Topology optimization of deep sea acoustic sensor networks for tsunami warnings

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Tsunamis have been recognized as one of the most terrible and powerful marine natural disasters that cause huge casualties to coastal residents and facilities when they occur. Therefore, it is of vital importance to establish a disaster and tsunami early warning system by exploring the propagation speed difference of the tsunami itself through sea surface and the associated seismic wave along the seabed. The main approach of current disaster and tsunami warning systems is to deploy sensor nodes on the bottom of the seabed to monitor changes in seabed pressure and transmit the data back to the shore. In view of the characteristics of warning systems, with the purpose to improve early warning efficiency of the bottom deployed deep sea sensor network, this study utilizes swarm intelligence algorithms and combines the features of deep sea Reliable Acoustic Paths (RAPs) to optimize the topology of monitoring nodes deployed on the bottom of the deep sea by formulating the problem as optimizing the coverage of monitoring nodes deployed on the deep-sea floor and enhancing their backhaul capability. Through simulation experiments, it provides a reference for selecting appropriate optimization methods in different deployment scenarios, in terms of the quantitative performance improvement of Deep Sea Acoustic Sensor Network (DSASN) enabled tsunami early-warning systems.

Keywords – Reliable acoustic path (RAP), topology optimization, tsunami warning, underwater acoustic

1. INTRODUCTION

Tsunamis are gravity-driven water waves occurring in the ocean, typically triggered by subduction zone thrust earthquakes, submarine landslides and volcanic eruptions. During propagation in the deep ocean, tsunamis are characterized by long wavelengths, small wave heights and slow energy attenuation, enabling them to travel long distances across the ocean without a significant loss of energy. As a tsunami approaches shallow coastal waters, the rapid decrease in water depth leads to shortened wavelengths and a sharp increase in wave height, causing great damage to coastal residents and facilities [1]. Historically, multiple catastrophic tsunami events have resulted in devastating consequences. For instance, the 2004 Indian Ocean tsunami and the 2011 Fukushima tsunami in Japan caused more than 300 000 fatalities and triggered serious consequences such as nuclear accidents. Since the 20th century, there have been a total of seven major tsunamis worldwide [2]. Following the Sumatra tsunami in 2004, international attention to tsunami monitoring and early warning systems increased substantially. Under the auspices of IOC/UNESCO, tsunami mechanisms have been better understood, advanced real-time tsunami observation systems have been deployed in multiple high risk areas, and tsunami warning and mitigation systems have been established for the four main ocean basins at risk from tsunamis [3]. Numerous studies have demonstrated that establishing an effective tsunami monitoring system can effectively reduce the disasters caused by tsunamis [2].

In existing tsunami warning systems, seabed monitoring nodes play a critical role in sensing key parameters such as pressure variations and seabed disturbances. For smaller areas, such as national or local regions, these are typically served by cable-based warning systems [4]. Cable-based warning systems provide faster and more reliable data communications [5]. However, such systems are constrained by cable coverage and incur high deployment and maintenance costs. To extend monitoring coverage, wireless tsunami early warning systems based on Underwater Acoustic Sensor Networks (UASNs) have emerged as the primary solution. Among them, the most representative system covering a broad area across multiple countries is the Deep-ocean Assessment and Reporting of Tsunamis (DART) system [4] deployed by NOAA. The DART system consists of Bottom Pressure Recorders (BPRs) and surface buoys, where monitored data is transmitted from seabed nodes to surface buoys via acoustic links and subsequently relayed to shore stations through satellite communications (as shown in Fig. 1). This architecture plays a vital role in confirming tsunami generation and capturing initial wave characteristics, highlighting the important role of underwater acoustic links in deep sea early tsunami warnings.

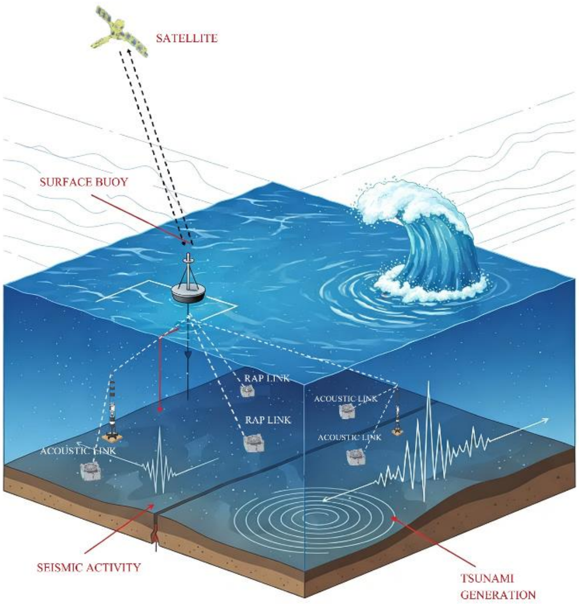

Figure 1 – Illustration of the DSASN tsunami early-warning system

Owing to their ability to support long-range wireless transmission and adaptability to complex deep-sea environments, a deep sea acoustic sensor network (DSASN) has the potential to pave the way for unexplored applications and to help observe and predict ocean movement. Unmanned or Autonomous Underwater Vehicles (UUVs, AUVs), equipped with underwater sensors, are contemplated for the investigation of natural undersea resources and gathering of scientific data [6]. Relevant research on DSASNs for tsunami early warning systems is steadily advancing. Given that deep sea tsunami early warning systems feature limited data volume and prioritize transmission reliability over throughput, the core focus of such research lies in improving the reliability and real-time performance of DSASNs. For instance, Park et al. [4] proposes a Hybrid Duplex Medium Access Control (HDMAC) protocol designed for a tsunami warning system, which relies on wireless acoustic communication technology to achieve fast and reliable transmission of early warning data in deep sea environments. An energy-saving and reliable routing scheme is proposed by Sedaghat [7] in combination with the SDN of underwater acoustic wireless sensor networks to reduce the interference of tsunami waves themselves and transmit data back. A Multipath Clusters (MCs) joint equalization approach is proposed by Zhao et al.[8]. In deep sea trial experiments, the approach described in this article achieved error-free communication at a horizontal distance of 20 km and a maximum data rate of 6000 bps with a two-element receiver, providing an efficient and reliable data backhaul solution for the application of DSASN in early tsunami warnings. Furthermore, Sung Hyun Park [9] conducted an energy analysis of the asymmetric MAC protocol for tsunami early warning systems and reached the conclusion, that is to deploy such a system in real-world underwater environments, especially where long-term unattended operation is essential, it is necessary to incorporate energy-aware mechanisms; this showed the importance of energy constraints.

Despite these advances in communication protocols and network mechanisms, significant challenges remain at the system deployment level. On one hand, few countries can afford to develop and deploy dedicated tsunami observation systems [3]. Under conditions of limited resources, it will become a key approach to breaking through the resource constraints by scientifically planning the deployment of the seabed monitoring nodes in the tsunami warning system. On the other hand, most existing studies emphasize communication protocols or network operation strategies, while paying limited attention to the spatial deployment and topological design of seabed monitoring nodes. In the deep sea, once nodes are deployed, subsequent adjustments incur substantial costs. Therefore, topology optimization during the deployment stage has a significant impact on the overall integrity of the system.

Traditional coverage-based deployment algorithms can indeed be applied to tsunami early warning systems and are capable of ensuring sufficient coverage of seabed monitoring areas. However, the deep-sea environment is highly complex and time-varying, and cross-layer data transmission in DSASN remains inherently challenging. Consequently, how the observational data collected by seabed monitoring nodes can be transmitted in deep-sea environments constitutes a critical issue that must be carefully addressed in tsunami early warning system design.

In deep-sea environments, there is a special communication link called a Reliable Acoustic Path (RAP). It is a particularly special and highly reliable water acoustic passage. A RAP's transmission loss is relatively low compared to other paths [10], and it can establish a direct communication link that connects nodes in the surface with the seabed.

Against this background, this paper focuses on the topology optimization of seabed monitoring nodes for tsunami early warning applications. The objective is to achieve efficient coverage of critical monitoring regions under limited node resources while improving the ability of monitoring data to be transmitted back to the sea's surface.

Distinct from existing studies, this work adopts a system-level perspective centred on bottom-node deployment. The monitoring area is discretized into weighted grid to characterize spatial heterogeneity in monitoring importance. And both coverage performance and RAP-based data return capability are jointly incorporated into the optimization objective, which can ensure that the topology of the seabed monitoring nodes not only has sufficient coverage in space, but also enhances the data transmission capacity of the underwater monitoring nodes by considering a RAP.

Based on the above analysis, the main contributions of this paper are summarized as follows:

1. For the underwater acoustic sensor network of tsunami warning scenarios, the problem of topology optimization faces different difficulties as the conventional optimization methods for other types of underwater acoustic sensor networks, such as for environment monitoring, in terms of the network constraints and the cost function. Considering that few investigations have been reported in this aspect, our work is specially designed to explore the feature of the tsunami warning underwater acoustic network to address the challenges of it. Specifically, it is considered to perform topological optimization on the seabed monitoring nodes under a specific number of nodes. The coverage of the seabed monitoring area and the data transmission capability of the seabed monitoring nodes are comprehensively taken into account.

2. The spatial importance of a seabed region is modelled as an uncertain variable, and a random weighting strategy is introduced to capture environmental heterogeneity and limited prior knowledge. This enables robust topology optimization under uncertain monitoring demands. And by varying the different weights of importance of the seabed, the sensitivity and robustness of different algorithms can be analyzed.

2. NETWORK MODELS

2.1 System overview

This study considers a disaster and tsunami warning system in deep-sea scenario composed of a set of ocean-bottom monitoring nodes and a surface data collection infrastructure. The bottom nodes are deployed on the seabed within a predefined monitoring region of interest, where potential tsunami-generating seismic activities may occur. Each bottom node is equipped with pressure sensors to detect seabed pressure variations associated with tsunami generation.

In the considered system, bottom monitoring nodes transmit their observation data to the sea surface using acoustic communication links. Surface stations, such as moored buoys, are assumed to provide reliable uplink connections to shore-based warning centres via satellite communication. Therefore, the focus of this work is on the deployment of bottom monitoring nodes and their ability to relay observation data through RAPs to the sea surface.

2.2 Sensing model

This study adopts the 0/1 disk sensing model. Its mathematical expression is given below [11].

$$c_{ij} = \begin{cases} 1, & d_{ij} \le R_c \\ 0, & d_{ij} > R_c \end{cases} \tag{1}$$

Where d_{ij} refers to the distance between node i and node j, R_c means the sensing radius of sensors.

Within a circular area centred on the sensor node with a specific sensing radius, the perception probability is 1; outside this area, the perception probability is 0.

Based on the above model, we will respectively determine the perception radius of the seabed monitoring nodes and the communication range from the seabed monitoring nodes to the sea surface gateway nodes.

In this study, the sensing radius R_c of each bottom monitoring node is defined as the maximum distance within which the node can be considered to "cover" or monitor the seabed area. Although actual BPR sensors in DART systems are capable of detecting pressure changes corresponding to millimetre-level variations in sea level [12], there is no established physical distance corresponding to a coverage area. Therefore, for the purpose of deployment optimization, three candidate values of R_c (20 km, 30 km and 50 km) are used to represent sparse, medium and dense monitoring scenarios. That is to say, the R_c here will reflect the deployment spacing of the nodes.

The above describes the sensing model of seabed monitoring nodes with respect to the monitored seabed area. It should be emphasized that, in tsunami early warning systems, seabed nodes primarily function as independent sensing units for detecting pressure variations or seismic anomalies. Unlike conventional UASNs, inter-node communication between seabed sensors is not a necessary requirement. Instead, the effectiveness of deployment is mainly determined by the coverage of the monitored seabed area and the ability of seabed nodes to reliably transmit observation data to upper layer nodes or surface gateways. Therefore, in the proposed modelling framework, explicit connectivity constraints among seabed nodes are not enforced.

The communication range between the seabed monitoring nodes and the surface gateway nodes is described by the coverage range of RAPs.

We know that the bottom monitoring nodes need to transmit the observation data to the sea surface through the acoustic communication link, either in a single-hop or multi-hop manner. This study focuses on the deployment of seabed monitoring nodes and does not cover the design and placement of relay nodes. Therefore, during the communication modelling stage, only the scenario where the seabed monitoring nodes directly reach the surface nodes via a single-hop RAP is considered.

In the deep-sea acoustic field, there exists a very special communication link, the reliable acoustic path (RAP), when there is a critical depth in the ocean and there is a depth margin between it and the seabed. The sound propagation of the nodes located between the critical depth and the seabed will follow the RAP sound propagation [13] and a relatively stable acoustic channel is formed over a wide horizontal distance range. In recent years, the characteristics of RAP and the design of related communication systems are gradually being carried out [14].

It should be noted that RAP is not the only method for the seabed monitoring nodes to transmit observation data back to the surface. In actual environments, these nodes may still complete data transmission through other acoustic links. However, in deep sea long-distance communication scenarios, especially for communication between nodes below the critical depth and the sea surface, RAP often demonstrates higher stability and accessibility [10]. Therefore, in this paper, the RAP-based data transmission back method is considered as a representative and effective transmission mechanism.

To reduce the complexity of the model and highlight the network topology optimization problem, we adopt the existing conclusions from the RAP research as approximate assumptions: when a 100-Hz source radiates from a near-surface depth of 30 m, at approximately at 30 km, the RAP ceases to converge with the bottom [10]. This means that the seabed monitoring nodes can "listen" to the nodes on the sea surface within a horizontal distance of 30 km from them. Based on the reversibility of the acoustic path, the communication relationships are further simplified. It is believed that when the horizontal distance between the seabed monitoring nodes and the surface nodes is within the aforementioned effective range, there is the potential for direct communication through RAP between the two. That is, the communication range R_c between the underwater monitoring nodes and the surface gateway nodes is 30 km.

2.3 Seabed monitoring importance model

Due to the heterogeneous distribution of tsunami generation mechanisms, different seabed regions do not contribute equally to early tsunami warnings. Areas located near active subduction zones or major fault systems are more critical, as observations in these regions are more sensitive to initial seafloor deformation and tsunami generation. Therefore, this study assigns different weights of importance to seabed regions, and prioritizes the deployment of bottom monitoring nodes in high importance areas.

In practice, the importance of seabed regions for tsunami monitoring depends on physical factors such as local bathymetry, proximity to seismic sources and potential tsunami generation sites.

However, due to the lack of detailed bathymetric and seismic data in this study, and the fact that the focus of this research is not on accurately modelling the seabed area, we assign the importance of different seabed areas randomly in the simulation. By using the random weighting method to depict the importance of different underwater areas, on the one hand, it can reflect the spatial heterogeneity of the underwater environment. On the other hand, it can be used to evaluate the adaptability and robustness of the topological evaluation algorithm proposed in this paper under the condition of uncertain regional importance.

The seabed weights of importance are generated via a random uniform distribution followed by L1 normalization. Specifically, we first initialize a pseudo-random number generator using the input random seed to ensure the reproducibility of the results. And generate an $M \times N$ weight matrix w_0, where the M and N represent the number of rows and columns of the bottom grid layout. Each element w_{ij}^0 is independently sampled from the standard uniform distribution $U(0,1)$. The final weight matrix w is obtained by normalizing w_0 with its L1-norm. Its mathematical expression is as follows.

$$w_{ij} = \frac{w_{ij}^0}{\sum_{i=0}^{M}\sum_{j=0}^{N} w_{ij}^0} \tag{2}$$

This process guarantees that all weights are non-negative and sum to 1, conforming to the properties of a probability distribution for seabed importance. One of the heat maps of the bottom weight distribution is given in Fig. 2.

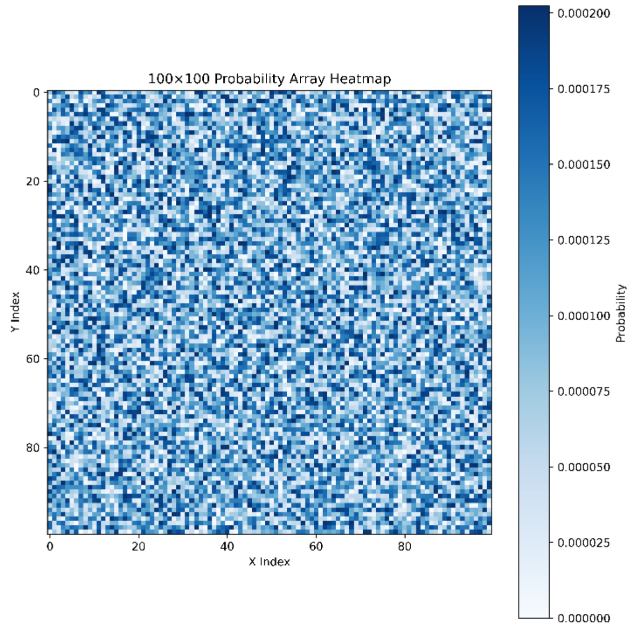

Figure 2 – Weight distribution graph

3. ALGORITHM INTRODUCTION

We used the Simple Particle Swarm Optimization (PSO-simple) algorithm [15] and the Genetic Algorithm (GA) [16] as the basic algorithms for the study of topology optimization. To prevent the PSO algorithm from falling into local optimum, we added random perturbations to the simple PSO (PSO) algorithm. In addition, we introduced uniform deployment and random deployment as benchmarks to compare and analyse the results of the above five algorithms.

The principle of the algorithms mentioned above will only be described briefly for they have been widely used in the research of topology optimization [17].

The Particle Swarm Optimization (PSO) algorithm mimics the foraging behaviour of birds and utilizes the information sharing between each particle to find the optimal solution. The PSO algorithm has the advantages of simplicity, strong ability to search for the global optimal solution, and fast convergence speed. It is regarded as one of the mainstream swarm intelligence algorithms that are widely used in hybrid technologies at present [18].

The core idea of the particle swarm algorithm is to optimize through the collaboration of individual particles and the entire swarm. Each particle in the swarm will record its own individual optimal solution (pBest) during the iterative process, while the global optimal solution (gBest) is the best among all individual optimal solutions. The particles achieve optimization by updating their own velocity and position during the iterative process. The formulas for velocity update and position update are as follows [18].

$$V_k(i+1) = \omega V_k(i) + c_1 r_1 (p_{\text{best},i}^k - X_k(i)) + c_2 r_2 (g_{\text{best},i} - X_k(i)) \quad (3)$$

Here, $V_k(i+1)$ represents the velocity of the k particle at the $(i+1)$ iteration, $X_k(i)$ represents the position of the k particle at the i iteration, $p_{\text{best},i}^k$ represents the individual optimal solution of the k particle up to the i iteration, $g_{\text{best},i}$ represents the global optimal solution up to the i iteration. ω is the inertia weight, used to balance the global convergence and the convergence speed, c_1 and c_2 represent the learning factors of the individual and the group respectively, r_1 and r_2 are random numbers uniformly distributed within the range of $[0,1]$ and used to maintain an adequate level of diversity.

Regarding the inertia weight ω, it typically undergoes a linear change from 0.9 ($\omega_{\max}$) to 0.4 ($\omega_{\min}$) as the number of iterations increases. The expression is as follows:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{i_{\max}} \times i \quad (4)$$

The position update formula is as follows:

$$X_k(i+1) = X_k(i) + V_k(i+1) \quad (5)$$

The Genetic Algorithm (GA) is a biological evolution algorithm that simulates the principles of natural selection and genetics. It generates solutions with higher fitness in the target space by simulating the natural evolution of organisms. It represents the evolutionary process mathematically and encodes each individual. Each individual has unique "genes". During the iteration process, new individuals are obtained through "reproduction".

The evolutionary process of GA mainly consists of four stages: population initialization, selection, crossover and mutation, and iteration. In this study, we employed the tournament selection, single-point crossover and random mutation methods [19] to implement the GA.

For the swarm intelligent algorithm mentioned above, it is necessary to design the fitness function, or sometimes referred to as the objective function, to guide the algorithm to find the optimal solution.

This study is oriented towards disaster and tsunami warning systems. The fitness function is designed as follows:

$$\text{fitness} = \alpha \cdot r_{\text{cov}} + (1-\alpha) \cdot r_{\text{RAP}} \quad (6)$$

Where r_{cov} refers to the coverage rate of the bottom monitoring area, and r_{RAP} represents the proportion of bottom nodes that can communicate with the sea surface gateway node through the RAP.

Since the bottom grid has weights, the coverage rate here is the weighted coverage rate. The mathematical formula for coverage rate calculation is as follows[17]:

$$f(x,y) = \begin{cases} 1, & \text{if } \exists i \in \mathbf{X} \text{ such that } \forall v_j \in \mathbf{V}_{x,y}, d(i,v_j) \le r \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

Where $\mathbf{X}$ refers to the set of bottom nodes, $\mathbf{V}_{x,y}$ refers to the set of vertices of a grid. When $f(x,y)$ is 1, this means the grid indicating x th row and y th column has been covered. The mathematical formula means that only when all the vertices of the grid are covered by the same node is the grid considered covered. And if the grid is covered by at least one node in the network, the area is considered covered.

Ultimately, the coverage rate at the bottom can be expressed as follows:

$$r_{\text{cov}} = \sum_{x=0,y=0}^{x=r,y=c} \left(w(x,y) \cdot f(x,y) \right) \quad (8)$$

Where $f(x,y)$ indicates whether the grid indicating x th row and y th column is covered, $w(x,y)$ refers to the weight of grid indicating x th row and y th column. And the r and c refer to the number of rows and columns divided into the monitoring area, respectively.

The optimization mainly focuses on two aspects: one is the coverage range of the seabed monitoring nodes, and the other is the proportion of bottom nodes that can transmit data back to the surface through the RAP. Here, the proportion of nodes that can transmit data back through the RAP is regarded as an optimization objective rather than a hard constraint. This is because in the actual design of the seabed network, to ensure reliability and stability, relay nodes are usually deployed instead of relying solely on the direct RAP link for data transmission. Therefore, this study considers RAP accessibility as an optimization metric while maintaining the flexibility of the network design.

4. SIMULATION

4.1 Simulation setup

This study is about topology optimization of DSASN. Thus, we use the Munk deep sea sound speed profile and the Bellhop model is used for simulation. The parameters for the sound field simulation are set as Table 1.

Table 1 – Sound field parameter settings

Parameters (unit)	Values
Sound source frequency (Hz)	5500
Depth of deep-sea (m)	5000
Seabed sound speed (m/s)	1600
Seabed density (g/cm³)	1.8
Seabed attenuation coefficient (dB/λ)	0.8

The sound field transmission loss is shown in Fig. 3.

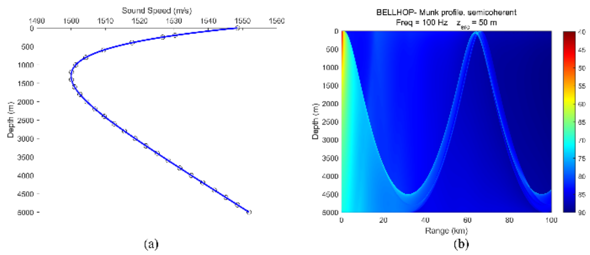

Figure 3 – (a) Sound speed profile; (b) Sound field transmission loss

Other network simulation parameter settings are shown in **Table 2**.

Table 2 – Network simulation parameter settings

Parameters (unit)	Values
Experimental area *(x,y)* (km)	(100,100)
Mesh size *(x,y)* (km)	(1,1)
The position of surface node *(x,y,z)* (km)	(50, 50, −0.05)
RAP horizontal monitoring range (km)	30
Sensing radius of seabed nodes R_s (km)	20/30/50
Weight of fitness function α	0.8
Size of the population in evolutionary algorithms	50
Number of iterations of the evolutionary algorithm	100
Individual learning factor (PSO) c_1	0.45
Group learning factor (PSO) c_2	0.45
Cross probability (GA) P_c	0.8
Mutation probability (GA) P_m	0.05
Number of repeats	20

We set the size of the target monitoring area to 100 km×100 km, and divided it into 100×100 grids. The sea surface buoy is located at the centre of this rectangular area, and the depth of the surface buoy is 50 m. We divide the bottom area into 100×100 grids and randomly set the weight of each grid.

The parameter settings related to PSO and GA are shown in the table above.

The solutions generated by the evolutionary algorithm such as PSO and GA, are not the only solutions, and there may be differences in different runs. Therefore, we conducted multiple experiments to evaluate the stability of the proposed algorithm. The "Number of repeats" in Table 2 is the number of times we conducted the repeated experiment. Additionally, since the spatial importance of the seabed area is modelled as a random weight allocation to reflect the uncertainty of the environment and limited prior knowledge, it is also necessary to assess the robustness of the algorithm to changes in the seabed weight pattern. Therefore, repeated multiple experiments not only reflect the stability of the algorithm itself but also reflect the robustness of the algorithm in the face of unstable seabed weight conditions.

To ensure the statistical significance and reproducibility of the experiments, we predefined a set of random seed arrays with a length of "Number of repeats", and in each repeated experiment, a random seed will be assigned to it to conduct a fair comparison of different algorithms and ensure the reproducibility of the experiments.

Based on the simulation parameter settings described in this section, the topology optimization of the seabed monitoring node for the disaster and tsunami warning system is carried out.

4.2 Result analysis

We used the same fitness function and conducted the simulation of topology optimization respectively with PSO-simple, PSO and GA algorithms. One of the topological structures generated by the algorithm is shown in Fig. 4. The heat map at the bottom represents the weights of the grid area at the bottom. We hope that the nodes we deploy can cover the bottom area as much as possible and at the same time be able to transmit information back through the RAP acoustic link.

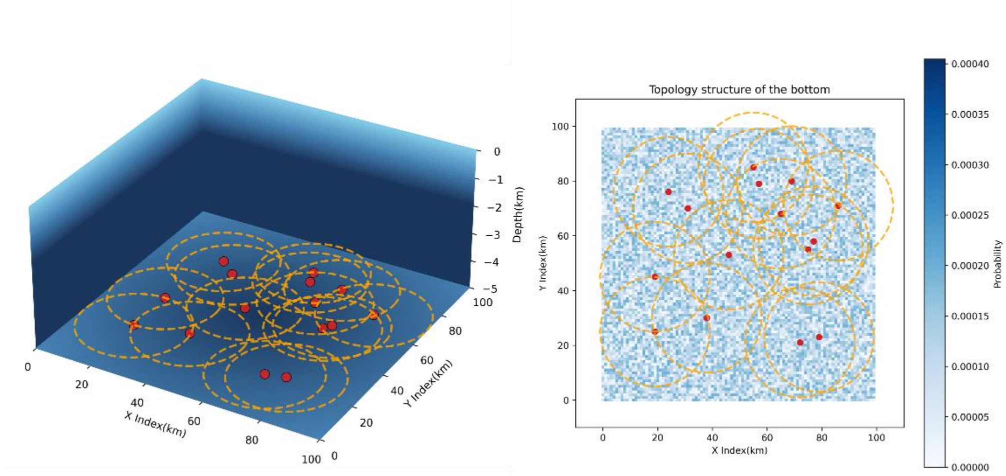

Figure 4 – One of the topological structures (max deployment spacing radius is 20 km, number of bottom nodes is 15)

When the max deployment spacing radius of the bottom monitoring node is 30 km, the coverage result of the bottom is given in Fig. 5.

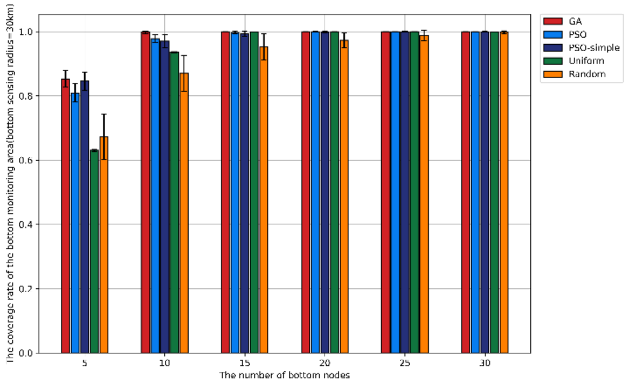

Figure 5 – The coverage rate of the bottom monitoring area (max deployment spacing radius = 30 km)

It can be seen that when the number of seabed monitoring nodes reaches 15, except for random deployment, other algorithms can basically achieve full coverage of the bottom monitoring area when the sensing range is 30 km. When the number of nodes is less than 15, the swarm intelligence algorithm (including PSO and GA) achieves a higher coverage rate for the bottom monitoring area compared to uniform deployment and random deployment.

When the number of seabed monitoring nodes is 5, the coverage rate achieved by the GA algorithm is approximately 22% higher than that of the uniform deployment and about 18% higher than that of the random deployment; the coverage rate achieved by the PSO algorithm is about 18% higher than that of the uniform deployment and about 14% higher than that of the random deployment; the coverage rate achieved by the PSO-simple algorithm is about 21% higher than that of the uniform deployment and about 17% higher than that of the random deployment.

This indicates that, under conditions of limited resources, the application of swarm intelligence algorithms yields better results, and among GA and PSO, GA performs even better.

The values of the bar chart represent the average results of multiple experiments. This paper will further analyse the stability of the algorithm. The error bars in the figure indicate the Standard Deviation (SD) of multiple experiments.

It can be seen that as the number of monitoring nodes on the seabed increases, the standard deviation of the experiments gradually decreases. This is because the seabed area is limited. As the number of nodes gradually increases, the coverage of the bottom can basically maintain a high level, and at this time, the error of multiple experiments will be smaller.

The SD variation curves of the results of different algorithms in multiple experiments are shown in Fig. 6.

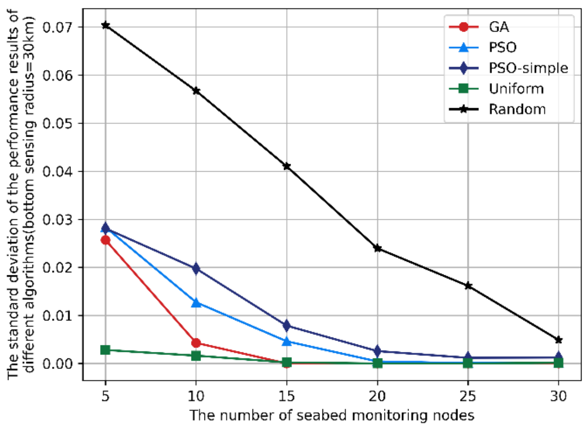

Figure 6 – The SD of the performance results of different algorithms (bottom sensing radius = 30 km)

Among them, the random algorithm is the least stable algorithm, while the uniform deployment is the most stable algorithm. This is because, under the condition of a fixed number of nodes and a determined area, uniform deployment can be regarded as a fixed deployment. The errors of all swarm intelligence algorithms are between the uniform deployment and the random deployment. Among them, the GA algorithm has the smallest error.

The optimization results of different algorithms with different perception radius are as Fig. 7.

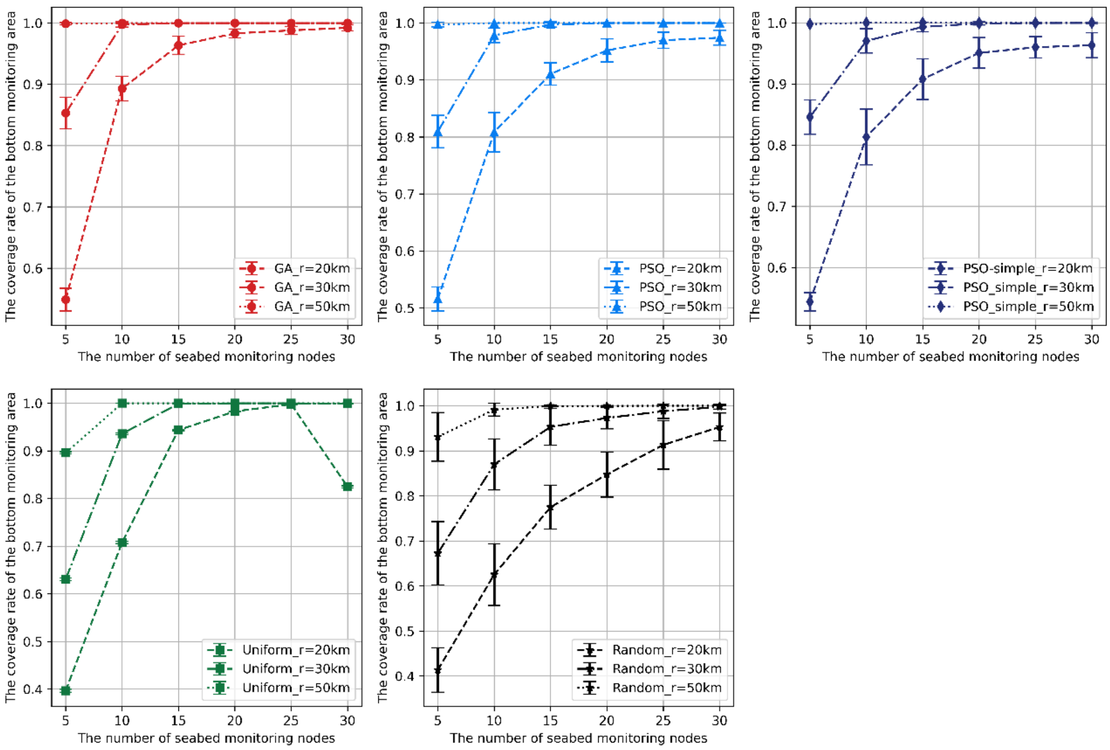

Figure 7 – The coverage rate of the bottom monitoring area with different algorithms and different spacing radii

When the number of seabed monitoring nodes is 20, even if the nearest deployment distance is 20 km, the coverage rate can still reach over 90%. Moreover, we can observe that the PSO with random perturbations (PSO) does not perform as well as the PSO-simple, indicating that this problem is less likely to fall into a local optimal solution. The addition of random disturbances may instead make the PSO find the optimal solution more slowly.

From Fig. 7, we can see that when the sensing radius of the seabed monitoring nodes is 20 km, the uniform deployment algorithm actually decreases when the number of underwater monitoring nodes is 30. The reason is that this paper has performed a grid operation on the underwater area and limited the nodes to be deployed only at the grid points. This will cause the uniform deployment algorithm to be unable to possibly deploy at the planned continuous coordinate points and instead shift to the corresponding grid points, resulting in the decrease.

After analysing the coverage performance, we will analyse the ability of the deployed nodes to return data through the RAP. During the optimization process using swarm intelligence algorithms, we simply set 30 km as the indicator for the connectivity between the seabed monitoring nodes and the sea surface gateway through the RAP. In the verification stage, to avoid circular reasoning, we model the RAP-based data return capability as a function related to distance. The RAP-based data return capability of the *i*-th node $r_{\mathrm{RAP}}(i)$ can be expressed as follows:

$$r_{\mathrm{RAP}}(i)=\begin{cases}\dfrac{1}{1+\exp(\beta\cdot|d_i-d_{\mathrm{RAP}}|)}, & d_i\le d_{\mathrm{RAP}}\\ 0, & \text{otherwise}\end{cases} \tag{9}$$

Where d_i represents the distance between the *i*-th seabed monitoring node and surface gateway node equals 30 km, is the limited coverage radius that the RAP can reach. Then, for a certain topological structure, its RAP-based data return capability can be expressed as follows:

$$r_{\mathrm{RAP}}=\sum_{i=0}^{N} r_{\mathrm{RAP}}(i) \tag{10}$$

This model links the horizontal distance with the probability of establishing a feasible RAP, following the general abstract principles adopted in underwater acoustics and wireless networks. The experimental results are shown in Fig. 8.

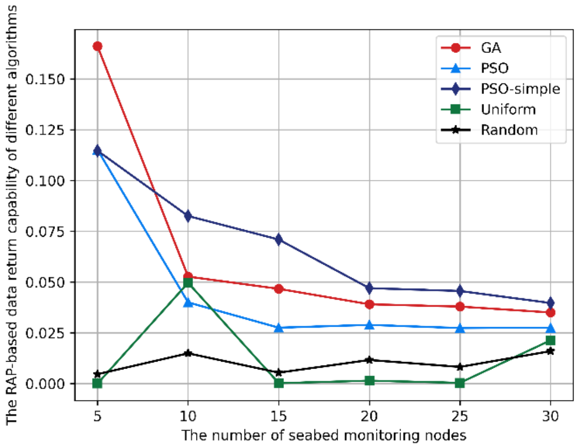

Figure 8 – The RAP-based data return capability of different algorithms

It can be observed that when the number of seabed monitoring nodes is small, the swarm intelligence algorithm can achieve a relatively high RAP-based data return capability. However, as the number of nodes increases, the RAP-based data return capability decreases. This is because the optimization of the swarm intelligence algorithm is influenced by the designed fitness function. The fitness function designed in this paper includes two parts: coverage rate and RAP backpropagation capability. Although the weight settings of the two are such that the coverage rate has a higher weight than the RAP backpropagation capability, when the number of nodes is small, the value of the coverage rate is small. At this time, the value of RAP backpropagation capability can be reflected as a factor to distinguish different solutions. However, when the number of nodes increases, the value of the coverage rate will increase, and with its larger weight setting, the value of the RAP backpropagation capability will be difficult to be used as a factor to distinguish different solutions. From Fig. 8, it can be seen that when the number of nodes is large the RAP backpropagation capabilities of the three swarm intelligence algorithms tend to be stable. The information in the figure can also reach the above analysis conclusion.

We further analysed the time complexity of different algorithms and the results are as shown in Fig. 9. For both the PSO and GA algorithms, the population size is 50 and the number of iterations is 100. As the number of seabed monitoring nodes to be deployed increases, the time consumption for each optimization increases. Among the three algorithms, the one with the best time complexity is PSO-simple.

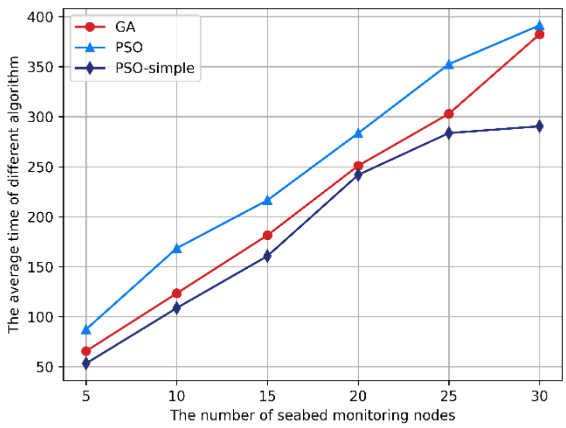

Figure 9 – Comparison of running time consumption of different algorithms

5. CONCLUSION

In this work, we studied the optimization of seabed monitoring node deployment for tsunami early warning systems. Two main optimization algorithms, Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), were applied and compared in terms of coverage performance and computational efficiency. Simulation results indicate that when the number of deployed nodes is relatively small, GA can achieve slightly higher seabed coverage than PSO. However, GA requires significantly longer computation time compared to PSO. These findings suggest a trade-off between coverage performance and computational efficiency, providing guidance for selecting appropriate optimization methods under different deployment scenarios. Looking forward, this trade-off framework could also inform the exploration of more advanced techniques, such as the machine learning-based approaches applied in related domains [20-21], for future network topology optimization.

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