Optimizing the Waiting Time of Sensors in a MANET to Strike a Balance between Energy Consumption and Data Timeliness

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***Abstract*—Oceans are important for scientific research and also for global economic and military security. Usually, wireless ad hoc networks are chosen to transform real-time data collected by ocean monitoring sensors (nodes). Due to the random motion of waves or the random direction of the wind, nodes in the network might become detached from the coverage of the network. In this case, the detached nodes can either send the collected data directly to the base station at the cost of consuming more energy or wait for a period of time to rejoin the network with the price of sacrificing the real time of the collected data. In this paper, we model the optimal waiting time for detached nodes before directly sending the data in the dynamic environment of ocean monitoring. For this purpose, we need to address two problems. The first is how to calculate the rate of coverage with a different number and different broadcast radii of nodes. The second is when a node detaches from the coverage of the network, how much time will it need to wait before it rejoins the network. We first establish the motion model of nodes, which is the basis to deduce the probability distribution of a certain time when the detached node rejoins the network. Based on the probability distribution, the waiting time of the detached nodes can be optimally determined, aiming to achieve a good balance between energy consumption and data timeliness. Finally, a series of simulations is conducted to validate the effectiveness of our proposed method.**

***Index Terms*—delay tolerant network, waiting time, mobile ad-hoc network, ocean information collection**

I. Introduction

The real-time observation of oceans is a very important research topic. In this scenario, various sensors (nodes) are widely used to collect ocean data for different applications [1] [2]. The collected data is usually communicated between sensors and gathered by one or more head nodes which send all the data to the base station or the satellite.

However, the randomness of the ocean environment makes it challenging to provide stable communications between nodes. To deal with this dynamic, it is effective to use a mobile ad-hoc network (MANET) to build up the connections between nodes when the communication environment is mobile [3], but the frequent reorganization of the network caused by the changing ocean conditions is catastrophic to the energy consumption of the whole network. In addition, a delay tolerant network (DTN) can support an intermittent connectivity demand, which means that each node can save the collected data temporarily and wait until the node moves into the network and the connection is rebuilt [4].

The movement of nodes in the ocean can be simulated as a random walk in two dimensions, which can represent the changing ocean conditions to some extent [5]. If a node moves out of the network and back in, there are actually two possibilities. One is that the node returns to communicate with the original head node, and the other is that it may build up connections with other head nodes in the network. We can easily see that with a different number and various broadcast radii of nodes, the proportion of the effect of the two possibilities on the result, namely the time spent to rejoin the network, changes as well.

Therefore, when a node is detached from the network, there are two actions that can be taken. The first is that the node can directly send the collected data to the base station but at the cost of consuming more energy. The second is that the node waits for some time to rejoin the network and sends the data to a head node, which may affect the real time of data. In the dynamic ocean environment, each detached node needs to make a decision as to how long it should wait before directly sending the data in order to strike a balance between energy consumption and data timeliness.

In this paper, we model the relationship between the re-joining time and the number and broadcast radius of the nodes in the network, which is utilized to optimally determine the waiting time for nodes when they are detached from the network. In addition, based on the timeliness model of data, this paper proposes a way to determine the maximum waiting time before the detached node gives up waiting to rejoin the network and sends the data directly to the base station.

The main contributions of this paper are summarized as follows:

- We build a random walk model to mimic the motion of nodes, and simulate the time spent on restoring a

connection with the original cluster for detached nodes. A formula (model 1) is provided to calculate the possibility that a node rejoins the original cluster in a designated time.
- We use statistic results to represent the coverage rate of the network with a different number and broadcast radius of nodes. A relationship (model 2) is discovered between the coverage rate and these two variables.
- We introduce a new concept, called equivalent scale, to describe the shape and size of the areas that are not covered by the network. We calculate the proportion of model 1 and model 2 in the effect of rejoining time, and build up the relationship between this proportion and the equivalent scale.
- We choose exponential decay characteristics as the model of data timeliness [6] and propose a method to optimally determine the waiting time under consideration of both energy consumption and data timeliness.

The rest of the paper is organized as follows. Section II briefly introduces the background knowledge. Section III reviews the related work. Section IV provides details on three proposed models and determines the optimal solution to the waiting time. Section V presents the simulation results. Section VI concludes the paper.

II. Background

To ensure this paper is self-contained, we briefly introduce the background knowledge of wireless sensor networks.

A. Basic Terms

A mobile ad hoc network (MANET) is a continuously self-configuring, infrastructure-less network of mobile devices connected by a wireless link [7]. In a MANET, sensors (nodes) are divided into different groups and the group to which nodes belong may adjust dynamically according to the clustering rules and their positions [8]. In a cluster, nodes can act in different roles which means they are assigned different functions and the role of nodes also changes over time. In the ocean scenario, there are three roles which nodes can perform.

- Slave node: Sends the collected data to a head node.
- Head node: Gathers the data sent by the slave nodes and forwards the gathered data to a gateway node.
- Gateway node: Sends the gathered data to a base station or satellite.

B. The Network Protocol

Many routing protocols have been proposed for MANETs [9], but this is not our main point, so we do not discuss this in detail. After the network has been built and the nodes start to work, the head node of a cluster will broadcast its identity to the slave nodes at intervals, in order to let the slave nodes know whether they are still in the network or not. If a slave node does not receive the information from the head node, it moves out of the network and it waits until it finally receives the broadcast from the head nodes. During the waiting time, the slave node can choose to send data directly to the base station or continue waiting. Our later work is to propose a method to optimally determine the waiting time for the detached slave nodes with the aim of balancing between energy consumption and data timeliness.

III. Related Work

Current work related to this paper includes mobile ad hoc networks and delay tolerant networks, which are discussed in the following two subsections.

A. Mobile Ad hoc Networks

The mobile ad-hoc network (MANET) is a kind of wireless sensor network. There are many routing protocols or algorithms for different networking purposes [10] [11] [12], including the consideration of energy consumption. In addition, the influence of the number of nodes and broadcast radius to connectivity has been studied frequently [13], and several studies have investigated the coverage of MANETs [14], focusing on the design of node deployment to improve coverage. However, when the motion of nodes is random, deployment becomes meaningless, so we propose a model to calculate the coverage of nodes in MANETs with random distribution.

B. Delay Tolerant Networks

The delay tolerant network (DTN) was firstly proposed because of the unstable communication in mobile or extreme environments [15]. Of the different alternatives, the spray and wait routing protocol is widely used in DTN [16]. In most works, when a DTN node is waiting, there are often two strategies. One is to wait until the connection is rebuilt, and the other is to abandon the information if no connection is rebuilt after waiting a certain time [17]. But it is the best of authors' knowledge that few studies have focused on the optimal waiting time of nodes in different situations, and no research has proposed that the waiting node can increase the transmit power to enlarge the broadcast radius to build up the connection with base stations, instead of just waiting or abandoning the information.

Different from existing works, in our scenario, when a node detaches from the network and loses its connection with the head node, it has two choices. The first is to change itself into a head node or even a mobile ad-hoc network and send data directly to the base station on its own. The other is to wait for the connection request from the head node of the network and rebuilding the connection. This decision is basically whether to split a new small mobile ad-hoc network from the original one or to change part of it into a delay tolerant network. Of course, there are many advantages of this MANET-DTN combination and many research studies have contributed greatly to its development and refinement, some of which is strongly related to our work. [18] shows the protocols to switch between MANET and DTN; [19] shows how to select nodes in MANET-DTN to build a stable connection. Many studies have contributed significantly to the basic theory

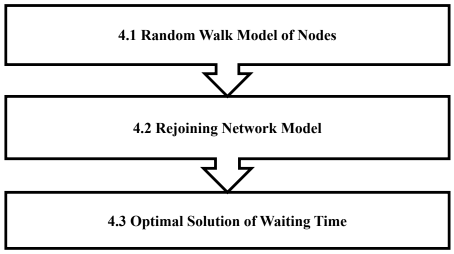


Fig. 1. Whole framework

of this hybrid network, and our paper can be seen as a way of implementing this network application.

It should be noted that no matter which strategy is chosen, either waiting or sending, the decision making is always based on data timeliness, energy consumption and other costs. The core is to compute the optimal waiting time for detached nodes for a given optimization objective. This paper provides a method to calculate the waiting time for detached nodes and comprehensively considers energy consumption and data timeliness.

IV. Optimal Solution to Waiting Time

Aiming to strike a good balance between energy consumption and data timeliness, we propose a method to find the optimal waiting time of detached nodes before they directly send data to the base station. As shown in Fig. 1, we first establish the motion model of nodes, which is the basis to deduce the time probability distribution when the detached node rejoins the network. Based on the probability distribution, the waiting time of the detached nodes can be optimally computed.

A. Random Walk Model of Nodes

To simulate the motion of nodes in the dynamic ocean environment, we introduce a two-dimensional random walk model, which can distinguish different ocean conditions by the changing parameters. The model is that, in each time interval, the node chooses a random direction and moves a step towards the direction. For example, assume that the time interval is 1, the length of each step is also 1, and the number of steps is 100. Fig. 2(a) shows the scatter plot of nodes originally located at the origin (0, 0) by repeating 10,000 simulations, which can reflect the probability distribution to some extent.

There are two ways to simulate the motion speed of nodes. One is to change the number of steps N, and the other is to vary the length of each step l. Suppose the maximum displacement of nodes is d_{max}, which is equal to the product of N and l, $d_{max} = N * l$. We can see that d_{max} can be seen as a parameter to measure the motion speed, but a same d_{max} with different N and l can cause different probability distribution, such as shown in Fig. 2(b) and Fig. 2(c), which respectively depict the probability distribution for $N = 1,000$, $l = 1$ and $N = 100$, $l = 10$.

This can be explained by the difference of variance of the two probability distributions. Assume that the variance in Fig. 2(a) is D_1, where each step is recorded as a random variable X_i, and Y_1 represents the whole random walk, we have

$$Y_1 = \sum_{i=1}^{N} X_i.$$

For Fig. 2(b), N is increased 10 times, so the formula changes to

$$Y_2 = \sum_{i=1}^{10N} X_i = \sum_{i=1}^{10} Y_1 i.$$

As the variance of Y_1 is D_1, so the variance of Y_2 is $10D_1$. For Fig. 2(c), l is increased 10 times, so the formula changes to

$$Y_3 = \sum_{i=1}^{N} 10X_i = 10Y_1.$$

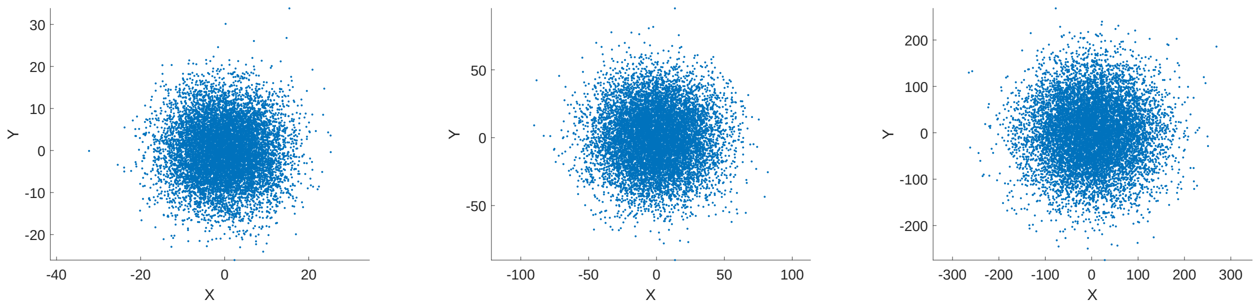
so the variance of Y_3 is $(10D_1)^2 = 100D_1$.

In this paper, the model in Fig. 2(b) is used to describe different motion speeds. That is, the length of each step l is constant, but the number of steps N is changing, considering the factor that influences the speed of the nodes is mostly the ocean condition. When the ocean condition is rough, the direction of the waves or the wind may change more frequently and the force can be stronger, making the node move in the same distance in a shorter time compared with a calm ocean condition. We assume that in a certain time interval, the node goes through a whole random walk process: moves N steps and the length of each step is l, which means that the node moves l with $1/N$ time intervals. Therefore, changing N can better reflect the different motion speeds of nodes in a dynamic ocean environment.

B. Rejoining Network Model

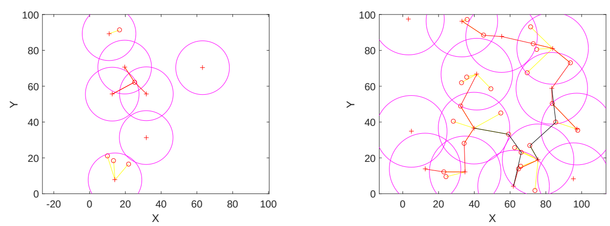
To calculate the rejoining time probability distribution of the detached nodes, we first assume two extreme conditions, shown in Fig. 3, which compares networks with low and high values of n and r, where n denotes the number of nodes and r represents the broadcast radius of nodes. We can see that if n and r have small values, the coverage of networks is low as well, and vice versa. From Fig. 3(a), if a node leaves a cluster, its surroundings are probably empty without any other clusters, so the time probability distribution of nodes to rejoin the network in this condition is similar to that of rejoining the original cluster of the node, which will be discussed in section IV-B1. Simultaneously, from Fig. 3(b), if n and r are large, because the scale of the uncovered area is much smaller than the motion range of the node, then whether the node can rejoin the network is equivalent to scattering a node in the area to observe whether the node is covered by the network, which will be discussed in section IV-B2.

After analyzing the two extreme models (or we can see them as two factors), we can infer that when calculating the normal conditions where n and r are neither too low nor too high, it can be seen as the sum of the two models after each of which is multiplied by a given weight that is determined by the coverage of the network, and this relationship will



(a) $N = 100$, $l = 1$ (b) $N = 1000$, $l = 1$ (c) $N = 100$, $l = 10$

Fig. 2. Motion model of nodes



(a) Low coverage rate (b) High coverage rate

Fig. 3. Networks with different coverage rate

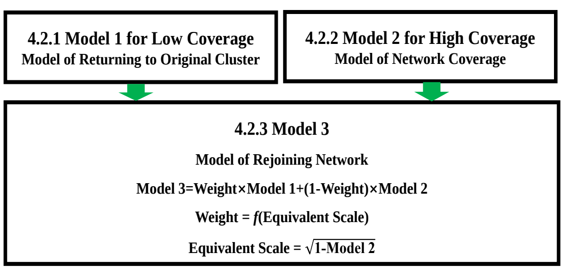


Fig. 4. Framework of the rejoining network model

be discussed in section IV-B3. The framework to build the rejoining network model for detached nodes is depicted in Fig. 4.

Of course, directly calculating the rejoining time probability distribution seems a simple solution to this problem, but it has several disadvantages. Firstly, the simulation time might be much longer by considering a large number of combinations of n and r. Secondly, the simulation may not directly build specific relationships with n or r of networks easily. Thirdly, the results can be discrete because there are still many differences between networks with the same n and r. Therefore, we choose to use an extreme condition weighting method to calculate the rejoining time of detached nodes.

1) Rejoining the Original Cluster:

In cases where the network coverage is low, when a node moves out of the cluster, the following will show how many time intervals have passed before the node is detected to rejoin the original cluster. Based on the motion model of nodes described in section IV-A, a series of simulations is conducted where the number of steps N varies from 1 to 100 to represent different motion speeds. 100,000 nodes are accounted for in each speed, and the results are shown in Fig. 5.

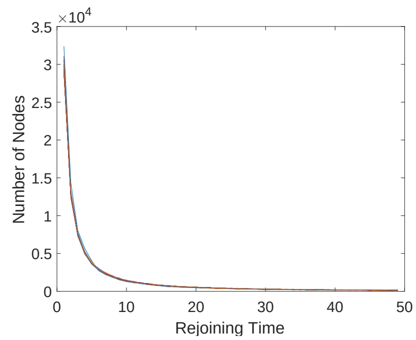
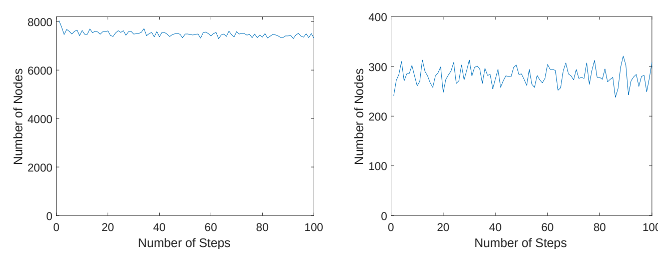


Fig. 5. Rejoining time with different motion speed



(a) $t = 3$ (b) $t = 30$

Fig. 6. Probability distribution for a certain rejoining time

This figure shows the number of rejoined nodes in different time intervals ranging from 1 to 49, where different curves indicate different motion speeds. However, in this figure, we cannot distinguish between different curves, because the rejoining time probability distribution has little relevance to the node speed, which can also be seen in Fig. 6, which respectively represents the number of rejoined nodes with different speeds for 3 and 30 time intervals.

Fig. 6 shows that the probability distribution has little relevance to the speed. Of course, this conclusion is not to say that no matter how fast the node moves, the time that a detached node takes to rejoin the original cluster does not change any more. When the speed is quite fast (N is much larger than 100), this conclusion may not be effective. However, the speed cannot reach such a high level in the real condition, so we can consider that the probability distribution has no relevance with the speed in this paper.

Data fitting is used to express the probability distribution of the rejoining time more specifically. After we know that speed

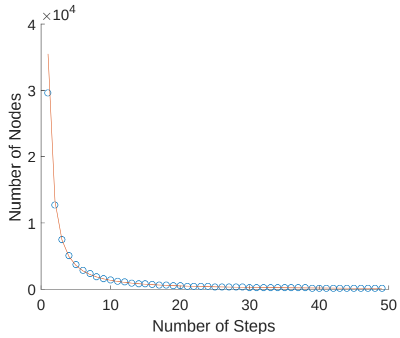


Fig. 7. Fitting of the rejoining original cluster model

is not one of parameters influencing the results, the fitting data is the average of different speeds for a certain rejoining time. The target function is

$$num = At^p$$

where num is the number of rejoined nodes, and t is the rejoining time. The fitting results are

$$A = 35496.9,\ p = -1.4210,$$

and the determination coefficient is 0.97, which means the relationship is very clear. Fig. 7 shows the fitting results. Dividing parameter A by the total number of nodes, namely 100,000, gets

$$prob = 0.354969t^{-1.4210} \qquad (1)$$

where $prob$ represents the probability that a detached node rejoins the original cluster in a certain time t.

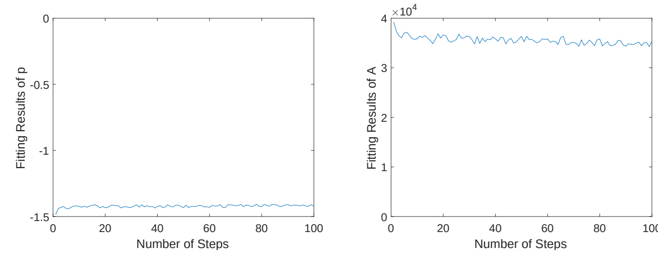
To reach a conclusion, parameters A and p are also calculated with different speeds (number of steps N), and the results are shown in Fig. 8. We can see that even if the speed changes, the fitting results of A and p do not show much difference. Thus, the conclusion is effective.

2) Network Coverage Model:

In this section we discuss the other extreme case where n and r have large values. It is apparent that as n and r increase, the coverage rate increases as well. Suppose the nodes are scattered in a 100*100 area, the number of nodes ranges from 10 to 50 and the broadcast radius also ranges from 10 to 50. We use a statistical method to calculate the coverage rate of the network. With a given n and r, we first generate 100 networks. Then, in each network, we randomly scatter 1,000 nodes, count the number of nodes in the network and calculate the average number for different networks with the same n and r. The quotient of the average number divided by 1,000 is seen as the coverage rate of the network.

Fig. 9 shows part of the simulation results. Fig. 9(a)- 9(d) show the relationship between the coverage rate and n (r) with constant r (n). From Fig. 9, we can see that the relationship between coverage rate and both the number of nodes and the broadcast radius can be described by the function

$$Cov = 1 - e^{ax+b}$$



(a) p (b) A

Fig. 8. Fitting results of parameters

where Cov represents the rate of coverage and x is either the number of nodes or the broadcast radius. Taking a logarithm of the two ends of the equation gets

$$ln(1 - Cov) = ax + b$$

Then, the binary function should be introduced to let n and r be expressed in a whole equation

$$ln(1 - Cov) = krN + sN + mr + t$$

where k, s, m, and t are the parameters waiting to be fitted. The fitting results are

$$k = -0.007137156,\ s = -0.023377563$$
$$m = -0.05977249,\ t = 0.514174569$$

and the determination coefficient is 0.996, which means that the fitting results are excellent. The function of the coverage rate to the number of nodes and the broadcast radius is expressed as

$$Cov = 1 - e^{krN+sN+mr+t} \qquad (2)$$

where k, s, m and t are shown above.

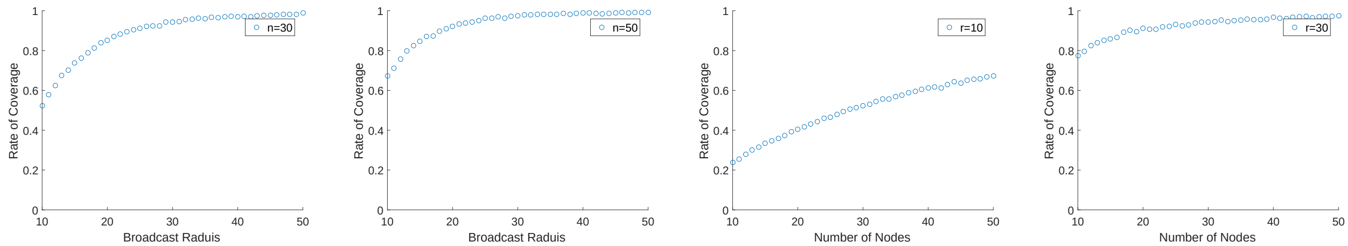
To better reveal the fitting results, Fig. 10 makes a comparison between the scatter plot of the simulation data and the surface of the fitting function. From this, we can see that the two are very similar, which proves the effectiveness of the fitted function.

3) Rejoining Time Calculation:

In this subsection we discuss the calculation of the weight of the two proposed models when they are synthesized to a general model. First, we need to identify the reason why the coverage of networks can influence the weights of the two models proposed in section IV-B1 and IV-B2. As the coverage rate increases, the uncovered area becomes smaller and more crowded, which means that the detached node can only move in a shorter distance to rejoin the network. Obviously, the distance is directly related to the rejoining time of the node. So, we create the concept equivalent scale to describe the distance the node will move, which is defined as

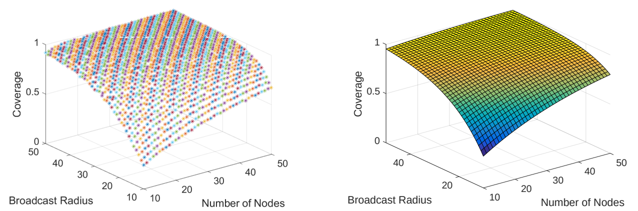
$$L = \sqrt{1 - Cov} \qquad (3)$$

where L is the equivalent scale, and Cov is the coverage rate of network. $1 - Cov$ means the uncovered area, and its square root reflects the distance the detached node moves before it rejoins the network, as explained above.



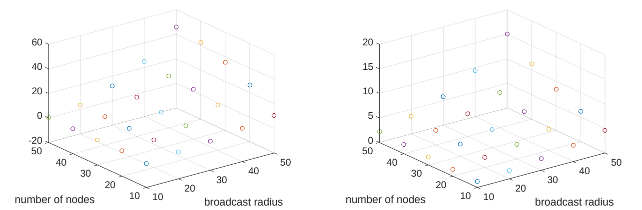
(a) $n = 30$ (b) $n = 50$ (c) $r = 10$ (d) $r = 30$

Fig. 9. Part of the simulation results



(a) Simulation results (b) Fitting results

Fig. 10. Comparison between simulation and fitting



(a) K (b) $\frac{1}{L}$

Fig. 11. Comparison of K and $\frac{1}{L}$

Now, we have two models. The first is Equation (1), characterizing the probability distribution of a detached node rejoining the original cluster in a certain time t. The second is Equation (2), modeling the relationship between the coverage rate of networks and the number or broadcast radius of nodes. Based on these two models, the probability of a detached node rejoining the network can be generalized as

$$PROB = W * prob + (1 - W) * Cov$$

where W is the weight of the first model, and $1 - W$ is the weight of the second model. From the equation above we can get W

$$W = \frac{PROB - Cov}{prob - Cov}$$

and the ratio of the two weights

$$K = \frac{1 - W}{W} = \frac{prob - PROB}{PROB - Cov} \tag{4}$$

From the analysis above, the larger the equivalent scale, the fewer the existing clusters surrounding the detached node. In this case, the weight of the first model becomes larger, and the ratio defined in Equation (4) becomes smaller. Therefore, we assume that the ratio is highly related to the equivalent scale, and obviously, they are negatively correlated.

With the given number of nodes $\{10, 20, 30, 40, 50\}$, and the broadcast radius $\{10, 20, 30, 40, 50\}$, 10 networks are constructed in each condition to calculate the rejoining time of the detached nodes, and the whole process is repeated 2,000 times. It is worth noting that if a node reaches the boundary of the 100*100 area, its movement will meet the reflection law. Fig. 11(a) and Fig. 11(b) respectively show the ratio of weights K and the reciprocal of the equivalent scale when the rejoining time is set to 1.

The linear relationship is obvious, so the fitting equation is

$$K = \frac{a}{L} + b \tag{5}$$

where K is the ratio of weights and L is the equivalent scale. The fitting results are

$$a = 3.8250, \ b = -5.30412$$

Fig. 12 shows the fitting results, and the correlation coefficient is 0.87, so they are highly correlated.

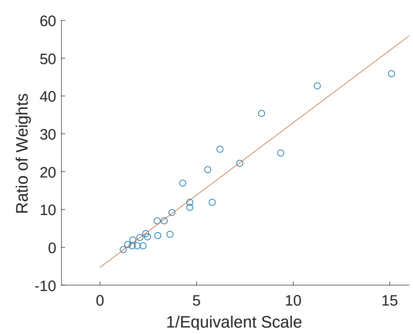


Fig. 12. Fitting results of equation (5)

After discussing the probability when the rejoining time is equal to 1, this paper also discusses the probability when $t > 1$. When $t > 1$, this means the distance between the boundary and the detached node becomes larger and the influence of the shape of the uncovered area reduces. That is, if the node has not rejoined in a short time, the probability distribution of the rejoining time has little relationship with the rate of coverage. So, we assume that when $t > 1$, the probability of the rejoining time conforms to the probability distribution of the detached node rejoining the original cluster, which is modelled in Equation (1).

It should be noted that when $t > 1$, $PROB$ divided by the whole $t > 1$ probability $(1 - PROB_{t=1})$ is equal to $prob$ divided by $(1 - prob_{t=1})$, instead $PROB$ is directly equal to $prob$ when $t > 1$. This means $PROB_{t=i}$ is equal to $prob_{t=i}$ under conditions where the detached node has not rejoined when $t = 1$. Here is an example: If $PROB$ is 0.8 and $prob$ is 0.354969 when $t = 1$; when $t = 2$, $prob$ is 0.132564, and $PROB$ is calculated as below:

$$PROB_{t=2} = 0.132564 * \frac{1 - 0.8}{1 - 0.354969}$$

To sum up, when $t > 1$, the probability can be written as

$$PROB = prob * \frac{1 - PROB_{t=1}}{1 - prob_{t=1}} \tag{6}$$

C. Optimal Solution of Waiting Time

Considering energy consumption and data timeliness, this part proposes a method to get the optimal solution of waiting time as a reference. The data timeliness conforms to the exponential decay model, where $Value$ represents the value of data with time t.

$$Value = Ae^{-at}$$

Assume that the time the detached node decides to send data directly to the base station is T, and sending data collected in one time interval to the head node is assumed to be 1. At the same time, data is continuously collected during the waiting time, so if the node has waited for T, then the energy consumption of sending all this data to the head node is T, and to the base station is M times that to the head node, which is MT. Of course, the timeliness of data is the sum of all the values of data which have not been sent in T, which is

$$Value_T = \sum_{i=1}^{T} Ae^{-ai}$$

After comprehensively considering both the timeliness of data and energy consumption, the whole profit P_T for waiting time T can be seen as

$$P_T = Value_T - E_T$$

where $Value_T$ and E_T respectively represent the timeliness of data and the energy consumption when the waiting time is T. Then we can get the expectation of the whole profit when the waiting time is T

$$E(P_T) = \sum_{i=1}^{T} PROB_{t=i}(Value_i - i) + (1 - \sum_{i=1}^{T} PROB_{t=i})(Value_T - MT) \tag{7}$$

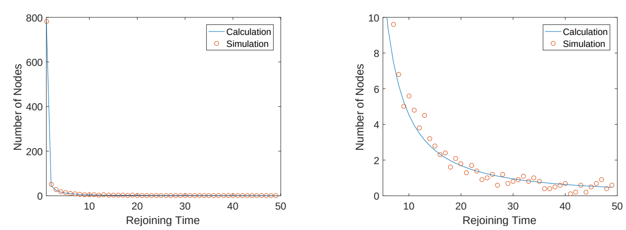
V. SIMULATIONS

A. Simulation of Rejoining Network Model

To prove the effectiveness of the rejoining network model detailed in section IV-B, the simulation assumes that the number of nodes is 25, and the broadcast radius is 25 as well. In this condition, the rate of coverage $Cov = 0.8661$ and the equivalent scale $L = \sqrt{1 - Cover} = 0.3659$. We calculate the probability distribution of the rejoining time and compare it with the simulation results. The simulation is repeated 1,000 times in MATLAB R2016a, and the results are compared with the 1000 corresponding calculation results, as shown in Table I. Fig. 13(a) compares the calculation curve and the simulation scatter plots, and Fig. 13(b) shows the partial enlargement of Fig. 13(a) ranging $RejoiningTime$ from 5 to 49.

TABLE I
COMPARISON RESULTS

t	Calc	Simu	t	Calc	Simu
1	782.9	780.8	26	1.165325	1.2
2	44.60266	51.1	27	1.104476	0.6
3	25.06889	28.8	28	1.048849	1.2
4	16.65701	19.3	29	0.997831	0.7
5	12.13076	14.4	30	0.9509	0.8
6	9.36206	11.2	31	0.90761	0.9
7	7.520384	9.6	32	0.867573	1.1
8	6.220617	6.8	33	0.830455	0.8
9	5.261938	5	34	0.795963	1
10	4.530273	5.6	35	0.763842	0.8
11	3.956447	4.8	36	0.733869	0.4
12	3.496293	3.8	37	0.705846	0.4
13	3.120404	4.5	38	0.679598	0.5
14	2.808513	3.2	39	0.65497	0.6
15	2.546236	2.8	40	0.631825	0.7
16	2.32311	2.3	41	0.61004	0.1
17	2.131358	2.4	42	0.589504	0.2
18	1.965088	1.6	43	0.570119	0.6
19	1.819766	2.1	44	0.551795	0.2
20	1.691846	1.8	45	0.534453	0.5
21	1.578522	1.3	46	0.518019	0.7
22	1.477548	1.7	47	0.502427	0.9
23	1.387104	1.4	48	0.487619	0.4
24	1.305702	0.9	49	0.473539	0.6
25	1.232116	1			



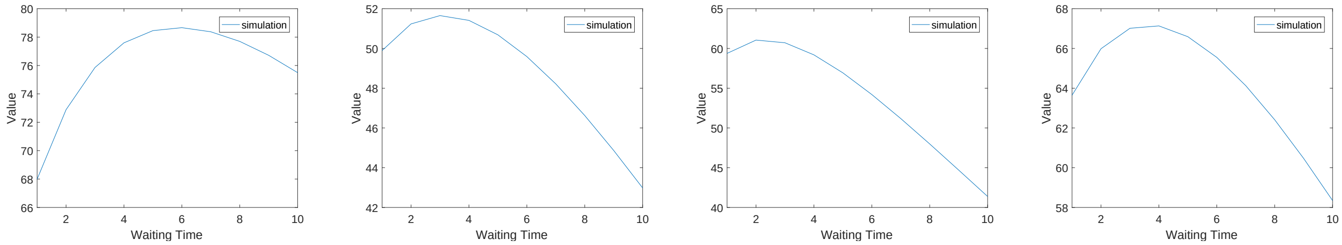
(a) *Comparison* (b) *Enlargement*

Fig. 13. Simulation results of rejoining network model

B. Simulation of Waiting Time Decision

From the relationship in Equation (7), let $n = 25$ and $r = 25$ as an example, and we undertake a simulation to verify the method to compute the optimal waiting time for the detached nodes. Assume the parameters A, a, M and *the prediction of waiting time* are shown in Table II.

The simulation is repeated 1000 times for each case. The average profits of different T from 1 to 10 are respectively shown in Fig. 14. From the results, we can see that $T = 6, 3, 2$ and 4 are all optimal solutions of the waiting time in those conditions which conform to the prediction results in Table II.



(a) $A = 100,\ a = 0.1,\ M = 100$ (b) $A = 80,\ a = 0.1,\ M = 100$ (c) $A = 100,\ a = 0.2,\ M = 100$ (d) $A = 100,\ a = 0.1,\ M = 120$

Fig. 14. Simulation results of optimal waiting time

TABLE II
SIMULATION PARAMETERS

A	a	M	Prediction
100	0.1	100	6
80	0.1	100	3
100	0.2	100	2
100	0.1	120	4

From the results, we can draw several conclusions:

- As A decreases, the optimal waiting time becomes shorter because a decrease in A means more energy consumption, so the data should be sent earlier to prevent accumulating.
- As a increases, the optimal waiting time becomes shorter, which means the value of the data decreases rapidly, so it should be sent earlier.
- From the rejoining time probability distribution, we can see that if the node has not rejoined in $T = 1$, then its rejoining probability is much lower later. So, after $T = 1$, if M increases, the data should be sent more quickly, because once the node has not rejoined after a long time, then the energy consumption will be huge because of the accumulation of data.

VI. CONCLUSION

In this paper, we propose a method to characterize the rejoining time probability distribution of a node that moves out of the network. Then, considering the timeliness of data as well as the energy consumption, we use the probability distribution to compute the optimal waiting time for a detached node before the node sends data directly to the base station or satellite instead of continuing to wait to rejoin the network and send data to the head node. This paper utilizes a new strategy to calculate the waiting time of the delay tolerant network, which is to separately calculate the simple factors influencing the waiting time, and to endue them with proper weights.

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