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Routing failure prediction and repairing for AUV-assisted underwater acoustic sensor networks in uncertain ocean environments ☆

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ABSTRACT

Underwater acoustic sensor networks (UASNs) provide temporary links, which is of great significance when it comes to dealing with abnormal situations or emergencies in Internet of underwater things (IoUT). However, UASNs are susceptible to changes and uncertainties in network topology, channel conditions, etc., which can easily lead to frequent link interruptions. In this paper, we introduce a link failure prediction mechanism and an autonomous underwater vehicle (AUV)-assisted routing holes repairing mechanism for routing design of UASNs in uncertain ocean environments, to save system energy consumption and improve network connectivity. The proposed link failure prediction mechanism takes into account residual energy of sensor nodes, node drifting information, and uncertain ocean ambient noise. When the energy of multiple sensor nodes is exhausted, the particle swarm optimization algorithm (PSO) is adopted to calculate the optimal repair location, and an AUV is used for fixed point repairing. The proposed method can effectively reduce the energy consumption of sensor nodes, increase the packet delivery ratio, and extend the life of entire network of UASNs.

1. Introduction

The underwater acoustic sensor networks (UASNs) can provide temporary links between underwater sensor nodes, which is particularly important when it comes to dealing with abnormal situations or emergencies on Internet of underwater things (IoUT), and is widely used in civil and military applications [1,2]. The UASN is susceptible to problems such as network topology changes and channel conditions due to ocean currents, resulting in frequent link interruptions. Network interruption will significantly affect network performance, and invalid data transmission will increase sensor node energy consumption and reduce packet delivery ratio. An effective link prediction strategy between underwater sensor nodes can reduce invalid data transmission [2], which is of great significance.

As of now, much work has focused on predicting link failures in terrestrial wireless communication networks, which mainly solve the problems of bandwidth, energy consumption, and packet delivery ratio. In [3], N. Desai *et al.* proposed a comprehensive mechanism for intelligent configuration based on machine learning. The mechanism can increase bandwidth utilization by copying frames only when the link has a high tendency to fail. In [4], E. Van den Berg *et al.* proposed a flexible and modular architecture that combines various link state-related measurements and prediction algorithms to accurately predict link failures of networks. This scheme has lower bandwidth and energy overhead. In [5], R. Kumar *et al.* discussed frequent link failures and limited resources in the mobile software-defined Internet of Things (SDWM-IoT). They proposed an active optimization strategy update mechanism, which is expressed in a promising algebraic modeling language (AMPL)

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and solved by the well-known algebraic solver (CPLEX). It helps to increase the packet sending rate and reduce the average delay. In [6], zone-based route discovery mechanism (ZRDM) and link failure prediction mechanism (LFPM), are proposed to enhance the on-demand source routing protocol. The goal of ZRDM is to control the flood of routing requests, and the goal of LFPM is to avoid routing damage caused by node movement. This scheme has better performance in terms of average end-to-end delay and packet delivery ratio.

The underwater uncertain topology and the complexity of the underwater acoustic channels require link failure prediction to reduce invalid data transmission. There are few related literatures on the research of failure prediction mechanisms for UASN. In [7], W. Cheng *et al.* proposed an eco-friendly underwater communication framework and introduced applicable prediction techniques to realize the idea of environmentally friendly underwater acoustic communications, with the ultimate goal of avoiding interference caused by man-made noise to marine mammals. In [8], J. Chen *et al.* proposed a model that uses historical link information and the channel state, obtained by periodic detection, to predict link and routing interruptions. The model optimizes routing through hop-by-hop decomposition and reorganization. Reselection ensures the reliable transmission of data, but the prediction mechanism cannot function well in uncertain network topology.

When designing the optimal routing for an UASN, energy consumption is a key indicator to consider. The optimal routing ensures the lowest energy consumption of a single data transmission path from the source node to the destination node. In the previous work [9], we proposed an ACOA-AFSA integrated dynamic coded cooperation (DCC) routing algorithm, renamed as the AAD routing algorithm for short in this paper. The AAD algorithm can obtain performance gain from both intelligent algorithm and cooperative communication. However, the routing principle with the lowest energy consumption for a single path makes certain nodes are frequently used, and their energy is easily exhausted prematurely. This leads to the energy holes problem in some areas of the UASN, and a network failure may occur because of this.

There has been much work in solving the energy holes problem of UASNs. In [10], W. L Rodolfo *et al.* proposed a topology control algorithm for adjusting the depth of nodes to establish the connectivity of the energy holes region. In [11], M. Ismail *et al.* proposed a routing design algorithm considering the depth, the energy of the current forwarding, and the average energy of the next expected forwarding area to solve the energy holes problem and improve the packet delivery ratio. In [12], I. Azam *et al.* proposed a balanced load distribution (BLOAD) scheme to avoid energy holes in UASNs due to unbalanced energy consumption. In the BLOAD scheme, data of the underwater sensor node is divided into components, which logically adjusts the transmission range of each sensor node to evenly distribute the data fractions among the next-hop neighbor nodes. This solution prolongs the stability and service life of the UASNs.

In recent years, due to the advancement in rechargeable and autonomous operations, autonomous underwater vehicles (AUVs) are widely adopted to perform tasks in UASNs. The AUV-based new sensor nodes have become a new research hotspot, and AUVs have been used to assist UASNs in underwater data collection to achieve more efficient energy consumption. In [13], an AUV-assisted UASN was introduced to balance energy consumption and network throughput. This algorithm has good application prospects in an UASN with large-scale communication, large system capacity, long-term monitoring, and high data traffic load. In [14], R. Duan *et al.* established a real model to characterize the environment of underwater robots and sensor nodes. AUV is used as the mobile collector, and the value of information (VoI) is used as the main indicator to measure the quality of information (QoI) to build a reliable hierarchical information collection system. Due to the movement of underwater robots, the changes of the network structure have brought new problems. In [15], J. Zhou *et al.* established an AUV underwater position prediction model based on time delay for the dynamic time slot MAC protocol, because time delay is the main factor of time slot length. The simulation results show that the dynamic time slot MAC protocol improves the network throughput, compared with the fixed time slot MAC protocol. In terms of solving the routing/energy holes problem, one solution is to use AUV to repair the relay function of a node in the area where the energy hole occurs. In [16], Z. Jin *et al.* proposed a routing void prediction and repair (RVPR) algorithm in an AUV-assisted UASN, which utilizes AUV to carry sensor nodes to repair the routing voids according to the results of energy holes prediction. The RVPR applies an energy-saving interaction mechanism between the sensor node and the AUV to ensure the reliable operation of the algorithm. However, when predicting link failure, the RVPR in [16] only considers the residual energy of sensor nodes and does not consider the actual complex uncertain ocean environments such as drifting of sensor nodes and changes of ocean ambient noise. Hence inaccurate prediction will cause the AUV to carry out unnecessary repair.

To address the drawback of the RVPR, based on our previous work of the AAD algorithm in [9], we propose a link failure prediction mechanism and an AUV-assisted void repair routing algorithm, named as AAD-FPVR routing algorithm. For the UASNs in uncertain ocean environments, the proposed scheme can improve link failure prediction accuracy and reduce unnecessary repair, thus reducing energy consumption and improving the energy efficiency of entire UASNs, while ensuring the reliability of transmissions.

The main contributions of this work are as follows:

1. In order to describe the drifting of underwater sensor nodes, we introduce a near shore shallow water flow model [17] to make the simulation environments more consistent with actual sea conditions. This is critical because the knowledge of the influence of uncertain ocean environments is the premise of accurate prediction of routing holes.
2. In the proposed link failure prediction mechanism of AAD-FPVR routing algorithm, the residual energy of the sensor node, node drifting information, and uncertain ocean ambient noise are considered to calculate the probability of successful link transmission. In addition, in order to simulate the ocean ambient noise under different sea conditions, we propose to adopt varying noise [18,19] to make the link failure prediction mechanism more accurate.
3. After a route is determined by the ADD routing algorithm, the link failure prediction mechanism will be used to predict the link failure of the selected route. If the prediction result shows that the link fails, our proposed scheme will save the collected data in the node and wait for the next prediction result to show that link is effective and the data can be sent, so as to avoid the waste of node energy caused by unnecessary data transmission. When the energy of multiple nodes is exhausted, the particle swarm optimization (PSO) algorithm is used to calculate the optimal repair position, and the AUV is used for fixed-point repair.

Note that, although uncertain ocean environment will affect the motion and positioning of AUV, in this paper we mainly consider the influence of uncertain ocean environment from the perspective of underwater acoustic communications. For more work on the relationship between uncertain ocean environment and AUV, please refer to [20–23], where reinforcement learning has been adopted to learn from both human rewards and environmental rewards at the same time.

The remainder of this paper is organized as follows. Section II presents the system model, node drifting model of UASNs and ocean noise model. The proposed AAD-FPVR routing algorithm for UASNs is detailed in Section III. The numerical results are presented and discussed in Section IV. Section V concludes the paper.

2. System model

As shown in Fig. 1, from the source node S to the destination node D, the AAD routing algorithm is adopted for routing design, where the S-D routing is optimally planned in a cooperative transmission method based on the principle of the lowest energy consumption. The ocean ambient noise is one of the main factors affecting underwater acoustic transmission. If the ocean ambient noise is too large, the underwater acoustic modem cannot decode the data with low signal-to-noise ratio (SNR), resulting in invalid data transmission and energy waste of underwater sensor nodes. In the meantime, the nodes can move with the water flow, the network's topology is dynamically changing and uncertain, and the link that can successfully transmit data at the previous moment may be disconnected at the next moment, resulting in uncertain data packet loss. The link failure prediction mechanism can effectively solve the above concerns.

After transmitting a certain number of packets in accordance with the routing design of AAD, the frequently used sensor nodes will cause the nodes to run out of energy prematurely, as shown in nodes *a* and *b* in Fig. 1, and then an energy hole will appear in the red circled area in Fig. 1. We propose to apply AUVs to assist in repairing routing nodes, to solve the issue of energy holes.

2.1. A. Node drifting model of underwater sensor nodes

Data transmission quality of underwater sensor nodes is closely related to connectivity, coverage and deployment of the network. At present, most of the node deployments are static in existing UASNs routing protocols, but the actual situation is that underwater sensor nodes can move with the flow of water. In a node drifting UASN, when the node moves, the connection and coverage of the network will be different. Hence it is necessary to introduce a water flow model to conform to reality. This section introduces the meandering current mobility (MCM) model proposed in [17] as the water flow model.

Although there are other models such as active Lagrangian particle swarm (ALPS) [24] to describe the node drift, the MCM model is typically applied in large coastal areas, which provides a good accuracy in simulating the near shore and shallow ocean current movement. The MCM model considers that the drifting of underwater nodes is affected by undercurrents and eddies, which is similar to the application scenario studied in this paper, and is suitable for simulating the drifting of underwater sensor nodes. The MCM model employs two-dimensional flow kinematics in fluid dynamics to describe the node drifting. It is assumed that all underwater sensor nodes move on the horizontal plane and their vertical displacements are ignored. This is because, in the shallow sea environments, two-dimensional model is usually considered in the simulation.

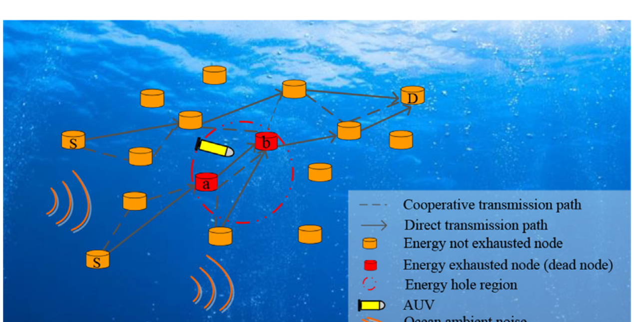

Fig. 1. Application scenario of an AUV-assisted UASN.

Any incompressible two-dimensional flow can be described by the flow function ψ; hence the MCM model uses the flow function ψ to describe the trajectory of underwater sensor nodes. Assuming that the initial position of an underwater sensor node is (x, y), the moving distance of the node at time t can be calculated as

$$\dot{x} = -\frac{\partial\psi(x,y,t)}{\partial y} \tag{1}$$

$$\dot{y} = \frac{\partial\psi(x,y,t)}{\partial x} \tag{2}$$

where $\dot{x}$ and $\dot{y}$ respectively represent the zonal (eastward) component and meridional (northward) component of the velocity field at time t, and the unit is km. The flow function ψ can be expressed as:

$$\psi(x,y,t) = -\tanh\left[-\frac{y - B(t)\ \sin\ (k(x-ct))}{\sqrt{1+k^2B^2(t)\ \cos^2(k(x-ct))}}\right] \tag{3}$$

$$B(t) = B_0 + \varepsilon\ \cos\ (\zeta t) \tag{4}$$

where k is the current wave number, c is the phase velocity, and $B(t)$ represents the current amplitude function. In the current amplitude function, B_0 represents the average width of the current in km; ε represents the modulation amplitude in km; ζ represents the modulation frequency. In the simulation analysis, the parameter settings of the MCM water flow model are shown in Table 1.

2.2. B. Ocean ambient noise model

The successful transmission of a data packet depends on the received signal strength, the interference caused by the transmitting node, and the level of ambient noise. Ocean ambient noise is the main factor that affects underwater acoustic transmission. The strength of ocean ambient noise is related to sea location, working frequency f and weather conditions, which will directly affect the received SNR of the signal via [19]

$$SNR = \frac{P_t(d,f)}{A(d,f)NL(f)\Delta f} \tag{5}$$

where $P_t(d,f)$ is the transmitting power, $A(d,f)$ is the transmission loss of the underwater acoustic signal with frequency f at distance d, NL is the ambient noise power spectral density (PSD), and Δf is receiver noise bandwidth (a narrow band around the frequency f).

Generally, ocean ambient noise can be modeled by four sources: turbulence, shipping, ocean waves, and thermal noise. Since most

Table 1
MCM parameters setting.

MCM Parameters	Value
Water wave number k	$2\pi/7.5$
Phase velocity c	0.12
Average width of water flow B_0	1.2 km
Modulation amplitude ε	0.3
Modulation frequency ζ	0.4

ambient noise sources can be described by Gaussian statistics and continuous PSD, the following empirical formula gives the continuous PSD of the four noise components, which is a function of frequency f in dB reμPa and the unit of frequency f is kHz [25]:

$$10\ \log N_t(f) = 17 - 30\ \log f \tag{6}$$

$$10\ \log\ N_s(f) = 40 + 20(s - 0.5) + 26\ \log\ f - 60\ \log\ (f + 0.03) \tag{7}$$

$$10\ \log N_w(f) = 50 + 7.5\sqrt{w} + 20\ \log f - 40\ \log\ (f + 0.4) \tag{8}$$

$$10\ \log N_{th}(f) = -15 + 20\ \log f \tag{9}$$

$$NL(f) = 10\ \log\ (N_t(f) + N_s(f) + N_w(f) + N_{th}(f)) \tag{10}$$

where N_t is turbulence noise, which usually only affects the extremely low frequency, i.e., f <10 Hz; N_s is shipping noise and long-distance shipping noise is dominant in the frequency range of 10 Hz-100 Hz, which can be modeled by the shipping activity factor s, and the value of s is between 0 and 1; N_w is sea surface noise, which is mainly affected by wind, and the frequency affected is 100 Hz-100 kHz, where w is wind speed in m/s; N_{th} is thermal noise, mainly affecting the frequency greater than 100 kHz; NL is the sum

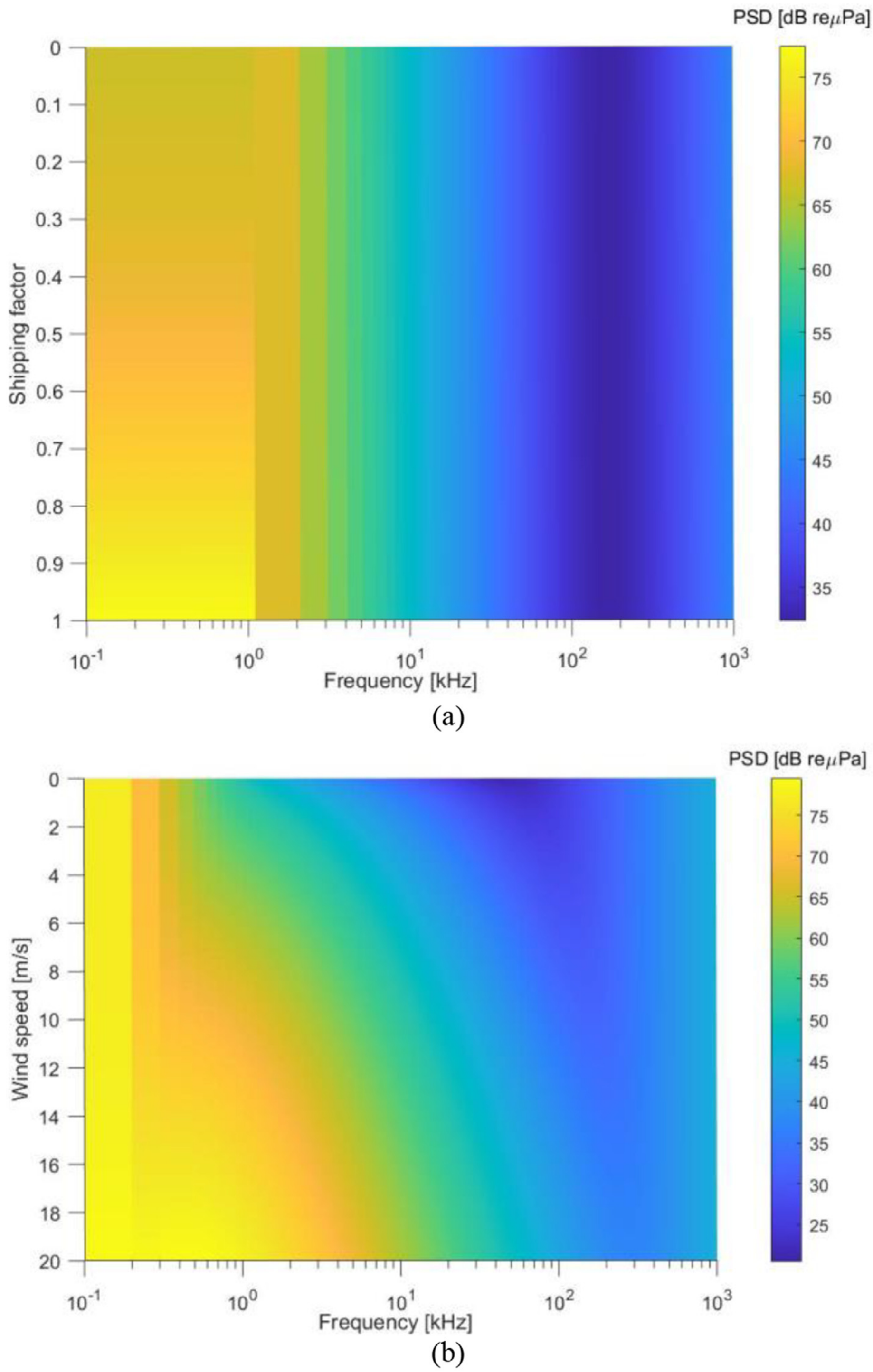

Fig. 2. Power spectral density of ocean ambient noise.

of the above-mentioned various ambient noises. Considering the application scenarios of UASNs, shipping noise and sea surface noise are the main factors affecting transmission frequency.

With shipping factors and wind speed as variables, Fig. 2 shows the corresponding total noise PSD. It can be observed that different shipping densities and different wind speeds have a great influence on ocean ambient noise, and the influence of uncertain noise must be taken into account in the prediction of underwater acoustic transmission quality.

3. AAD-FPVR routing algorithm for UASNs

This section introduces the proposed AAD-FPVR routing algorithm for cooperative UASNs with link failure prediction and AUV-assisted repair. The AAD-FPVR routing algorithm includes three components: the AAD routing algorithm, link failure prediction, and AUV-assisted routing repair. The entire algorithm's flow chart is shown in Fig. 3.

The key idea of the AAD algorithm is to use the advantages of the ACOA-AFSA algorithm in global optimization and DCC

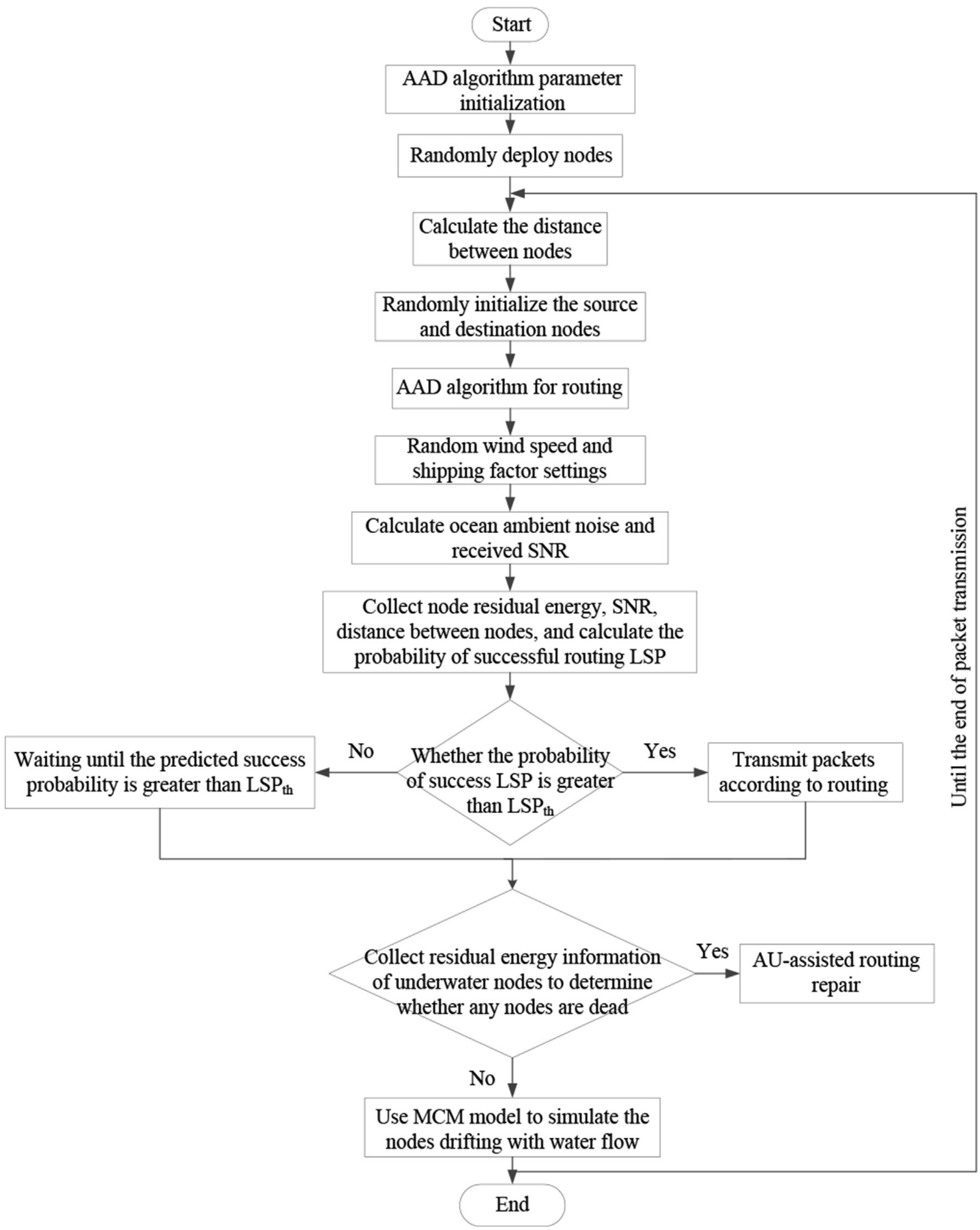

Fig. 3. AAD-FPVR algorithm flow diagram.

algorithm in enhancing bandwidth utilization of underwater acoustic channels to find an optimal route based on the principle of minimum energy consumption. Since the AAD algorithm has been introduced in our previous work [9], we will directly introduce the next two steps here. More information about AAD routing algorithm can be found in [9].

3.1. A. Link failure prediction mechanism

The drifting of sensor nodes, the received SNR of the signal, and the residual energy of the sensor nodes all affect the packet delivery ratio of data transmission to a certain extent. Therefore, in our proposed model, the drifting information of node, the received SNR of the signal, and the residual energy of node are all used to calculate the link success probability (LSP) of a specific hop, and to determine when a packet can be sent to the destination node of this hop.

We use link stability (LS) to represent the time that a connection between two connected sensor nodes can continue without interruption. Therefore, the LS between two sensor nodes is proportional to the LSP value. The form of LSP can be given as follows [6,26]:

$$LSP = 1 - e^{LP \cdot LS} \tag{11}$$

where LP is a constant, which can be adjusted to optimize the value of LSP for better predictions.

Inspired by Eq. (11), we use the transmission distance d between two nodes to describe the link stability, that is, if the actual transmission distance between two nodes exceeds the maximum transmission distance r of the two nodes, the link is disconnected. Therefore, LSP is inversely proportional to d. In a dimensionless form, we can use d divided by r to represent the percentage of distance between two connected nodes in the maximum transmission distance of the transmitting node, denoted as $Fr3$, i.e.,

$$Fr3 = \frac{d}{r} \tag{12}$$

The larger the $Fr3$, the smaller the LSP, then the relationship between LSP and $Fr3$ is as follows:

$$LSP = 1 - e^{\frac{LP}{Fr3}} \tag{13}$$

In the same way, let us consider the influences of the residual energy information of a node and the SNR of the signal to the LSP, denoted as $Fr1$ and $Fr2$ respectively, then we have:

$$Fr1 = \frac{E_{res}}{E_{ini}} \tag{14}$$

$$Fr2 = \frac{SNR_{\mathrm{rec}}}{SNR_{\mathrm{min}}} \tag{15}$$

where E_{res} represents the residual energy of a node, E_{ini} represents the initial energy of a node, SNR_{rec} represents the actual SNR of the signal received, and SNR_{min} represents the minimum SNR required for successful decoding. The larger $Fr1$ is, the larger the LSP is, and the larger $Fr2$ is, the larger the LSP is. Then the LSP is updated as follows:

$$LSP = 1 - e^{\frac{Fr1 \cdot Fr2 \cdot LP}{Fr3}} \tag{16}$$

The value of LSP ranges from 0 to 1. Let $\mathrm{LSP_{th}}$ be the link success threshold. When LSP is greater than $\mathrm{LSP_{th}}$, the packets can be successfully decoded. Therefore, a larger LSP means a higher packet delivery ratio, thus reducing retransmission and saving energy consumption. An effective LSP prediction can suspend the sending of packets when a transmission failure is predicted, thus avoiding unnecessary retransmission and saving system energy.

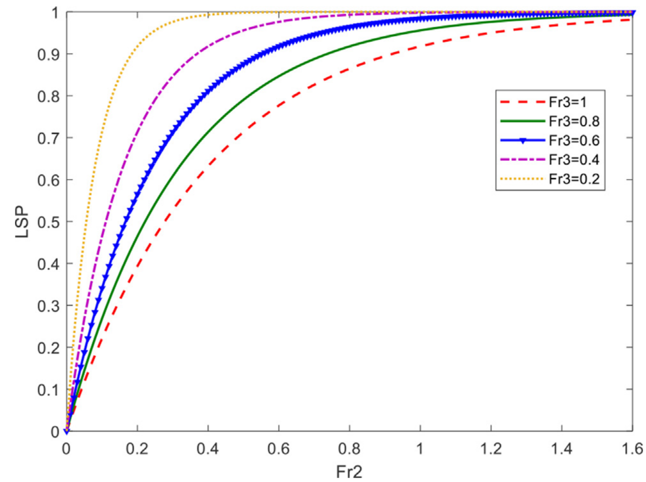

Fig. 4. When $Fr1$ = 1, the impact of changes in $Fr2$ and $Fr3$ on LSP.

From Eq. (16), it can be seen that $Fr1$ reveals the impact of residual energy of nodes, $Fr2$ reveals the impact of uncertain ocean ambient noise on SNR, and $Fr3$ reveals the impact of transmission distance between nodes caused by node drifting with ocean current. Fig. 4 shows the impact of changes in $Fr2$ and $Fr3$ on LSP when $Fr1$ = 1. It can be observed that LSP increases as $Fr2$ increases, and LSP decreases as $Fr3$ increases.

3.2. B. AUV-Assisted routing repair

Assume that there are N_{auv} AUVs that can be used to fix routing holes, which is much smaller than the number of sensor nodes N_{node} in the UASN.

When one sensor node dies, the node will send a repair request message to AUVs, which only save the request message received first. This can ensure that AUVs can repair the route to the nearest area as soon as possible.

For the case that an AUV received only one repair request from the sensor node, the repair location is the coordinate of the dead node. For the case that an AUV received multiple repair requests from the sensor nodes, the AUV needs to calculate the best repair location that it needs to reach to ensure the effective repair of multiple requests of routing holes repair. The objective function for solving the optimal repair position is to restore as many links as possible and minimize the moving distance of the AUV. As the particle swarm optimization (PSO) algorithm is a parallel algorithm with fast convergence speed, we adopt PSO algorithm to solve the optimal repair position. Suppose there are N_{dead} dead nodes, the dead nodes' coordinates are P_i (i = 1,2,...,N_{dead}), the repair position coordinate is P_{repair}, and the initial position of AUV is P_{AUV}. According to PSO algorithm, the distance between all dead nodes and the repair position must be less than the maximum transmission distance of a node r, which can be expressed as

$$\| P_{\mathrm{repair}} - P_i \| < r \tag{17}$$

When Eq. (17) is met, the travelling distance of AUV will be minimized next, which is taken as the fitness function of PSO algorithm F_{particle}. When F_{particle} converges to the minimum value, the corresponding position coordinate P_{repair} is the optimal repair position of AUV. Therefore, the objective function of PSO is to minimize the distance between the repair location and the AUV's initial location, as shown below:

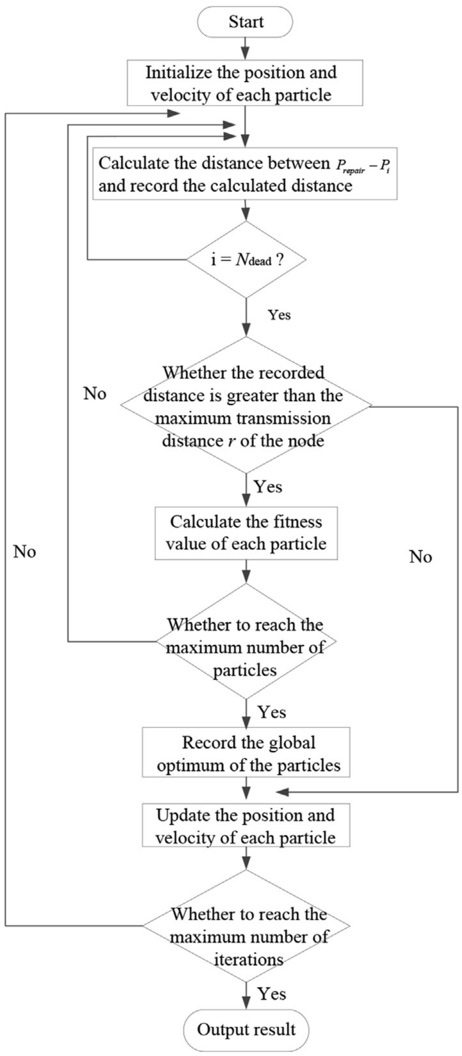

Fig. 5. Flow chart of PSO algorithm.

$$F_{\text{particle}} = \min \| P_{repair} - P_{AUV} \| \tag{18}$$

The flow chart of the PSO algorithm is shown in Fig. 5, and further details can be found in [16].

4. Simulation results and analysis

4.1. Simulation setup

The simulation is performed on the MATLAB software platform, the computer operating system is Windows 10 (64-bit), the CPU is i5-8400, and the RAM is 8 GB.

To study the performance of UASN with different network scales, the number of underwater sensor nodes is set as 50, 80, and 100, respectively. All the nodes have the same initial energy and maximum transmission distance for each hop. The initial energy of each node is 5000 kJ. All the sensor nodes are randomly deployed in an area of 3.5 km $\times$12.5 km. Taking 50 nodes as an example, the deployment situation is shown in Fig. 6. The MCM model is applied to simulate the underwater node movement with the ocean current, and Fig. 7 shows the change process of the positions of underwater sensor nodes over time. The shipping activity factor s is set as 0.5. According to our sea trial experience, the wind speed w is mostly below 5 m/s, Hence the wind speed value in the simulation is set to follow uniform distribution between 0 and 5, and then the sea surface noise is calculated according to Eq. (8). In order to overcome the unreliability of the underwater channels and ensure the reliable transmission of data, the node adopts the DCC transmission method proposed in [9]. Assuming that the minimum received power required for a node to be able to decode without error is 1 W, the optimal operating power of the transmitting node can be calculated according to the transmission distance and operating frequency [9,27].

In this section, we will verify the feasibility and effectiveness of the link failure prediction mechanism and AUV-assisted repair routing for UASNs routing algorithm in uncertain ocean environments. According to [16], we assume there are N_{auv} = 4 AUVs around the sensor nodes, and the initial positions of AUVs are (1.5, 4.2), (4.5, 4.2), (7.5, 4.2), and (10.5 4.2), respectively. The change of the initial AUVs positions does not affect the application of the PSO algorithm for repairing. After a large number of simulation tests, the parameters for PSO algorithm are similar to [16], that is, the number of particles N_{particle} is 20, the learning factor is 1, the inertia factor is 0.6, the maximum flight speed of the particles is 1, and the maximum number of iterations $N_{\text{iter\_p}}$ is 100.

4.2. Simulation results

Fig. 8 shows how the AUV assists in repairing routing holes after a dead node appears in the UASN. The red asterisk in the figure is the initial positions of AUVs, the red circles represent the dead nodes, the green dashed lines represent the travel path of AUVs during the repair task, and the green circles represent the optimal positions of AUVs for the repair. It can be observed from Fig. 8 that when there is only one dead node in an area, the optimal position for AUV to repair is the position of the dead node. When there are two or more dead nodes in an area, the optimal repair position of the AUV needs to be recalculated to restore as many links as possible. The PSO algorithm is used to calculate the optimal repair position. When the fitness value F_{particle} converges to the minimum, the corresponding P_{repair} is the optimal repair position. The change of the fitness value F_{particle} with the number of PSO iterations is shown in Fig. 9. It can be observed from Fig. 9 that the fitness value F_{particle} decreases as the number of iterations increases. The value converges when the number of iterations reaches 30, which takes only 0.1946 s in our simulation platform. Therefore, the optimal repair position can be calculated in a short time, which means the AUVs can quickly perform repair tasks.

In the following, the effectiveness of the prediction mechanism and the repair mechanism will be evaluated from the aspects of packet delivery ratio and energy consumption.

It can be seen from Fig. 10 that before the routing repair, the introduction of the link failure prediction mechanism consumes less energy than the original AAD algorithm, which can save the system energy consumption, and as the number of nodes increases, the energy saved will further increase. This is because, after the introduction of the link failure prediction mechanism, if the prediction result is that the link transmission success rate is lower than the threshold (that is, the link fails), the packet enters the waiting state. The packet will not be transmitted until the link transmission success rate is higher than the threshold, which can reduce invalid transmission of packets, thereby saving the system energy consumption. Moreover, as the number of nodes increases, the total energy of the system increases, and more packets can be transmitted before repairing, leading to consuming more energy of the system. For the network size of 100 nodes, in the case of link failure, as the number of packets transmitted increases, the energy saved increases owing to introducing the link failure prediction mechanism. As shown in Fig. 10, it can save more than 50% of the system's energy by introducing the link failure prediction mechanism.

Fig. 11 shows the comparison of the number of packets delivered by the AAD algorithm integrated into the link failure prediction

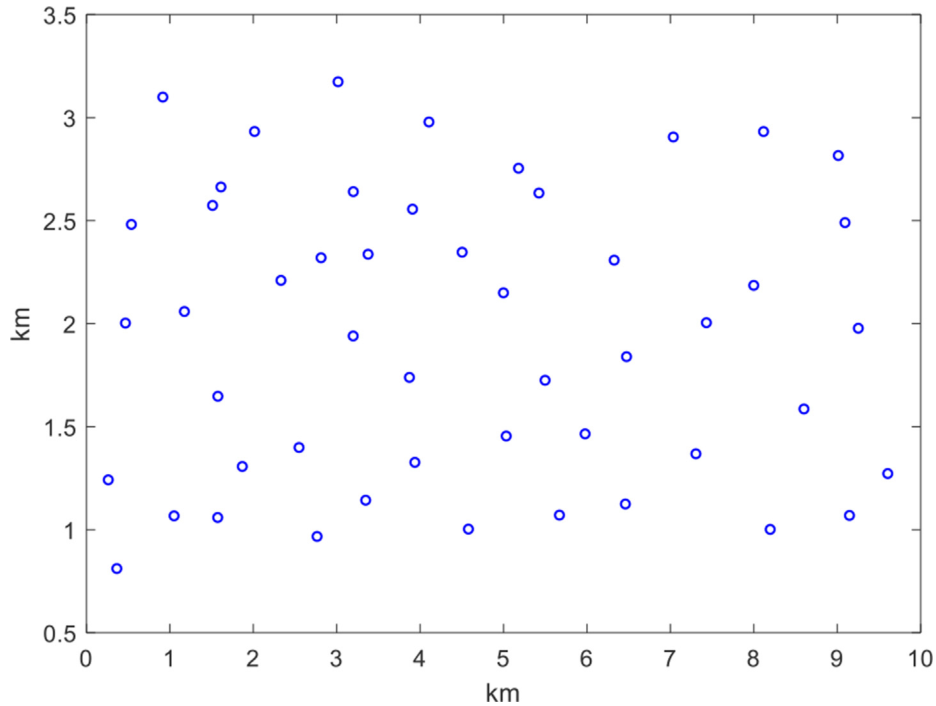

Fig. 6. Network topology of an UASN with 50-node.

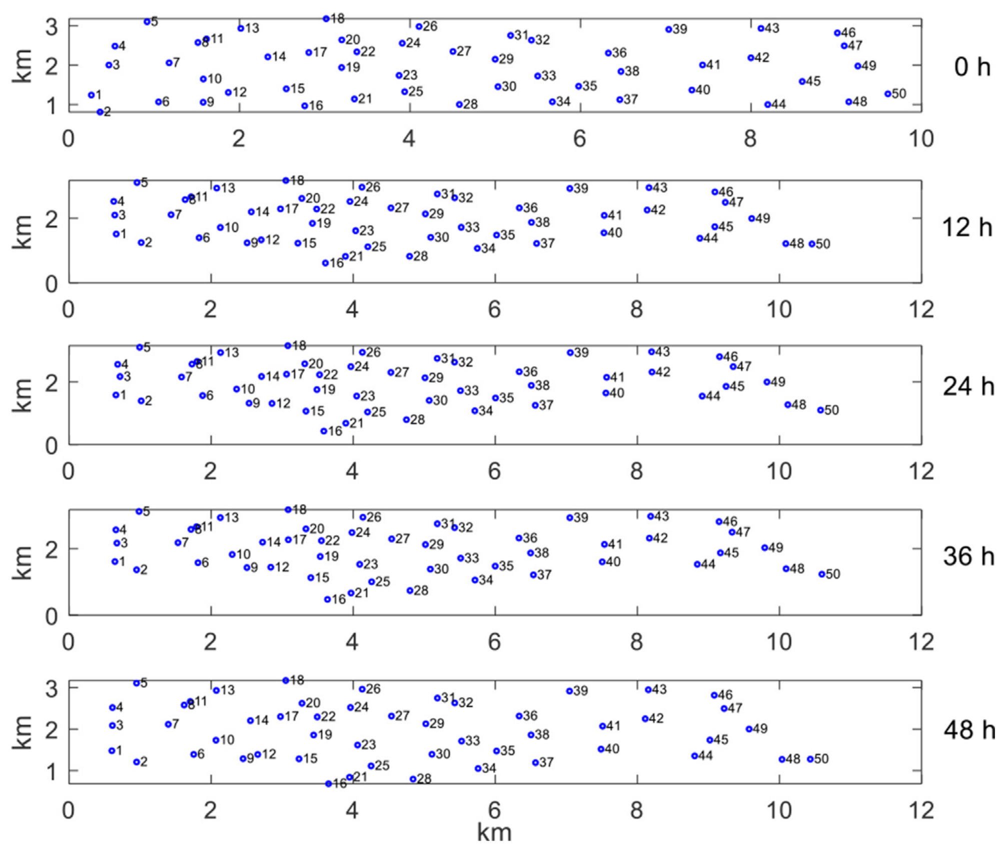

Fig. 7. The change process of the position of the underwater sensor node over time.

mechanism and the original AAD algorithm. It can be seen from the figure that compared with the original AAD algorithm, the introduction of a link failure prediction mechanism can effectively save system energy, thereby increasing the number of packets delivered by the system.

It can be seen from the comparison between Fig. 10 and Fig. 11 that when the number of network nodes is 50, before the dead node appears, the original AAD algorithm can successfully deliver 24 packets, and the energy consumption is 9.22×10^7 J. After introducing the prediction mechanism, 28 packets can be successfully

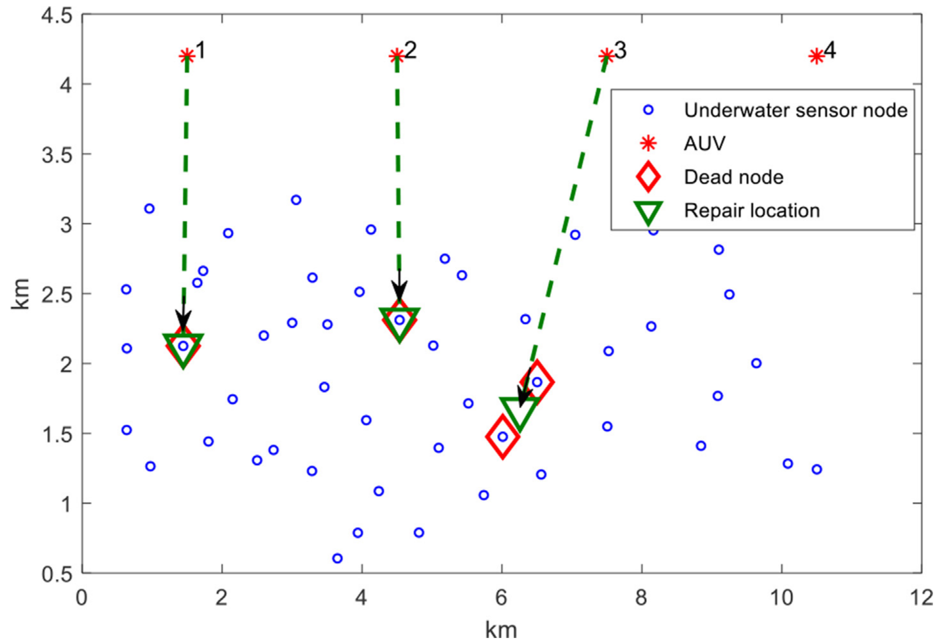

Fig. 8. Network topology after AUV-assisted repair.

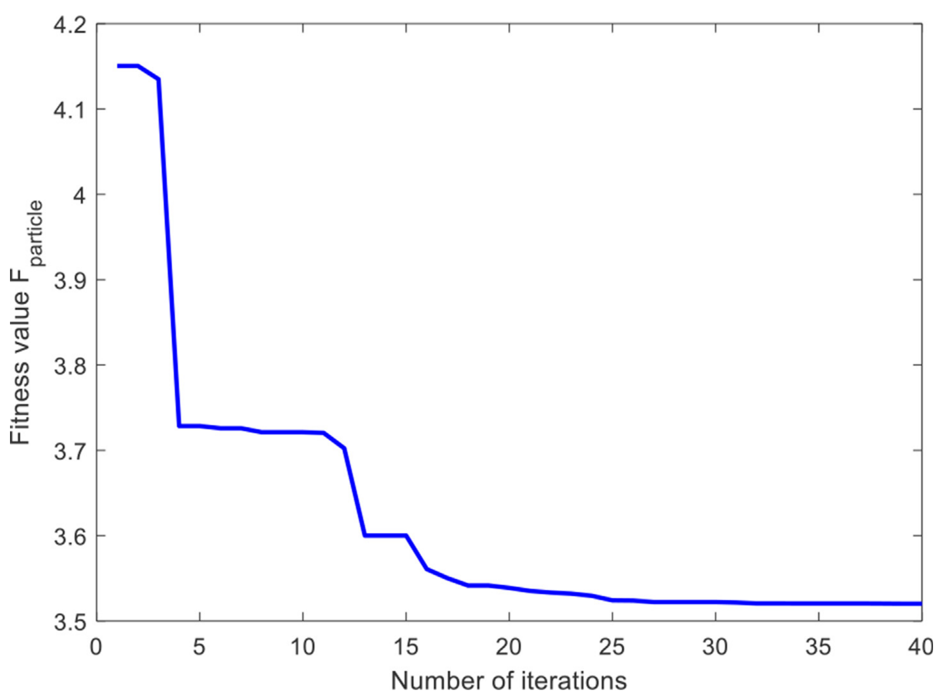

Fig. 9. The fitness value changes with the number of iterations of PSO algorithm.

delivered, and the energy consumption is 4.75×10^7 J. Therefore, the routing algorithm after the introduction of the prediction mechanism can successfully deliver more packets while consuming less energy and the same trend appears when the number of network nodes is 80 and 100.

Fig. 12 shows the comparison of the number of packets that can be successfully received at the receiver node between the algorithm that introduces the link prediction and repair mechanism and the original AAD algorithm when trying to transmit 80 packets. It can be seen from the figure that on the basis of the link failure prediction mechanism, the further introduction of a routing repair mechanism can effectively increase the number of packets delivered, and the number of effectively transmitted packets increases as the number of nodes increases. This is because AUV-assisted routing repair can effectively repair the network energy holes problem, thereby increasing the connectivity of the link. When the number of nodes is 50, the number of successfully delivered packets with the original AAD algorithm is 24. After the prediction mechanism is introduced, the number of packets successfully delivered is 28, and the number of packets success-

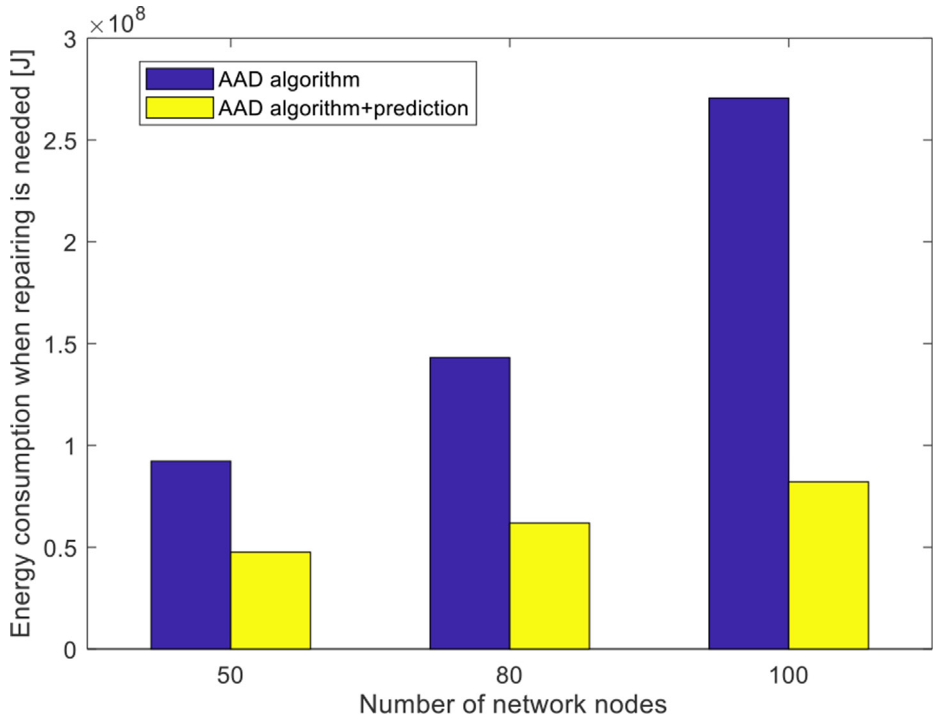

Fig. 10. Comparison of energy consumption between the original AAD algorithm and the AAD algorithm incorporating link failure prediction mechanism.

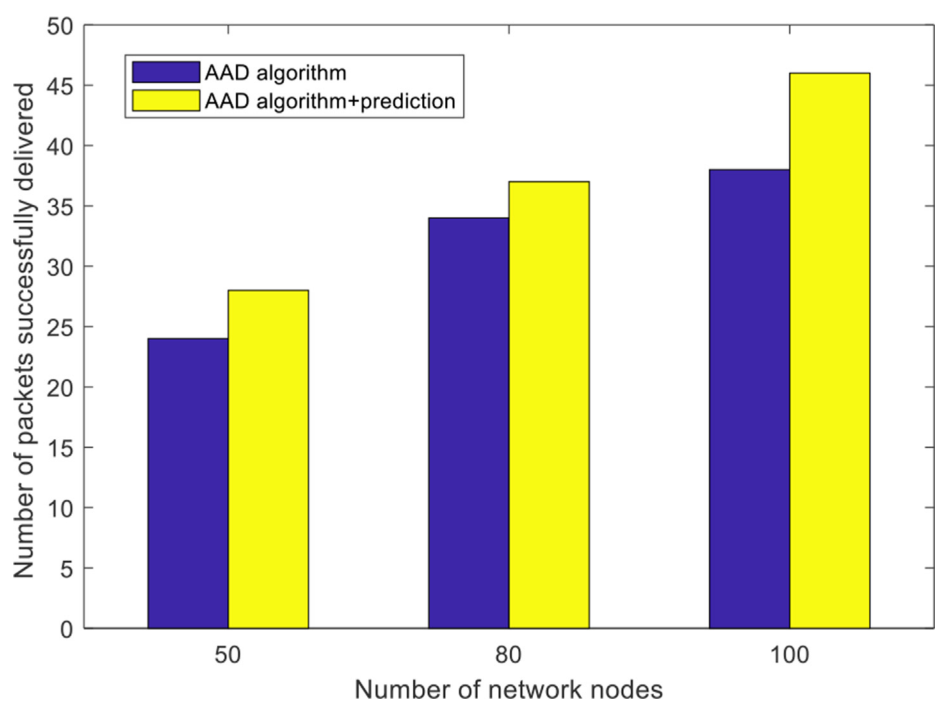

Fig. 11. Comparison of the number of packets successfully delivered by the original AAD algorithm and the AAD algorithm incorporating link failure prediction mechanism.

fully delivered after repairing by the AUVs is 42. Compared with the original AAD algorithm, the packet delivery ratio has increased by 25%. When the number of sensor nodes is 80, the packet delivery ratio increases by 23.5%. When the number of sensor nodes is 100, the packet delivery ratio increases by 36.8%.

Fig. 13 shows the comparison of the average residual energy of the two algorithm nodes when trying to transmit 80 packets. It can be seen from the figure that the introduction of the link failure prediction mechanism and the repair mechanism, the average residual energy of the sensor node is higher than that of the original AAD

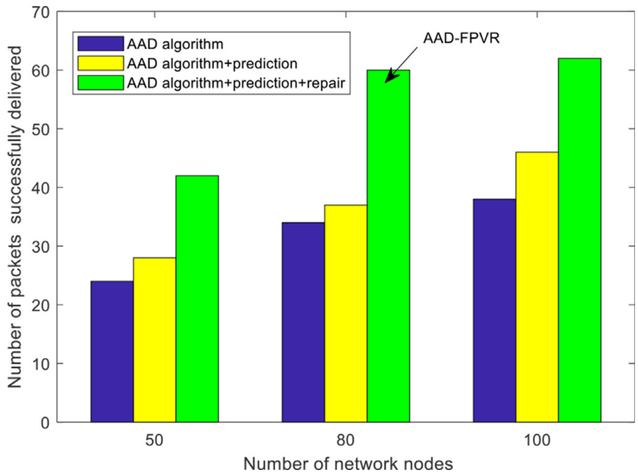

Fig. 12. Comparison of the number of packets successfully delivered between the algorithm with the repair mechanism and the original ADD algorithm.

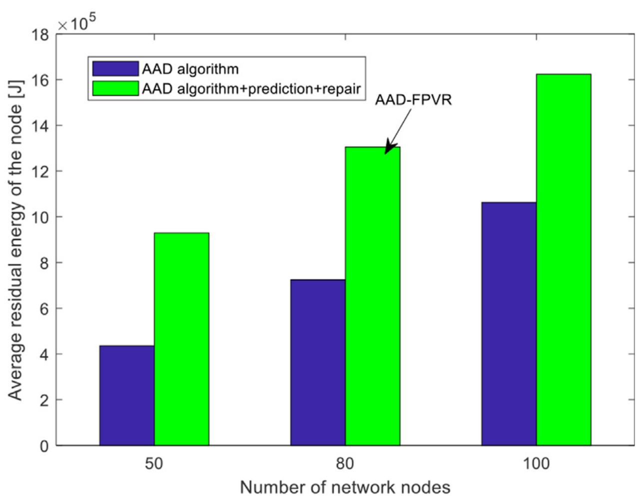

Fig. 13. Comparison of average residual energy of nodes between AAD-FPVR algorithm and the original AAD algorithm.

algorithm, which means that the proposed ADD-FPVR algorithm can effectively extend the lifetime of the network.

4.3. C. Complexity analysis of AAD-FPVR routing algorithm

The proposed AAD-FPVR routing algorithm includes three steps: AAD algorithm routing, link failure prediction, and AUV-assisted routing repair. Therefore, it should be analyzed for its complexity for reference in practical applications. We next analyze the complexity of AAD-FPVR routing algorithm, mainly the running time of the algorithm.

1) AAD algorithm: The original AAD algorithm is used for optimal routing design. First, the artificial fish school algorithm (AFSA) is used for global selection, and then the ant colony algorithm (ACOA) is used for local optimization to obtain the global energy optimal routing. If the number of artificial fish is N_{fish}, the number of ants is N_{ant}, and the AAD algorithm converges in N_{iter} iterations, then the running time of the AAD algorithm is $O(N_{fish}N_{ant}N_{iter})$.
2) Link failure prediction: If the number of routing hops designed by AAD algorithm is N_{hop}, then failure prediction is performed for each hop after the routing path is determined, and the total running time is $O(N_{hop})$.
3) AUV-assisted routing repair: After completing a certain packet transmission, the proposed algorithm uses AUVs to perform auxiliary repair after the death of a node, and use the PSO algorithm to calculate the optimal repair position. If the number of particles is $N_{particle}$, and the number of iterations required for the convergence of PSO algorithm is N_{iter_p}, then the running time is $O(N_{particle}N_{iter\_p})$.

In summary, it can be obtained that running time of the AAD-FPVR routing algorithm is $O(N_{fish}N_{ant}N_{iter} + N_{hop} + N_{particle}N_{iter\_p})$. However, the AUV-assisted routing repair step is needed when the dead node appears. $O(N_{particle}N_{iter\_p})$ is much less than $O(N_{fish}N_{ant}N_{iter})$ or $O(N_{hop})$, hence can be ignored. Therefore, the running time of the AAD-FPVR routing algorithm can be recorded as $O(N_{fish}N_{ant}N_{iter} + N_{hop})$, which does not significantly increase the complexity Compared with the original AAD algorithm.

5. Conclusion

Based on the AAD algorithm, we introduce the link failure prediction mechanism and the AUV-assisted routing repair mechanism, which is called the AAD-FPVR routing algorithm. The proposed algorithm considers node drifting information, uncertain ocean ambient noise, and node residual energy to predict link failure. When a certain number of packets are transmitted, and some nodes die and cause energy holes, AUVs are used to assist in repairing. The simulation results show that compared with the existing algorithms, the proposed scheme can further effectively increase the number of packets delivered, save system energy consumption, and extend network lifetime of UASNs.

CRediT authorship contribution statement

Yougan Chen: Conceptualization, Methodology, Writing – review & editing. **Jianying Zhu:** Writing – original draft. **Lei Wan:** Writing – original draft. **Xing Fang:** Writing – review & editing. **Feng Tong:** Conceptualization, Writing – review & editing. **Xiaomei Xu:** Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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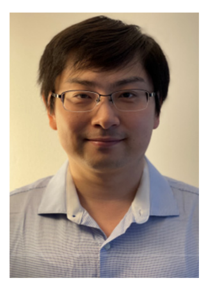

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