lifetime of the UWSN.

The rest of the paper is organized as follows. In Section 2, some related works of underwater energy-saving schemes are reviewed. In Section 3, the network model and the energy balancing equations are given, and a path planning and energy-saving scheme is proposed. In Section 4, the path planning scheme of AUVs is proposed and discussed. The simulation results are analyzed in Section 5. The conclusions and future works are presented in Section 6.

2. Related Works

Several methods have been proposed to address the problem of energy-saving problem in UWSNs. Some related works are listed below.

2.1. Energy-Efficient Protocol

Because of the limitations of battery technology, the communication protocol design can help save energy. Lee et al. presented a comparative analysis of various energy-efficient MAC protocols based on the network topology for UWSNs [11]. Zenia et al. reviewed energy-efficient and reliable MAC and routing protocols for UWSNs [12]. Khan et al. designed a communication protocol to send packets to reduce redundancy and improve channel quality [13]. Su et al. developed a hybrid-coding-aware routing protocol for underwater acoustic sensor networks (UASNs) [14], which can reduce the transmission overhead while ensuring reliability.

Clustering also plays a vital role in underwater sensor networks by enhancing energy efficiency, promoting effective data aggregation, facilitating resource management, and prolonging the network's lifetime [15]. It divides the network into smaller groups, or clusters, with each cluster having a designated cluster head (CH), which can aggregate and relay information from individual nodes within their respective clusters, reducing redundant transmissions [16]. This helps to conserve energy and reduce bandwidth usage in underwater environments where communication resources are limited [17].

In [18], Sun et al. designed a communication protocol that collects and sends data by clustering, which greatly reduced the energy consumption of each sensor node. Jin et al. proposed a topology control mechanism for underwater sonar detection networks

(USDNs), which can obtain superior coverage performance and prolong the network lifetime with guaranteed coverage and connectivity [19]. Liu et al. designed a distributed node deployment algorithm based on virtual forces to increase the network coverage of a UWSN [20]. To prolong the UWSN lifetime and improve data delivery, Wei et al. [21] construct a network topology control model with multiple underwater factors such as topology, energy consumption balance, and strong robustness.

2.2. AUV-Aid Technology in WUSNs

Autonomous underwater vehicles have numerous applications in underwater environments, including data collection, charging, and more.

One of the primary uses of AUVs is data collection. Equipped with various sensors and instruments, AUVs can navigate through underwater environments to collect data on water conditions, marine life, and geological features. Zhu et al. [22] applied the measure of AUV-assisted communication, where the AUV itself acts as a mobile node that can collect information for energy saving. Yan et al. [23] proposed a scheme that utilizes AUVs to collect data and carry out path planning using K-means algorithms [24]. In a three-dimension situation, Zhang et al. [25] tackle the three-dimensional path planning of AUVs based on a whale optimization algorithm, which avoids falling into the local optimum value. Multi-hop [26] and autonomous underwater vehicle-aided (AUV-aided) data collection methods [27] are both used in underwater detection.

AUVs also play a crucial role in underwater communication and networking. They can act as relays, collecting data from stationary or mobile sensors and transmitting it to a central station or other AUVs. This facilitates seamless communication and enables real-time monitoring and control of underwater operations. Kan et al. [28] proposed a three-phase wireless charging system that could be used in a field-deployable charging station capable of rapid, efficient, and convenient AUV recharging. Ramos et al. [29] used dynamic system theory for navigation, which applies to 0–100 m depth of oceans and increases the battery life of AUVs by increasing the speed.

Furthermore, AUVs are being developed with capabilities for autonomous docking and battery charging. This enables them to operate for extended periods without human intervention. AUVs can dock with a charging station or a surface vessel equipped with charging capabilities, replenishing their self-power supply and charging other sensor nodes. This eliminates the need for frequent retrieval and manual recharging, enhancing their autonomy and operational efficiency.

AUV path planning is also an important method to improve energy efficiency. To reduce power consumption and prolong the network lifetime, Cheng et al. give global planning of the AUV's path planning, avoiding underwater obstacles and analyzing its energy consumption model from its kinematic and dynamical models [30]. A new type of hybrid algorithm is used for subsea exploration using AUVs proposed by Kumar et al. [31], which greatly reduces their exploration range. Golen et al. divided the exploration area into several areas [32], and each area has its own data-receiving point. AUVs can save energy while collecting data through reasonable path planning. In [33], the authors proposed an energy balancing and path plan strategy for rechargeable UWSNs, which can extend the network lifetime while balancing the energy.

3. Analytical Model

3.1. Network and Energy Model

The network model is shown in Figure 1. All sensing nodes interact with each other by underwater acoustics links and send the information to SINK nodes. The AUV with a magnetic resonance coupling system starts from a charge station (CS), travels to every sensor node to charge them, and then returns to the CS to rest and charge itself. It also can collect the data as a mobile sink.

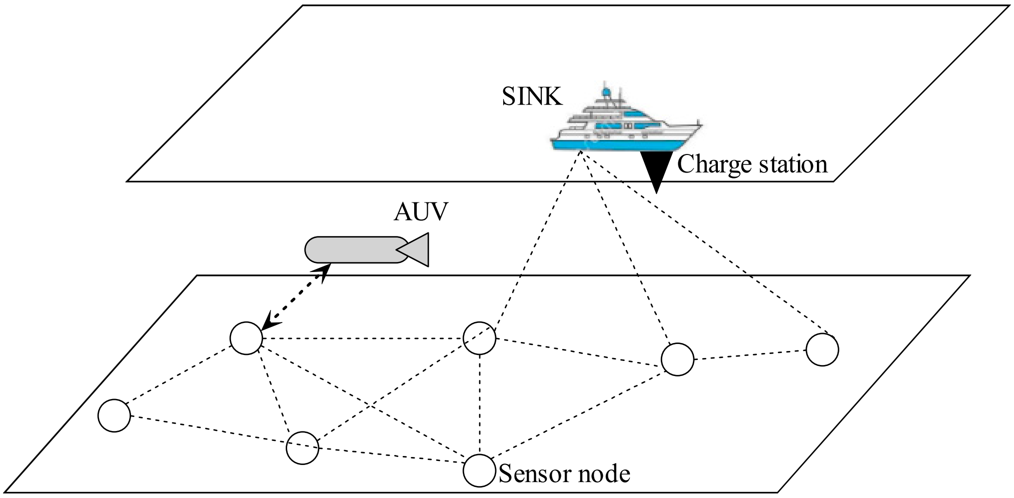

Figure 1. Network model.

In the UWSNs, the energy consumption balance of underwater sensors is a very important problem. To solve the unbalanced energy consumption problem, in some studies [34–36], an AUV has been used to collect underwater data. The AUV moves and visits all sensor nodes according to a certain strategy to balance the energy consumption of nodes.

The energy consumption of sensor nodes is used for data transmission and reception. Assuming that there are N sensor nodes in the network, the maximum capacity of the node batteries is $E_{\max}$ and the minimum energy is $E_{\min}$ to keep the sensor nodes running. Each node collects the data and sends it to the SINK for aggregating. For each node i, the generated traffic can be expressed as Equation (1).

$$\sum_{k\in N}^{k\neq i} f_{ki} + R_i = \sum_{j\in N}^{j\neq i} f_{ij} + f_{iS}(i \in N) \tag{1}$$

Assuming that each sensor node i generates data at a rate of R_i (bps), the traffic from node i to node j is f_{ij}, traffic from node i to sink is f_{iS}, and f_{ki} represents the flow from K (points) to i. The consumed energy of node i can be shown in Equation (2).

$$r_i = \rho \sum_{k\in N}^{k\neq i} f_{ki} + \sum_{j\in N}^{j\neq i} C_{ij} f_{ij} + C_{iS} f_{iS} \tag{2}$$

The left term of Equation (2) r_i is the energy consumed by receiving, and the right term is the energy consumed by transmitting. ρ is the energy consumption factor for receiving data. C_{ij} is the energy consumption rate of the data unit sent by node i to node j, which is the signal attenuation coefficient of the underwater acoustics signal. Similarly, C_{iS} represents the energy consumption rate from node i to Sink. In this model, $\rho \sum_{k\in N}^{k\neq i} f_{ki}$ is the energy consumed for reception, and $\sum_{j\in N}^{j\neq i} C_{ij} f_{ij} + C_{iS} f_{iS}$ is the energy consumed by sending data. Unlike terrestrial networks, underwater communication must be carried out through acoustic channels due to the rapid attenuation of radio waves and the scattering effect of light waves [37,38]. In underwater acoustics communication, the channel model is essentially an empirical model and does not have a strict mathematical derivation, and it varies with changes in the underwater environment [39]. The communication model environments established in this paper are all in shallow waters and without current and tidal interference. Both the communication frequency (f_k) and the distance between communication nodes (d) have major effects on signal attenuation [34], as shown in Equation (3).

$$C_{ij} = d^e \times \partial(f)^d \tag{3}$$

where e is the signal expansion factor. It is a constant, since we use the shallow sea underwater acoustics model, so it is taken as 1.5. $\partial(f)$ is the frequency dependence factor in dB/km, and $\partial(f)$ is shown in Thorps Equation (4) [40].

$$\partial = \frac{0.11f^2}{1+f^2} + \frac{44f^2}{4100+f^2} + 2.75 \times \left(10^{-4}\right)f^2 + 0.003 \tag{4}$$

Besides the above energy consumption, the UWSN also has energy consumption during the dormant period, and it was set as E_r, so the total energy consumption must be Equation (5):

$$E_t = r_i + E_r \tag{5}$$

3.2. Charging Model

The energy level changes in two charging cycles for each sensing node when AUV charging is involved are shown in Figure 2. a_i is denoted as the time at which the AUV reaches node i in the first renewable energy cycle. E_0 is the initial energy, $E_{\max}$ is the maximum energy threshold of the node, and $E_{\min}$ is the minimum battery limit. In the first cycle, when $t \in [0, a_i]$, the node consumes energy at a constant slope when the AUV has not yet reached the node. When the AUV arrives at the node, it charges the node at the rate of μ. When the energy level of the node reaches $E_{\max}$, the AUV stops charging and leaves.

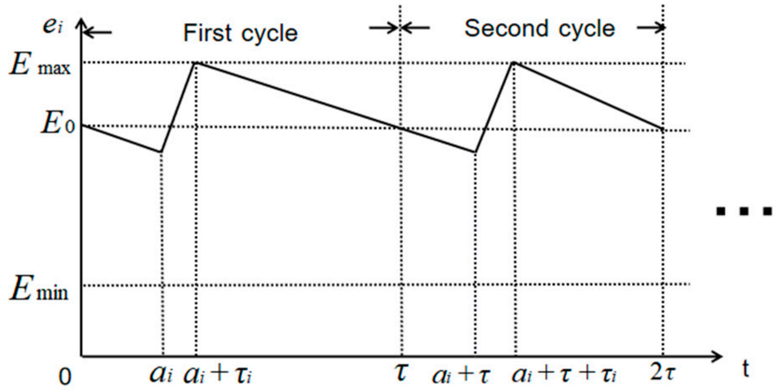

Figure 2. Remaining energy of sensing nodes after two charging cycles.

Therefore, to ensure that each node in the UWSN can satisfy the energy cycle, Equation (6) needs to be satisfied:

$$E_{\max}(\tau - \tau_i)r_i \geq E_{\min} \tag{6}$$

Since the AUV is also battery-powered, many different kinds of factors should be considered, not only to consume energy for traveling but also to charge other sensing nodes. Therefore, the energy consumption of the AUV has to be evaluated as well.

It was assumed that the AUV follows a uniform driving mode and does not consider obstacles in the water as well as the heaving of the water surface. In [41], the energy dissipation coefficients of AUVs underwater were calculated from four directional vectors by measuring specific actual underwater data. However, for the sake of simplifying the calculation, it is assumed in this paper that the AUV moves at a constant depth throughout its travel path, and only two degrees of freedom are considered: the AUV's horizontal and vertical coordinate motion.

Δx_i, Δy_i, and Δz_i represent the change in x, y, and z coordinates, respectively. k_1, k_2, and k_3, respectively, represent the energy calibration coefficients of the AUV in different directions of travel, where the unit is J/m, and the total energy consumption of an AUV is shown in Equation (7).

$$\Delta E = k_1 \Delta x_i + k_2 \Delta y_i + k_3 \Delta z_i \tag{7}$$

The calibration coefficients are 557.24 J/m, 1174.21 J/m, and 1354.16 J/m, respectively, so the average travel energy factor is 1.2 KJ/m for the AUV.

A number of questions need to be answered for such a network. First, is it possible to have each sensor node never run out of its energy? If this is possible, the UWSN will have an unlimited lifetime and will remain operational indefinitely. Second, there must be an optimal plan (including traveling path and stopping schedule) such that some objectives can be maximized or minimized. So, we want to quantify the optimization effect, which maximizes the percentage of time that the AUV is on vacation. η represents the charging efficiency, τ_a represents the time that the AUV spends on vacation, and τ represents the total time including the time to rest and charge to the sensing nodes. It is shown in Equation (8):

$$\eta = \tau_a / \tau \tag{8}$$

4. Path Planning of AUV

4.1. TSP Problem and Genetic Algorithm

The path planning problem of AUVs in Section 2 can be considered a traveler selling problem (TSP). There are two main types of methods to solve the TSP, the traditional search algorithm and the intelligent evolutionary algorithm [42]. The former includes the greedy algorithm, the artificial potential field method, and the fast progress algorithm. The latter includes the ant colony algorithm, the genetic algorithm, the particle swarm optimization algorithm, etc. The traditional search algorithm is simple in design and small in computation, which is suitable for small-scale networks. However, it is not suited for large-scale networks.

The genetic algorithm [43] is a stochastic search algorithm that draws on natural selection and natural genetic mechanisms in biology. Genetic algorithms are often used to solve complex and nonlinear optimization search problems that are difficult to solve through traditional search algorithms. In this paper, populations represent different species routes, and new solutions are obtained through crossover and mutation operations, which are less likely to fall into local optimal solutions compared with traditional algorithms.

The basic idea of genetic algorithms is to solve complex optimization problems by simulating biological evolution. Using a genetic algorithm to solve TSP questions, the first step is to define the individuals of the TSP solution and initialize the population. Each individual in the population is evaluated by a fitness function, and the best of them are selected for genetic operations, which include selection, crossover, and mutation. The termination condition of the genetic algorithm is the maximum number of iterations set. And the individual fitness for this paper is the total AUV energy consumption or the overall route size. In this situation, the sum of the distance of each sensing node can be used, so the calculation of the fitness of each individual is Equation (9).

$$Fitness = \sum_{i=1}^{N-1} \frac{1}{\sqrt{(x_i - x_{i-1})^2} + \sqrt{(y_i - y_{i-1})^2} + \sqrt{(z_i - z_{i-1})^2}} \tag{9}$$

To select a suitable algorithm for the TSP of our paper, we compared two common algorithms, the annealing algorithm and the greedy algorithm, with the genetic algorithm in Algorithm 1 and gave the result in Table 1. As can be seen in Table 1, The drawback of the annealing algorithm is that the speed of convergence is slow, which is fatal, and if the cooling speed is too fast, it is easy to obtain no global optimal solution. At the same number of iterations, the genetic algorithm can find the solution with a 3% to 5% error from the optimal solution of TSP, which is even smaller than the solution error of the simulated annealing to solve the same size TSP.

Algorithm 1. Pseudo-code for Genetic algorithm

Initialization of GA parameters (gene population size, maximum iterations, possibility of mutation, and possibility of crossover)
Return: total distance and index of gene numbers
//Initialize generation 0;

While (iteration < *maximum iterations*)
    Compute the *fitness* parameter for each initial *pop* (*total distance*)
    Record the best route
    //Crossover
        If (random number < *possibility of crossover*);
            Randomly select two positions of sensors from *pop*
            Recreate new gene populations and update the AUV deployment
            End *If*
    //mutation
        If (random number < *possibility of mutate*);
            Random exchange of two positions of sensors
            Recreate new *gene populations* and update the AUV deployment
        End *If*
End while
Return the fitness individual

Table 1. Comparison of the three algorithms.

	Convergence Speed	Error Rates	Optimization Effect
Greedy algorithm	Faster speed	20%	1. Trapped in a local optimum solution easily; 2. High error rate.
Simulated annealing algorithm	Slower speed	5%	1. Optimization on individuals; 2. Depending on the Annealing rate.
Genetic Algorithms	Average speed	3%	1. Easily to find better solutions but difficult to find the best solution; 2. Population-based algorithm.

The number of iterations increases substantially in scenarios with a larger range and more AUVs involved. Therefore, genetic algorithms may be able to obtain the optimal solution faster while satisfying the error rate, so we use genetic algorithms for path planning.

4.2. Single AUV Path-Planning

Since AUVs need to traverse all nodes for path planning and its optimization objective is the sum of trips, it can be considered a TSP [44]. This section is solved using a genetic algorithm, as shown in Algorithm 2.

Algorithm 2. Pseudo-code for multiple genetic algorithm

Initialization of MGA parameters (gene population size, maximum iterations, number of AUVs, the least distance of AUV, possibility of mutation, and possibility of crossover)
Return: total distance, index of gene numbers, insertion points number, and individual distance for each AUV

```
For (gene number < gene population size)//generate initial population
   Gene population size ← random sort
   create a matrix to save the initial distance between sensors
   index ← the best gene number, Total distance ← sum up the distance of all AUVs
end for;
While (iteration < maximum iterations)
    Create route insertion points ← number of AUVs, create two random numbers (0–1)
      Find the best individuality ← the minimum distance
      Record the best route
         If (random number < possibility of crossover);
            Randomly exchange two positions of sensors
            Recreate new gene populations and update the AUV deployment
               If (insertion points < the least distance of AUV);
                  Random generate one insertion point
               End if
         End if
         If (random number < possibility of mutate);
            Random exchange two position of sensors
            Random exchange one insertion point
            Recreate new gene populations and update the AUV deployment
         End if
         If (insertion points < the least distance of AUV);
            Random exchange one insertion point
         End if
 End while
```

4.3. Multiple AUV Path Planning

In our previous work [33], we used the simulated annealing algorithm, which allows the AUV to find the best traversal path and ensures that each sensing node can be replenished by the AUV before the energy is exhausted. However, this scheme, when targeting larger paths (especially for the detection of the marine environment), can take multiple AUVs for recharging, which can effectively reduce energy consumption and expand the exploration area due to the limited energy carried by a single AUV and the limited range of traversed nodes.

In this section, we propose a method to traverse the sensing nodes with multiple AUVs at the same time and use the genetic algorithm to find the best path to minimize the distance traversed by the AUVs. All AUVs first dive to the same depth and calculate the best dive point through the genetic algorithm and then start from this point and travel to charge the sensing nodes, finally completing the whole cycle, so this problem can also be attributed to the MTSP (multiple-traveler selling problem).

The MTSP differs from the TSP in that each individual will have a set of chromosome-separating points corresponding to it. The purpose of separating the chromosomes is to distinguish the different path choices for each AUV. As shown in the Figure 3, suppose there are three AUVs that need to visit 10 sensing nodes, that the chromosomes are a random arrangement of 10 sensing node serial numbers, and that the three AUVs correspond to two separator point markers, i.e., the two resulting separator points are marked at positions 5 and 7.

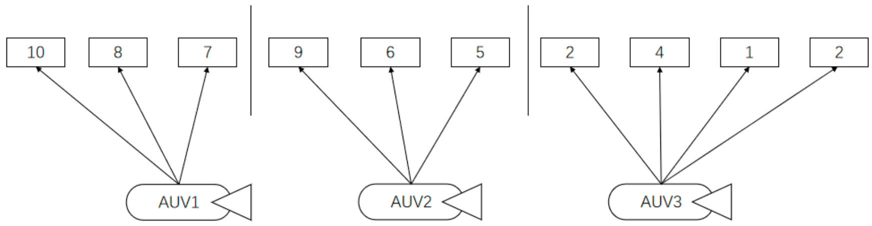

Figure 3. AUV deployment.

According to the above idea, the path planning of the genetic algorithm with mul-tiple AUV participation can be obtained as Algorithm 2.

5. Simulation and Analysis

5.1. Parameter Setting

The simulation scenario is a 500 m × 500 m × 500 m area with randomly generated node distribution to form the UWSN. In order to unify the experimental scene, if not specifically pointed out, the number of sensors in UWSN is 50. To simplify the analysis, SINK is located at the center (250 m, 250 m, 500 m) of this area, and it is also the charge station, which is the starting and ending point of all AUVs. The movement speed of AUVs is 3 nm/h (nautical miles/hour). The sensor node uses a battery with a conventional NiMH battery of 2.5 V/2.4 Ah. It was assumed that a sensor node transmits a data packet with a size of 1 k bits at regular intervals. The simulation parameters are shown in Table 2.

Table 2. Simulation parameter.

Symbol	Description	Value
$E_{\max}$	Maximum volume of sensor battery	3600 s × 2.5 V × 2.4 A = 21.6 KJ
$E_{\min}$	The minimum volume of sensor battery	0.05 × $E_{\max}$ = 1.08 KJ
speed_A	The speed of AUV	3 nm/h = 5.562 km/h
f	Frequency	10 (kHz)
α	Frequency factor in underwater	/
C_{ij}	Energy consumption rate of a data unit sent by node i to node j	/
r_i	Energy consumption rate of each sensor node	/
ρ	the energy consumption factor for receiving data.	50 NJ/b
k_1	The coefficient value of AUV on x axis	557.24 J/m
k_2	The coefficient value of AUV on y axis	1174.21 J/m
k_3	The coefficient value of AUV on z axis	1354.16 J/m
P_{rest}	Idle power	30 mW
P_t	Transmission power (0.5 km)	20–40 W
$P_{receive}$	Receiving power	3 W
τ	Total time cost by AUV	/
τ_a	Traveling time cost by AUV	/
η	Charging efficiency	/

In this table, "/" Indicates that the numerical value will change with changes in parameters such as distance and is not a fixed value.

5.2. Effect of Iterations on Optimization Effect

The simulation scenario is shown in Figure 4, where sensor nodes are randomly distributed in the three-dimensional space below. The simulations are performed by using MATLAB. We first analyze the effect between the number of iterations.

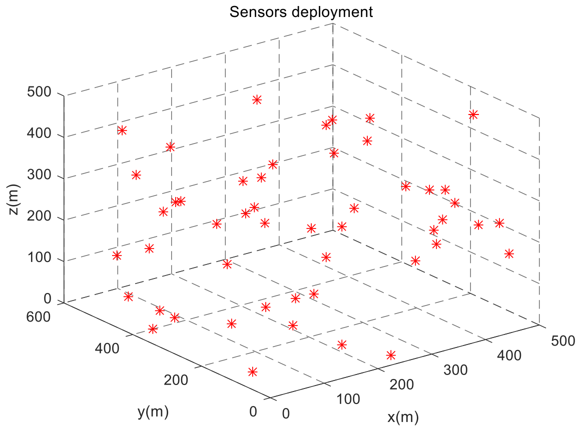

Figure 4. Sensor deployment.

Figures 5 and 6 show the path planning diagram when using a single AUV and four AUVs. In Figure 6, different colors indicate the planned paths for different AUVs. As can be seen in Figures 5 and 6, both a single AUV and four AUVs can plan optimal paths when charging the UWSN using our proposed methods.

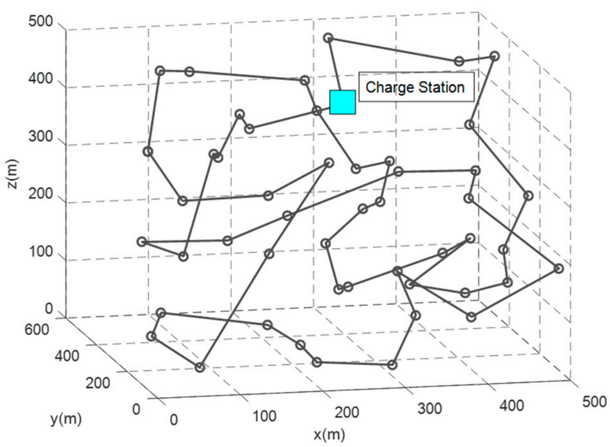

Figure 5. Single-AUV path planning.

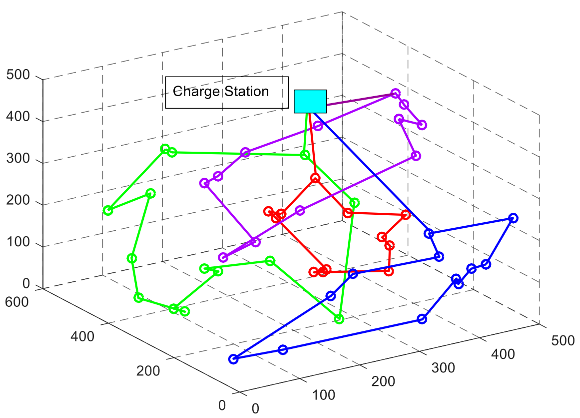

Figure 6. Four-AUVs path planning.

Figure 7 shows the relationship between the total distance and iterations. From Figure 7, we can see that our genetic algorithm can converge to the optimal distance with the least iterations compare to the greedy algorithm and the simulated annealing algorithm in [33]. Moreover, our algorithm saves about 300 iterations compared to the result in [33].

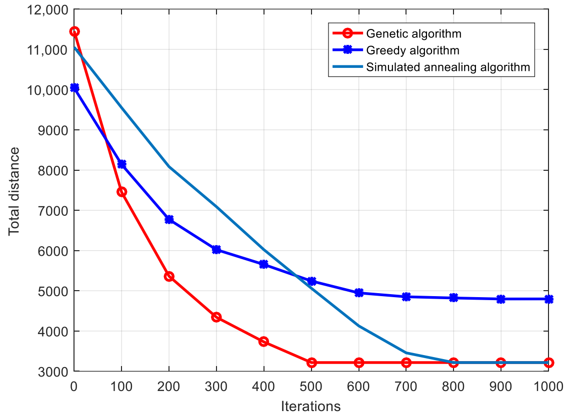

Figure 7. The relationship between Iterations and total distance.

Figure 8 is the performance comparison between a single AUV and four AUVs. As the number of iterations increases, the total distance gradually decreases and converges to the optimal value. As the number of AUVs increases, more iterations are needed to approach the optimization objective.

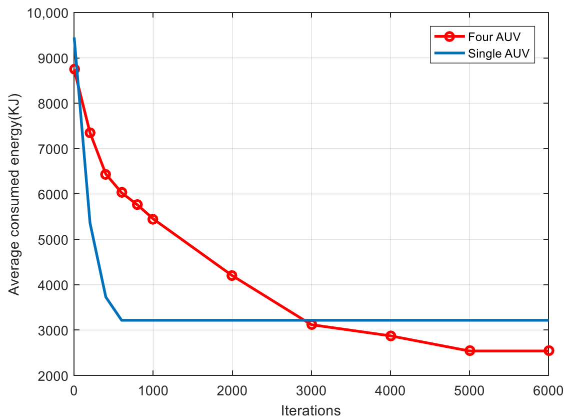

Figure 8. Comparison of Single and four AUV iterations.

5.3. Effect of Node Density

Different numbers of sensing nodes are distributed from 30 to 110 in a 500 m $\times$ 500 m $\times$ 500 m area, using different numbers of AUVs, and the average energy dissipation of the AUVs is counted.

Figure 9 is the average energy consumption of an AUV to the node density. This figure shows that energy consumption tends to increase with the increase in node density. And the higher the number of AUVs deployed, the smaller the average energy dissipation. Therefore, the path planning of multiple AUVs using the genetic algorithm can save considerable energy when the density of sensing nodes is high, and, thus, a larger exploration radius can be reached. And it can also be observed that when there is a high density of sensor nodes (>90), for each additional AUV, the average energy consumption is reduced by about 15 percent.

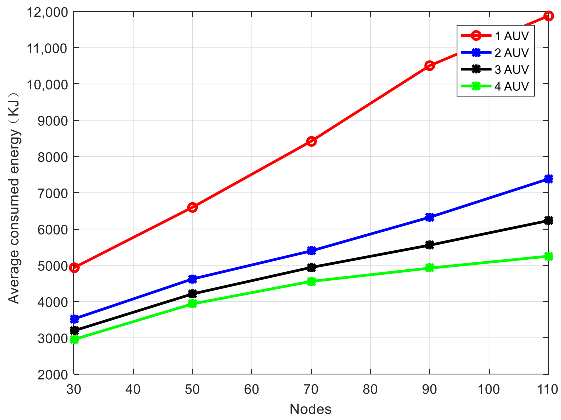

Figure 9. Density of sensor nodes to average energy dissipation of AUV.

5.4. Effect of Transmitting Speed

It was assumed that all sensing nodes are sending and collecting data at a fixed time. Figure 10 shows the graph of the remaining energy of a sensing node when it sends data to SINK, which is 500 m away from each other. The figure shows that the remaining energy of the sensing node gradually decreases as time goes on. If the data are sent every 30 s, it can only last less than 5000 s. And the longer the interval, the longer the node sustains. If no data are sent, the node is in a sleep state and can sustain for a longer time.

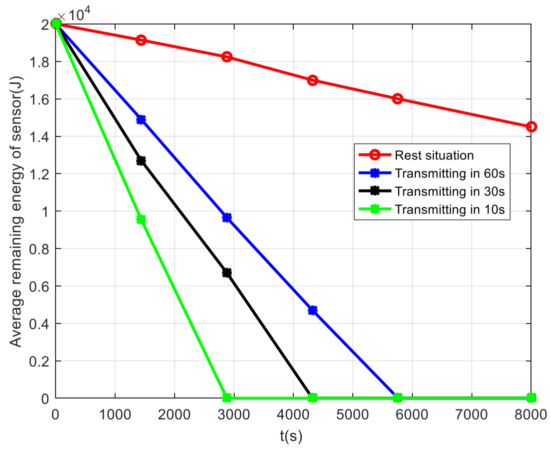

Figure 10. The remaining energy of sensors to different transmitting intervals.

5.5. Effect of Different Exploring Areas

Since the exploration range of a single AUV is limited, the use of multiple AUVs can extend the cruising range, but the corresponding multiple AUVs may also make the overall energy consumption larger, especially when the sensing network is unevenly dispersed and dense.

In Figure 11, the graphs of different minimum numbers of traversing nodes versus the overall energy consumption of AUVs are shown in this case. It can be seen that under the above constraints, in a 500 m exploring radius, it is more suitable to select three AUVs for expanding the search radius and more suitable to apply four AUVs in a bigger exploring area (exploring radius > 800 m).

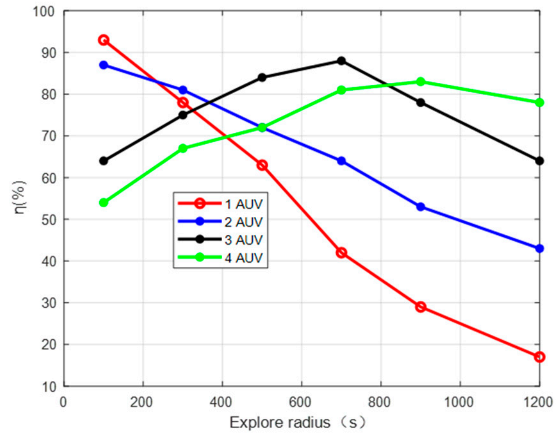

Figure 11. Different exploring areas to charging efficiency.

In Section 4, it can be calculated that the full range of an AUV under ideal conditions is about 10 km, and the maximum cruising distance can be expanded to about 1200 $\times$ 1200 m under four AUV cruising conditions in simulation.

Relatively, after the overall exploration range becomes larger, the attenuation of underwater acoustic signal further increases with distance and the transmitting power becomes larger, so more AUVs are needed to charge the sensing nodes in the UWSN.

6. Conclusions

In today's growing demand for ocean exploration, a longer range and larger exploration ranges are the focus of current research. Because of the limited energy supply of the UWSN, we address the problem from the perspective of charging, so in this paper, we theoretically analyze the total energy consumption of the underwater acoustics sensor network and propose an efficient path planning method using an autonomous underwater vehicle with limited battery power for charging the UWSN. Charging the UWSN with multiple AUVs to further increase the exploration network is an effective and practical method. And the selection of suitable dive points and the respective path planning according to the node location and data flow will effectively improve the charging efficiency as well as the exploration scale.

The simulation results show that in this test scenario, using our algorithm for path-planning and using multiple AUVs to charge the sensing network will greatly reduce the average energy consumption of AUVs to expand the overall exploration range. Depending on the node density, the appropriate number of AUVs can be selected.

In underwater acoustics communication, the transmitting energy consumption grows exponentially with distance, and the position of the sensors changes with the current, so our future research direction will consider underwater sensors' real-time and precise positioning, which helps plan the optimal path to charge the sensor node. Moreover, how to plan a path in a more complicated ocean environment with obstacles is another research direction.

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