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A Multi-layer Information Dissemination Model and Interference Optimization Strategy for Communication Networks in Disaster Areas

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***Abstract*—The communication network in disaster areas (CNDA) can disseminate the key disaster information in time and provide basic information support for decision-making and rescuing. Therefore, it is of great significance to study the information dissemination mechanism of CNDA. However, a CNDA is vulnerable to interference, which affects information dissemination and rescuing. To solve this problem, this paper established a multi-layer information dissemination model of CNDA (MMND) which models the CNDA from the perspective of degree distribution of nodes. The information dissemination process and equilibrium state in CNDA is analyzed by an improved dynamic dissemination method. Then, the effects of the node density, node communication range and other parameters on the equilibrium state are clearly formulated. In addition, an interference optimization algorithm for MMND is proposed, which uses the convex optimization method to minimize the network deployment cost. With this algorithm, the optimal node density and communication range are obtained to alleviate the network interference. Simulation results show that the proportion of each state node in equilibrium state are 0.28, 0.38 and 0.34, respectively, which is consistent with the theoretical analysis. And it proves that the MMND can describe information dissemination process of the CNDA. When the dissemination thresholds are 0.1, 0.3 and 0.5, respectively, the optimal node density and communication range gradually decreases with the interference coefficient, and the deployment cost also gradually decreases, indicating that the interference of the CNDA has a significant impact on the information dissemination.**

***Index Terms*—Communication network in disaster areas, dissemination model, interference, multi-layer network.**

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I. Introduction

In recent years, the communication network in disaster areas (CNDA) has attracted more and more attention [1]–[8]. It overcomes the communication interruption of the traditional network when the core node is damaged, provides support for the dissemination of disaster information, and plays a key role in disaster rescue. The CNDA nodes usually comprise of emergency vehicles [9], [10], rescuers and unmanned aerial vehicles (UAVs) [11]. Generally, emergency vehicles have a large communication range to help distribute the disaster information of the CNDA [12]. Rescuers assist in information dissemination [13] and rescue work [14] through portable communication equipment. As a supplement, UAV is introduced into the CNDA to overcome the limitations of complex terrains which are challenging to access by vehicles or rescuers. Its characteristics of flexible networking and high mobility are suitable for completing tasks such as environmental monitoring [15] and disaster investigation [16]. At the same time, as device-to-device communication (D2D) matures gradually [17], [18], it has been widely used in the CNDA [19]–[22], allowing devices to establish connections without a base station under low power consumption. D2D communication not only overcomes the obstacle of damaged network infrastructures, but also ensures the endurance capacity of various equipment in disaster areas. As the working environment of CNDA is usually sophisticated, there exists significant interference in the channels. Affected by the interference, important disaster information may be distorted or lost during the transmission process. Therefore, it is of great significance to study the information dissemination and interference optimization of the CNDA under a severe interference impact.

At present, the research on information dissemination in the network is usually based on the dynamic dissemination model [23], [24]. Chen *et al.* proposed an interference aware flooding scheme, and analyzed the information dissemination dynamics between user devices under this scheme through the dynamic

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dissemination model and random geometry [25]. In [26], a dynamic dissemination model based on heterogeneous networks is proposed, which combines two methods to describe the dissemination of potential rumors in the network. Another team of researchers proposed a group-based continuous time Markov general dynamic dissemination modeling framework to analyze the critical dynamic characteristics of random epidemics propagating on large complex networks [27]. Kim *et al.* modeled the spatiotemporal dissemination characteristics of information under V2V communication and analyzed the dissemination characteristics of the information flow [28]. The authors of [29] established a model that includes contact strengths and periodic incidence rate to explore the dissemination of disease on the weighted interconnected network. Marialisa et al. shaped the D2D data dissemination process as a social contagion dynamic of two co-evolving spreading processes, weigh the dynamic interactions by the concepts of homophily and awareness, and analyze the effect of homophily, awareness and network heterogeneity on information diffusion [30]. In [31] a novel intelligent information diffusion phenomenon in heterogeneous social networks is proposed, which introduces a new type of uncertain psychological state into classic susceptible-infected-recovered model. Prasse *et al.* proposed a general compartmental epidemic model in discrete time [32], which describes the viral spread between groups of individuals. The above research attempts use the dynamic dissemination model to effectively analyze the information dissemination in the network, but they do not consider the dissemination range of information in the network, nor do they layer the network to provide robustness or easy controlling.

There are also some research on the dynamics of information dissemination in multi-layer networks. Gao *et al.* studied the dynamics of epidemics in two-layer networks based on SIR model and micro-Markov chain method [33]. In [34], the authors studied the cross-dissemination problem in multi-layer social networks and proposed a new SIR model to analyze the rumor dissemination in the network. Authors of [35] proposed a SIHR rumors dissemination model to study the dissemination dynamic of rumor in multi-layer social networks. In [36], the dissemination dynamic of the double virus transmission on double-layer networks is investigated. Yang *et al.* proposed a dual virus competitive dissemination model based on a continuous time double-layer network [37]. Petrov *et al.* proposed a novel notion of exact and approximate role equivalence for multi-layer networks to obtain non-trivial partitions over nodes and layers and provide a fine-grained hierarchy of role equivalences [38]. Authors of [39] concentrated on stability of complex-valued multi-layer networks via time-varying hybrid intermittent pinning control, proposed a novel strategy to achieve stability for a portion of nodes in the networks. The above papers analyzed the information dissemination in multi-layer networks. However, in practical applications, the deployment of a CNDA needs to consider not only the network information dissemination process, but also the impact of the interference on the information dissemination results, providing insights on the correlation between the spatial distribution of nodes, connections, interference and information dissemination in the network.

TABLE I
LIST OF PARAMETERS

Parameters	Definition
λ_1	UAV node density
λ_2	vehicle node density
λ_3	rescuer node density
r_1	communication range of UAV node
r_2	communication range of vehicle node
r_3	communication range of rescuer node
K_1	degree of a node in layer I network
K_2	degree of a node in layer II network
K_3	degree of a node in layer III network
α_k	transition probability from U_k to I_k
β	transition probability from I_k to U_k
γ	transition probability from I_k to B_k
θ_1	probability that neighbor node in state B_k
δ	probability of successful transmission
c_0	power consumption cost of node in unit distance
c_1	cost of deploying a UAV node
c_2	cost of deploying a vehicle node
c_3	cost of deploying a rescuer node
η	path loss

In order to solve the above problems, this paper proposes a multi-layer information dissemination model of a CNDA (MMND) and an interference optimization algorithm for MMND to help deploy a CNDA. Based on an improved dynamic dissemination model, the dissemination process and equilibrium state of disaster information are analyzed. The interference optimization algorithm for the MMND not only meets the requirements of the information dissemination and avoids the impact of interference, but also uses limited resources to design an economic and stable CNDA. The main contributions of this paper are as follows:

1) A multi-layer information dissemination model of a CNDA is established, which considers the communication capability and spatial distribution of nodes in the network and uses the degree distribution of nodes to describe the connection between nodes in the CNDA.

2) Considering the sophisticated deployment scenarios of CNDA, the dissemination dynamic of single and multiple information is analyzed based on the improved dynamic dissemination model, and the correlation between network parameters such as interference in the equilibrium state is proved mathematically.

3) The interference optimization algorithm for the MMND is proposed, and the convex optimization method is used to obtain the best network parameters that help the network alleviate interference, so as to meet the information dissemination requirements of rescue tasks at the least cost possible.

4) According to the specific rescue requirements, numerical experiments of the MMND and the interference optimization algorithm for the MMND are carried out, and the experimental results are analyzed in detail.

II. SYSTEM MODEL

In this section, the components of the CNDA are introduced in detail, and then it is abstracted into a multi-layer information dissemination model. For the sake of clarity, all the symbols and their definitions in this paper is summarized in Table I.

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A. Communication Network in Disaster Areas

The CNDA is shown in Fig.1, including network nodes such as UAVs, emergency vehicles and rescuers. The D2D communication technology is used between nodes. Each node in the CNDA can be regarded as a Poisson point. According to the difference of the communication ability of each node, the nodes are divided into three types: UAV node, vehicle node and rescuer node. The UAV node is deployed in the air, and its node density is λ_1 (nodes/km^2). The UAV is equipped with class A antenna and class B antenna, and their communication ranges are r_1 (m) and r_2 (m), respectively. A vehicle node is an emergency vehicle with a node density of λ_2 (nodes/km^2). An emergency vehicle is equipped with class B antenna and class C antenna, in which the communication range of class C antenna is r_3 (m). The density of rescuer node is λ_3 (nodes/km^2), and the rescuer carries communication module equipped with class C antenna. Only nodes with the same class of antennas and within the communication range can communicate with each other. If a node can communicate with another node, the two nodes are neighbor nodes.

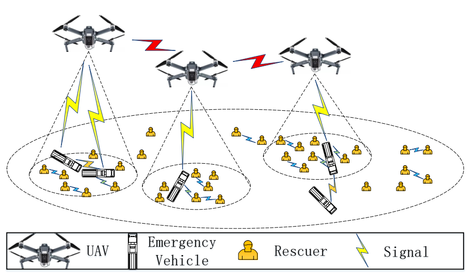

Fig. 1. Communication Network in Disaster Area.

The information transmitted in the CNDA includes UAV's position, terrain, disasters and a rescue plan. The UAV's position information is transmitted between UAVs to avoid the collision. The terrain and disaster information are collected by the UAVs and used by emergency vehicles as the basis for formulating rescue plans. The information is transmitted between the UAVs and emergency vehicles. The rescue plan information needs to be processed by emergency vehicles and rescuers, so it is transmitted between emergency vehicles and rescues.

B. Multi-layer Information Dissemination Model of CNDA

In order to analyze the information dissemination of the CNDA, it is abstracted as a multi-layer information dissemination model of a CNDA, which is shown in Fig.2.

According to the scope of the information dissemination, the whole CNDA is divided into three layers. The layer I network comprises of UAV nodes and transmits the position information of UAVs. The layer II network comprises of UAV nodes and vehicle nodes and disseminates the terrain and disasters information collected by UAVs. The layer III network is composed of vehicle nodes and rescuer nodes, which disseminates the information related to the specific rescue plan.

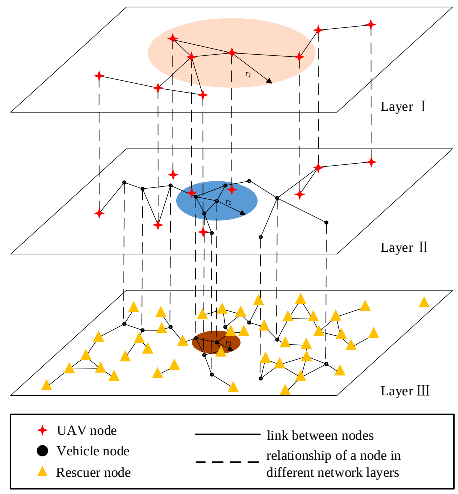

Fig. 2. Multi-layer information dissemination model of CNDA.

C. Network Connections

In this paper, the degree of a node is defined as the number of neighbor nodes of this node, which is used to describe the network connections. The connection between nodes in three network layers is achieved through class A, B, and C antennas, respectively. The degree distribution and antennas are elaborated below.

Degree distribution in layer I network: There are only UAV nodes in the layer I network, and the nodes in this layer mainly communicate through class A antennas. Therefore, the degree distribution of nodes in this layer depends on the connection relationship between class A antennas, i.e.,

$$p\left(K_1=k\right)=e^{-\lambda_1 \pi r_1^2} \frac{\left(\lambda_1 \pi r_1^2\right)^k}{k!}\left(k \geq 0\right), \tag{1}$$

where K_1 denotes the degree of a UAV node in layer I network. Thus, the average degree of nodes in layer I network is computes as

$$E\left(K_1\right)=\lambda_1 \pi r_1^2. \tag{2}$$

From (2), it can be concluded that the average degree of nodes in layer I network depends on the node density and communication range of nodes in this layer.

Degree distribution in layer II network: The average degree of nodes in layer II network is denoted by $E\left(K_2\right)$. In this layer, UAV nodes communicate with each other through class A antennas, and vehicle nodes communicate with the UAV and vehicle nodes within the communication range through class B antennas. Therefore, the degree distribution of nodes in layer II network is related to the connection of class A antennas and class B antennas. Through derivation, the average degree of nodes in layer II network is given by

$$E\left(K_2\right)=\pi \frac{\lambda_1^2 r_1^2+2 \lambda_1 \lambda_2 r_2^2+\lambda_2^2 r_2^2}{\lambda_1+\lambda_2}, \tag{3}$$

which is elaborated in Appendix A.

Degree distribution in layer III network: Similar to layer II network, the average degree of nodes in layer III network can

be given by

$$E\left(K_3\right)=\pi\frac{\lambda_2^2r_2^2+2\lambda_2\lambda_3r_3^2+\lambda_3^2r_3^2}{\lambda_2+\lambda_3}. \tag{4}$$

III. ANALYSIS OF INFORMATION DISSEMINATION

In this section, the information dissemination process of the whole CNDA is analyzed based on the dynamic dissemination model, and the equilibrium state of the information dissemination is obtained.

A. Information Dissemination Process

Assume that in layer I network, a node with a degree of k can be in three states: uninformed state (U_k), informed state (I_k) and broadcast state (B_k). Its state transition model is shown in Fig.3.

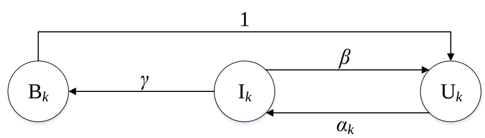

Fig. 3. Node State Transition Model.

A node with a degree of k is in state U_k, which will transfer to state I_k with the probability of α_k. Since the node in state U_k becomes state I_k after receiving the information from the neighbor node, α_k is actually the average probability that the node with degree of k receives the information from the neighbor node, and its expression is $\alpha_k=k\theta_1\delta$, where θ_1 is the average probability that the neighbor node in state B_k. For the node in state I_k, if the information it receives contains the rescue task arrangement for the node, it will change to state B_k with a probability γ, otherwise it will change to state U_k with a probability β, where $\beta+\gamma=1$. When a node changes to state B_k, it will perform the rescue task and broadcast the received information to the neighbor nodes. Because it needs to wait until it receives new information, it will change to State U_k.

This paper mainly discusses the effect of parameters such as node density and communication range on information dissemination, without the need for detail wireless channel analysis. Instead, the average probability of successful transmission of information between two neighbor nodes, i.e., δ, is used as the wireless channel factor to discuss the nodes connection in the CNDA. There are many factors affecting δ, such as signal quality, antenna quality and interference [35]. The value of δ is used as a parameter to quantify the interference degree of the CNDA in this paper as the interference is the most interesting factor being studied. The information dissemination of the CNDA includes single information dissemination and multi information dissemination. In the same layer network, the dissemination of different information is independent of each other, so the different information dissemination process of the same layer network can be decomposed into single information dissemination of the layer network. In fact, there is different information disseminating at the same time in different network layers. Therefore, it is necessary to further analyze the multi-information disseminating in order to describe the information disseminating process of the whole CNDA. The specific definitions of the two information dissemination processes are as follows.

Single information dissemination: According to the node state transition model, the information dissemination dynamic equation of the system is given by

$$\frac{dI_k\left(t\right)}{dt}=-I_k\left(t\right)+\alpha_kU_k\left(t\right), \tag{5}$$

$$\frac{dB_k\left(t\right)}{dt}=-B_k\left(t\right)+\gamma I_k\left(t\right), \tag{6}$$

$$\frac{dU_k\left(t\right)}{dt}=-\alpha_kU_k\left(t\right)+\beta I_k\left(t\right)+B_k\left(t\right), \tag{7}$$

where $U_k\left(t\right)$, $I_k\left(t\right)$ and $B_k\left(t\right)$ denote the proportion of nodes with degree k in state U_k, I_k and B_k at time t, respectively. Obviously, $U_k\left(t\right)+I_k\left(t\right)+B_k\left(t\right)=1$. β , γ and δ are all measured values. The value of α_k is directly proportional to θ_1 which is given by

$$\theta_1=\sum_{k'\geq 0}p\left(K'_1=k'\middle|K_1=k\right)B_{k'}\left(t\right). \tag{8}$$

where $p\left(K'_1=k'\middle|K_1=k\right)$ denotes the probability that the degree of a neighbor node of a node with degree k is k'. As the nodes of the whole network are independent, we have

$$\begin{aligned}&p\left({K_1}'=k'\middle|K_1=k\right)B_{k'}\left(t\right)\\&=\tfrac{k'p\left({K_1}'=k'\right)}{E\left(K_1\right)}B_{k'}\left(t\right).\end{aligned} \tag{9}$$

There is only one variable k' on the right of (9), so (10) can be got by letting $k'=k$, i.e.,

$$\begin{aligned}\theta_1&=\sum_{k\geq 0}\frac{kp\left(K_1=k\right)}{E\left(K_1\right)}B_k\left(t\right)\\&=\frac{1}{E\left(K_1\right)}\sum_k kp\left(K_1=k\right)B_k\left(t\right)\end{aligned} \tag{10}$$

Multi information dissemination: Assume that in MMND, each network layer has different information from the others transmitted at the same time. Information 1 is transmitted in layer I network, information 2 is transmitted in the layer II network, and information 3 is transmitted in layer III network. If the degree of a UAV node is k in layer I network and l in layer II network, the node may be in the following nine states: B_kB_l , B_kI_l, B_kU_l, I_kB_l, U_kB_l, I_kI_l, I_kU_l, U_kI_l and U_kU_l. The dynamic equations of multi-information dissemination could be set to

$$\frac{dB_kB_l\left(t\right)}{dt}=-2B_kB_l\left(t\right)+\gamma I_kB_l\left(t\right)+\gamma B_kI_l\left(t\right), \tag{11}$$

$$\frac{dU_kB_l\left(t\right)}{dt}=-\left(1+\alpha_k\right)U_kB_l\left(t\right)+\beta I_kB_l\left(t\right)+P_kB_l\left(t\right), \tag{12}$$

$$\frac{dB_kU_l(t)}{dt} = -(1+\alpha_l)B_kU_l(t) + \beta B_kI_l(t) + B_kB_l(t), \tag{13}$$

$$\frac{dI_kB_l(t)}{dt} = -2I_kB_l(t) + \gamma I_kI_l(t) + \alpha_kU_kB_l(t), \tag{14}$$

$$\frac{dB_kI_l(t)}{dt} = -2B_kI_l(t) + \gamma I_kI_l(t) + \alpha_lB_kU_l(t), \tag{15}$$

$$\frac{dI_kI_l(t)}{dt} = -2I_kI_l(t) + \alpha_kU_kI_l(t) + \alpha_lI_kU_l(t), \tag{16}$$

$$\begin{aligned}\frac{dU_kI_l(t)}{dt} = &-(1+\alpha_k)U_kI_l(t) + \beta I_kI_l(t)\\ &+\alpha_lU_kU_l(t) + B_kI_l(t),\end{aligned} \tag{17}$$

$$\begin{aligned}\frac{dI_kU_l(t)}{dt} = &-(1+\alpha_l)I_kU_l(t) + \beta I_kI_l(t)\\ &+\alpha_kU_kU_l(t) + I_kB_l(t),\end{aligned} \tag{18}$$

$$\begin{aligned}\frac{dU_kU_l(t)}{dt} = &-(\alpha_k+\alpha_l)U_kU_l(t) + \beta I_kU_l(t)\\ &+\beta U_kI_l(t), + B_kU_l(t) + U_kB_l(t)\end{aligned} \tag{19}$$

where θ_1 and θ_2 are the probabilities that the neighbor node of a node in state U_kU_l is in state B about information 1 and information 2, respectively, which can be given by

$$\theta_1 = \frac{1}{E(K_1)}\sum_{k\geq 0} kp(K_1=k)\left[B_kB_l(t) + B_kI_l(t) + B_kU_l(t)\right], \tag{20}$$

$$\theta_2 = \frac{1}{E(K_2)}\sum_{l\geq 0} lp(K_2=l)\left[B_kB_l(t) + I_kB_l(t) + U_kB_l(t)\right]. \tag{21}$$

In fact, only eight of the nine equations in (11)∼(19) are linearly independent, because $\sum_{S1}\sum_{S2} S1_kS2_l(t) = 1$, where $S1$ and $S2$ are the states of nodes about information 1 and information 2, $S1, S2 \in \{U, I, B\}$.

B. Equilibrium State of Information Dissemination

According to the above analysis of the information dissemination process, the dynamic equilibrium state of information dissemination is deduced by a mathematical method in this section.

For the case of a single information dissemination, using the stationarity condition of the dynamic dissemination model, then equations (22)∼(24) are obtained, i.e.,

$$\frac{dI_k(t)}{dt} = 0, \tag{22}$$

$$\frac{dP_k(t)}{dt} = 0, \tag{23}$$

$$U_k(t) + I_k(t) + P_k(t) = 1. \tag{24}$$

For the equilibrium state of a single information dissemination, equations (10), (22), (23) and (24) need to be solved which can be simplified to

$$\theta_1 = \frac{1}{E(K_1)}\sum_{k\geq 0}\frac{k^2\theta_1\delta\gamma}{1+k\theta_1\delta+k\theta_1\delta\gamma}p(K_1=k). \tag{25}$$

Obviously, $\theta_1 = 0$ is a solution of (25), but it is trivial because all nodes of the CNDA are in state U_k. Appendix B proves the condition that (25) has a non-zero solution: when $\gamma\delta > 1/E(K_1)$, (25) has only one solution in interval $0 < \theta_1 < 1$. Since the density and communication range of nodes in the network can be set, this condition can be easily met. Equation (25) is very complex, and it is difficult to obtain the specific expression of its exact solution. In Appendix C, an approximate solution of θ_1 is obtained. If $\gamma\delta > 1/E(K_1)$ holds, the approximate solution of (25) can be given by

$$\theta_1 = \frac{\gamma}{1+\gamma} - \frac{1}{(1+\gamma)E(K_1)\delta}. \tag{26}$$

According to (22)∼(24) and (26), the expression of $U_k(t)$ can be updated by

$$U_k(t) = \frac{1}{E(K_1)\delta\gamma}. \tag{27}$$

For the case of multi-information dissemination, the equations (28) and (29) are obtained by the stationarity condition, i.e.,

$$\sum_{S1}\sum_{S2} S1_kS2_l(t) = 1, S1, S2 \in \{U, I, B\}, \tag{28}$$

$$\frac{dS1_kS2_l(t)}{dt} = 0. \tag{29}$$

Solve (28) and (29), we have

$$\begin{aligned}U_{k\vee l}(t) &= I_kU_l(t) + B_kU_l(t) + U_kI_l(t)\\ &\quad + U_kB_l(t) + U_kU_l(t)\\ &= \frac{1}{E(K_1)\delta\gamma} + \frac{1}{E(K_2)\delta\gamma}\\ &\quad - \frac{1}{E(K_1)E(K_2)\delta^2\gamma^2},\end{aligned} \tag{30}$$

where $U_{k\vee l}(t)$ denotes the proportion of at least one information is uninformed to the UAV node at time t. According to the solutions of (28) and (29), it can be found that the value of $B_kB_l(t) + B_kI_l(t) + B_kU_l(t)$ is only related to θ_1 and independent of θ_2. Take it into (20), then (20) is transformed into the form of (25). Similarly, the value of $B_kB_l(t) + I_kB_l(t) + U_kB_l(t)$ is only related to θ_2 , and (21) will be updated by

$$\theta_2 = \frac{1}{E(K_2)}\sum_{l\geq 0}\frac{l^2\delta\theta_2\gamma}{1+l\delta\theta_2+l\delta\theta_2\gamma}\cdot p(K_2=l). \tag{31}$$

The equilibrium state of information dissemination can be obtained by solving (25), (30) and (31). The approximate solution of θ_1 has been obtained in (26), and the approximate solution of θ_2 can be obtained by the same method, i.e.,

$$\theta_2 = \frac{\gamma}{1+\gamma} - \frac{1}{(1+\gamma)E(K_2)\delta}. \tag{32}$$

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In layer III network, (33) and (34) can be given by

$$\begin{aligned} U_{l\vee m}(t) &= I_l U_m(t) + B_l U_m(t) + U_l I_m(t) \\ &\quad + U_l B_m(t) + U_l U_m(t) \\ &= \frac{1}{E(K_2)\delta\gamma} + \frac{1}{E(K_3)\delta\gamma} \\ &\quad - \frac{1}{E(K_2)E(K_3)\delta^2\gamma^2}, \end{aligned} \tag{33}$$

$$\theta_3 = \frac{1}{E(K_3)} \sum_{m\geq 0} \frac{m^2\delta\theta_3\gamma}{1+m\delta\theta_3+m\delta\theta_3\gamma} \cdot p(K_3=m), \tag{34}$$

where $U_{l\vee m}(t)$ denotes the proportion of at least one information is uninformed to the vehicle node at time t. The approximate solution of θ_3 is given by

$$\theta_3 = \frac{\gamma}{1+\gamma} - \frac{1}{(1+\gamma)E(K_3)\delta}. \tag{35}$$

IV. INTERFERENCE OPTIMIZATION ALGORITHM

In order to ensure that the CNDA can meet the requirements of information dissemination under the influence of interference, the interference optimization algorithm for MMND is designed based on the equilibrium state of information dissemination obtained above. Specifically, the algorithm is to adjust the node density and the communication range. Its principle is to use the minimal deployment cost on the premise of ensuring that the network can overcome interference and the information dissemination ability can meet the rescue requirements. The values of network parameters $\lambda_1 \sim \lambda_3$ and $r_1 \sim r_3$ are obviously limited by money and technology, i.e.,

$$\begin{aligned} &\lambda_{1\min} \leq \lambda_1 \leq \lambda_{1\max}, r_{1\min} \leq r_1 \leq r_{1\max} \\ &\lambda_{2\min} \leq \lambda_2 \leq \lambda_{2\max}, r_{2\min} \leq r_2 \leq r_{2\max} \\ &\lambda_{3\min} \leq \lambda_3 \leq \lambda_{3\max}, r_{3\min} \leq r_3 \leq r_{3\max}. \end{aligned} \tag{36}$$

The cost function of deploying the whole network is set to

$$\begin{aligned} &C(\lambda_1,\lambda_2,\lambda_3,r_1,r_2,r_3) \\ &= c_0(\lambda_1 r_1^\eta + \lambda_2 r_2^\eta + \lambda_3 r_3^\eta) \\ &\quad + c_1\lambda_1 + c_2\lambda_2 + c_3\lambda_3, \end{aligned} \tag{37}$$

where c_0 denotes the power consumption of the node in unit distance. c_1 , c_2 and c_3 denote the cost of deploying a single UAV, vehicle and rescuer node, respectively. η denotes the path loss of the CNDA.

As shown in (37), The deployment cost consists of two parts, one is the fixed cost such as production, hardware and software cost of the nodes during deploying the network, and the other is the cost of power consumption for communication purposes. In order to ensure the wide dissemination of information in the CNDA, the proportion of nodes in state B and state I in the network should be as large as possible. Since the proportion of nodes in the three states is linearly related, only the proportion of nodes in state U needs to be as small as possible. Taking $U(t)$ as the constraint condition, the optimization problem of the whole network can be given by

$$\underset{\lambda_1,\lambda_2,\lambda_3,r_1,r_2,r_3}{\text{minimize}} \; C(\lambda_1,\lambda_2,\lambda_3,r_1,r_2,r_3), \tag{38}$$

$$\text{subject to}\; U_k(t) \leq p_1, \tag{39}$$

$$U_l(t) \leq p_2, \tag{40}$$

$$U_m(t) \leq p_3, \tag{41}$$

$$U_{k\vee l}(t) \leq p_4, \tag{42}$$

$$U_{l\vee m}(t) \leq p_5, \tag{43}$$

$$\begin{aligned} &\lambda_1 \in [\lambda_{1\min}, \lambda_{1\max}] \\ &\lambda_2 \in [\lambda_{2\min}, \lambda_{2\max}] \\ &\lambda_3 \in [\lambda_{3\min}, \lambda_{3\max}] \\ &r_1 \in [r_{1\min}, r_{1\max}] \\ &r_2 \in [r_{2\min}, r_{2\max}] \\ &r_3 \in [r_{3\min}, r_{3\max}]. \end{aligned} \tag{44}$$

Equation (39)$\sim$(43) show the constraint of information dissemination requirements in the network. Let $p_1 \sim p_5$ denote the corresponding information dissemination threshold, where p_1 denotes the maximum allowed proportion of $U_k(t)$ in layer I network, similarly, p_2 and p_3 denote the maximum allowed proportion of state U in layer II, layer III network, respectively. p_4 and p_5 denote the maximum allowed proportion of $U_{k\vee l}(t)$ and $U_{l\vee v}(m)$ in multi-information dissemination, respectively. $p_1 \sim p_5$ can be set with different values according to the importance of the information. Equation (44) represents the hardware constraints of the node. Equation (39)$\sim$(43) are infinite dimensional constraints, but infinity cannot be obtained in practice. Therefore, the representative $k = E(K_1)$, $l = E(K_2)$ and $m = E(K_3)$ are taken to denote the whole constraint. The objective function C is an optimization problem about $\lambda_1, \lambda_2, \lambda_3, r_1, r_2 and r_3$. When solving it, the correlation between constraints and parameters needs to be considered, so as to determine the definition domain of the function. In the equilibrium state of single information dissemination in layer I network, the constraint of $U_k(t)$ is $U_k(t) \leq p_1$. Take (26) into the constraint condition, we have

$$E(K_1) \geq \frac{1}{\delta\gamma}\left(1+\frac{1}{p_1}\right). \tag{45}$$

Equation (45) is an inequality about $E(K_1)$, while (3) gives the calculation method of $E(K_1)$, which is only related to λ_1 and r_1, so the constraint on $E(K_1)$ is transformed into the constraint on λ_1 and r_1. Similarly, constraints on $E(K_2)$ and $E(K_3)$ can be transformed into constraints on λ_2, r_2, λ_3 and r_3, i.e.,

$$E(K_2) \geq \frac{1}{\delta\gamma}\left(1+\frac{1}{p_2}\right), \tag{46}$$

$$E(K_3) \geq \frac{1}{\delta\gamma}\left(1+\frac{1}{p_3}\right). \tag{47}$$

For constraint (42), equation (30) can be decomposed into the form of $U_k(t) + U_l(t) - U_k U_l(t)$, and constraint (43) is the same. Constraints (42), (43) are converted to constraints on $\lambda_1 \sim \lambda_3$ and $r_1 \sim r_3$. Therefore, the constraints denoted by (39)$\sim$(44) can be updated by

$$\begin{aligned} \underset{\lambda_1,\lambda_2,\lambda_3,r_1,r_2,r_3}{\text{minimize}} \; & c_0(\lambda_1 r_1^\eta + \lambda_2 r_2^\eta + \lambda_3 r_3^\eta) \\ & + c_1\lambda_1 + c_2\lambda_2 + c_3\lambda_3, \end{aligned} \tag{48}$$

$$\text{subject to}\; E(K_1) \geq \frac{1}{\delta\gamma}\left(1+\frac{1}{p_1}\right), \tag{49}$$

$$E\left(K_2\right) \geq \frac{1}{\delta\gamma}\left(1+\frac{1}{p_2}\right), \tag{50}$$

$$E\left(K_3\right) \geq \frac{1}{\delta\gamma}\left(1+\frac{1}{p_3}\right), \tag{51}$$

$$\begin{aligned} p_4 \geq & \frac{1}{\delta\gamma E\left(K_1\right)-1}+\frac{1}{\delta\gamma E\left(K_2\right)-1} \\ & -\frac{1}{\delta\gamma E\left(K_1\right)-1}\cdot\frac{1}{\delta\gamma E\left(K_2\right)-1}, \end{aligned} \tag{52}$$

$$\begin{aligned} p_5 \geq & \frac{1}{\delta\gamma E\left(K_2\right)-1}+\frac{1}{\delta\gamma E\left(K_3\right)-1} \\ & -\frac{1}{\delta\gamma E\left(K_2\right)-1}\cdot\frac{1}{\delta\gamma E\left(K_3\right)-1}, \end{aligned} \tag{53}$$

$$\begin{aligned} & \lambda_1 \in [\lambda_{1\min}, \lambda_{1\max}], r_1 \in [r_{1\min}, r_{1\max}] \\ & \lambda_2 \in [\lambda_{2\min}, \lambda_{2\max}], r_2 \in [r_{2\min}, r_{2\max}] \\ & \lambda_3 \in [\lambda_{3\min}, \lambda_{3\max}], r_3 \in [r_{3\min}, r_{3\max}]. \end{aligned} \tag{54}$$

For the optimization problem proposed by (48), the objective function and constraints are convex. Therefore, the convex optimization method can be used to solve this problem.

The interference optimization algorithm for the MMND will use the above methods to optimize and obtain the best network parameters. The specific process is as follows: In case of an emergency disaster, deploy the network nodes at $t=0$, and set the information dissemination threshold $p_1 \sim p_5$ according to the task emergency and importance. Then, the optimal network parameters are obtained and the network nodes are deployed by using the method shown in equations (48)~(54). During the rescue mission, if parameter δ changed, the interference optimization algorithm for MMND will re-optimize the network parameters and adjust the deployment of network nodes until the rescue is completed.

Algorithm 1 The interference optimization algorithm for MMND.

1: At $t=0$, set the information dissemination threshold of the communication network in disaster area, and measure the parameter δ.
2: Obtain the optimal network parameters $\lambda_1 \sim \lambda_3$ and $r_1 \sim r_3$ by optimization, and deploy the nodes according to the optimization results.
3: **repeat**
4: Measure parameter $\hat{\delta}$, $\hat{\beta}$ and $\hat{\gamma}$ according to the situation of communication network in disaster area.
5: **if** $\delta \neq \hat{\delta}$, or $\beta \neq \hat{\beta}$, or $\gamma \neq \hat{\gamma}$,**then**
6: According to the newly obtained parameter $\hat{\delta}$, $\hat{\beta}$ and $\hat{\gamma}$, the network is re-optimized to obtain new network parameters.
7: Redeploy the nodes according to the re-optimized parameters.
8: **end if**
9: **until** Rescue mission completed

TABLE II
LIST OF PARAMETER SETTINGS

Parameters	Value
λ_1	1~5 (device/km^2)
λ_2	1~10 (device/km^2)
λ_3	10~25 (device/km^2)
r_1	2000~4000 (m)
r_2	1000~2000 (m)
r_3	100~800 (m)
γ	0.8
δ	0.8
c_0	100
c_1	100
c_2	50
c_3	50
η	4

V. SIMULATION RESULTS AND ANALYSIS

In this section, the MMND and the interference optimization algorithm for the MMND are simulated and the results are analyzed. The parameter settings for the simulation are in Table II.

The physical parameters of the CNDA are selected based on practical scenarios. The maximum value of the UAV node density is $\lambda_{1\max} = 5$ (node/km^2), the minimum value is $\lambda_{1\min} = 1$ (node/km^2), the maximum value of its communication range is $r_{1\max} = 4000$ (m), and the minimum value is $r_{1\min} = 2000$ (m); The maximum value of vehicle node density is $\lambda_{2\max} = 10$ (node/km^2), the minimum value is $\lambda_{2\min} = 1$ (node/km^2), the maximum value of its communication range is $r_{2\max} = 2000$ (m), and the minimum value is $r_{2\min} = 1000$ (m); The maximum value of rescuer node density is $\lambda_{3\max} = 25$ (node/km^2), the minimum value is $\lambda_{3\min} = 10$ (node/km^2), the maximum value of its communication range is $r_{3\max} = 800$ (m), and the minimum value is $r_{3\min} = 100$ (m). The deployment cost of the UAV, vehicle and rescuer nodes are $c_1 = 100$, $c_2 = 50$ and $c_3 = 50$, respectively. The unit power cost of the node is $c_0 = 100$, the path loss is $\eta = 4$, and the average probability of the communication network node in the disaster area transferring to state B is $\gamma = 0.8$.

First, the information dissemination process of the MMND is simulated. Fig.4 shows the information propagation of the MMND, in which the abscissa represents the time, the ordinate denotes the node proportion, and the three curves in the figure represent the proportion of nodes in state U, state I and state B, respectively. The average degree of nodes in a CNDA is 10. At the initial time, the proportions of nodes in three states in MMND are set to 0.9, 0 and 0.1, respectively. The proportion of state I nodes gradually decrease to the stable value of 0.28 with the passage of time, the proportion of state nodes gradually increases in the early stage of information dissemination, then decreases to the stable value of 0.38, and the proportion of state B nodes gradually increases with time and finally stabilizes at 0.34. The results obtained by bringing the same parameters into equation (27) are in agreement with the simulation results, which shows that the MMND can describe the information dissemination process of the CNDA. The trend of the curve in Fig.4 is reasonable. At the initial moment, a

small number of nodes in the CNDA will generate information and broadcast it, and then the proportion of nodes in state U will decrease rapidly. At the same time, the proportion of nodes in state I will increase rapidly, and the proportion of nodes in state B will also increase. With the dissemination of information, the mutual transformation between nodes in various states will reach a dynamic equilibrium, thus making them stabilize in a proportion.

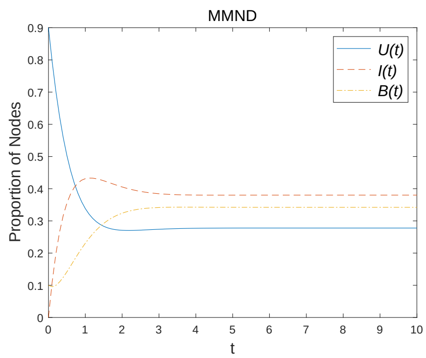

Fig. 4. Information Dissemination of the MMND.

In order to verify the anti-inference performance of the interference optimization algorithm for the MMND, simulation is carried out under three different information dissemination thresholds in this work.

Fig.5 shows the optimal node density under different propagation thresholds, where the abscissa coordinates the value of δ, and the ordinate represents the node density. The three curves in the graph represents the optimal λ_1, λ_2 and λ_3 optimized by the interference optimization algorithm for the MMND, respectively. In subgraph (a), when the information dissemination threshold is 0.1, λ_1 decreases monotonically with δ, while the curve of λ_2 is relatively flat, λ_3 decreases greatly when δ = 0.2∼0.3, and it is relatively flat in the other. From subgraph (b), when the information dissemination threshold is 0.3, both λ_1 and λ_2, decrease monotonically with δ and λ_3 remains at a minimum. Subgraph (c) shows that when the information dissemination threshold is 0.5, both λ_1 and λ_2 decrease monotonically with δ and λ_3 remains at a minimum. When the information dissemination threshold is low and the interference is large, a large number of nodes need to be deployed to meet the communication requirements. Therefore, when a threshold of 0.1 and δ is small, λ_1, λ_2 and λ_3 reach the maximum. The increase of δ means that the interference is weakened. There is no need for a large number of nodes to meet the communication requirements, thus making the node density decrease gradually. When the communication requirement is low, i.e., the information dissemination threshold is 0.3 and 0.5, only a small number of UAVs and vehicle nodes are required to complete the information dissemination task. Therefore, the values of λ_1 and λ_2 are large only when δ is small, and gradually decrease with the increase of δ, while λ_3 only needs to be at a minimum. This phenomenon is consistent with the results of our theoretical analysis.

Fig.6 shows the optimal communication range under different information dissemination thresholds. The abscissa of subgraph (a), (b), and (c) represents the value of δ and the ordinate represents the communication range of the nodes. The three curves in the figure represent the optimal r_1, r_2 and r_3 obtained by the interference optimization algorithm for the MMND, respectively. Subgraph (a) shows the curves of r_1, r_2 and r_3 obtained by the interference optimization algorithm for the MMND when the information dissemination threshold is 0.1. The three curves gradually decrease with the increase of δ. Subgraph (b) shows the curves of r_1, r_2 and r_3 when the information dissemination threshold is 0.3, in which r_1 and r_2 gradually decrease to a minimum with the increase of δ, and the overall trend of r_3 is downward with the increase of δ. Subgraph (c) shows the curves of r_1, r_2 and r_3 when the information dissemination threshold is 0.5, At this time, r_1 remains at a minimum, r_2 gradually decreases to a minimum with the increase of δ, and r_3 generally decreases with an increase of δ. The above results occur because with the increase of δ, a lower communication range can meet the requirements of the information dissemination. At this time, it is necessary to reduce the communication range of nodes as much as possible to save cost. r_1, r_2 and r_3 show a downward trend with the increase of δ. r_3 rebounds in subgraph (b) and subgraph (c) because the interference optimization algorithm for the MMND greatly reduces the node density in order to reduce the cost, resulting in the decline of the communication capacity, and the cost of increasing r_3 is the lowest. Therefore, slightly increase r_3 to enhance the communication capacity.

Combined with Fig.5 and Fig.6, the optimal communication range of the three nodes is the UAV, vehicle and rescuer nodes from high to low, and the optimal node density is the opposite. This is because the different communication capabilities of the three types of nodes lead to different deployment costs. The number of the high-cost nodes is often less than that of the low-cost nodes. In order to complete the information dissemination mission under the condition of low density, nodes must have a larger communication range.

Fig.7 shows the deployment cost with different information dissemination thresholds, where the abscissa coordinates the value of δ, and the ordinate is the cost and the curve denotes the deployment cost of the network. It can be seen that the deployment cost curves in subgraphs (a), (b), and (c) decrease with the increase of δ, because the increase of δ indicates the weakening of interference, reduces the difficulty of information dissemination, and saves the deployment cost of the whole CNDA.

This paper also studies the influence of information dissemination threshold on the optimization results of the interference optimization algorithm for the MMND.

In Fig.8, the multi-information dissemination threshold is fixed to $p_4 = p_5 = 0.5$, and the single information dissemination thresholds p_1, p_2 and p_3 are changed to obtain the regularity of the optimal parameters. Subgraphs (a)∼(f) show the curves of the optimal parameters optimized by the interference optimization algorithm for the MMND under different δ, in which the abscissa is the value of a single information dissemination threshold, the ordinates of subgraphs (a)∼(c) are node density and the ordinates of (d)∼(f) are the

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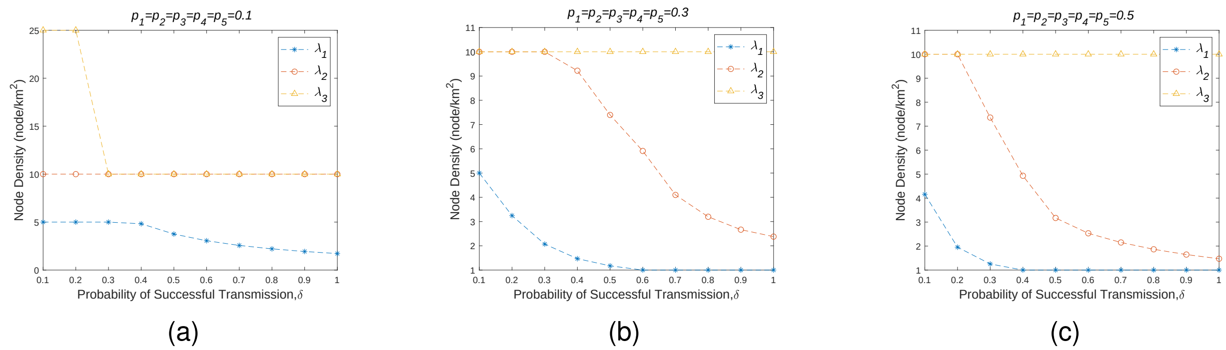

Fig. 5. The optimal node density in different information dissemination thresholds is (a) 0.1, (b) 0.3 and (c) 0.5.

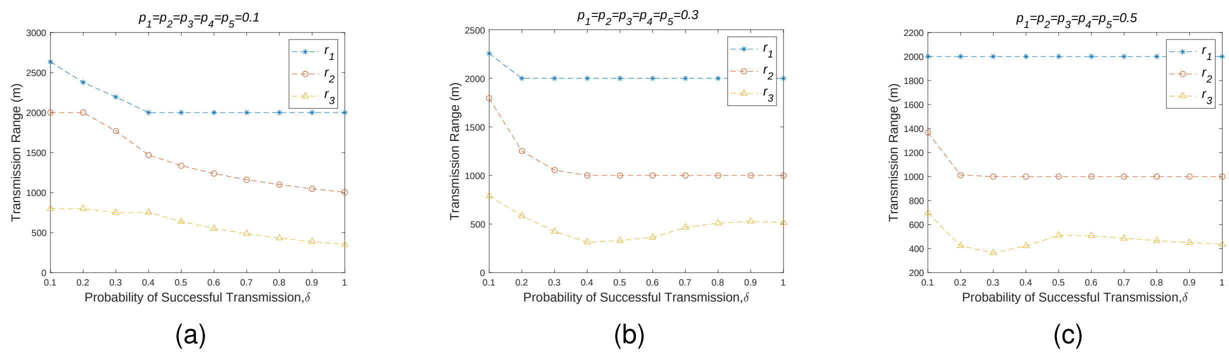

Fig. 6. The optimal node communication range under the information dissemination threshold of (a) 0.1, (b) 0.3 and (c) 0.5.

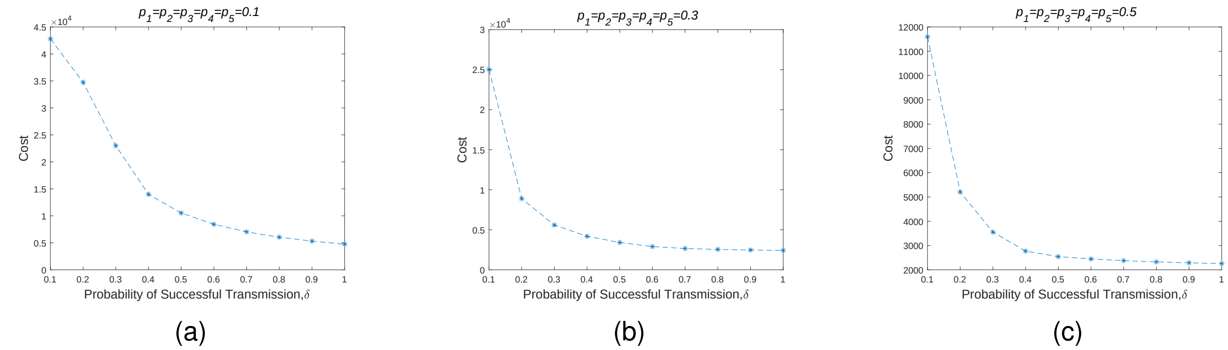

Fig. 7. The total cost when the information dissemination threshold is (a) 0.1, (b) 0.3 and (c) 0.5.

node communication range. The δ of the four curves in each subgraph are 0.2, 0.4, 0.6 and 0.8, respectively. Subgraph (a) shows the curve of the optimal λ_1 under different δ. When the single information dissemination threshold is high, the optimal λ_1 remains at a small value. When the single information dissemination threshold is low, the optimal λ_1 decreases with its increase, and the smaller the δ, the larger the λ_1. Because the lower δ is, the more serious the environmental interference is, and the lower the single information dissemination threshold indicates the higher requirements for the information dissemination, more nodes are needed to ensure it. This phenomenon also conforms to the curves of the optimal λ_2 and λ_3 in subgraphs (b) and (c). The curve of the optimal r_1 in subgraph (d) is stable at about 2km. Because the cost of increasing r_1 is much higher than the cost of increasing r_1, the interference optimization algorithm for the MMND will try to avoid increasing r_1 to obtain a strong communication capability. The optimal r_2 and r_3 curves in subgraphs (e) and (f) generally decrease with the increase of a single information dissemination threshold, which is consistent with the above analysis of the interference optimization algorithm for the MMND.

In Fig.9, the single information dissemination threshold is fixed as $p_1 = p_2 = p_3 = 0.5$, and the curves of the optimal parameters under different δ are obtained by changing the multi-information dissemination thresholds p_4 and p_5. The abscissa of subgraph (a)$\sim$(f) is the multi-information dissemination threshold, the ordinate of (a)$\sim$(c) is the node density, and of (d)$\sim$(e) is the node communication range. It can be seen that when δ is 0.2, 0.4, 0.6 and 0.8, respectively,

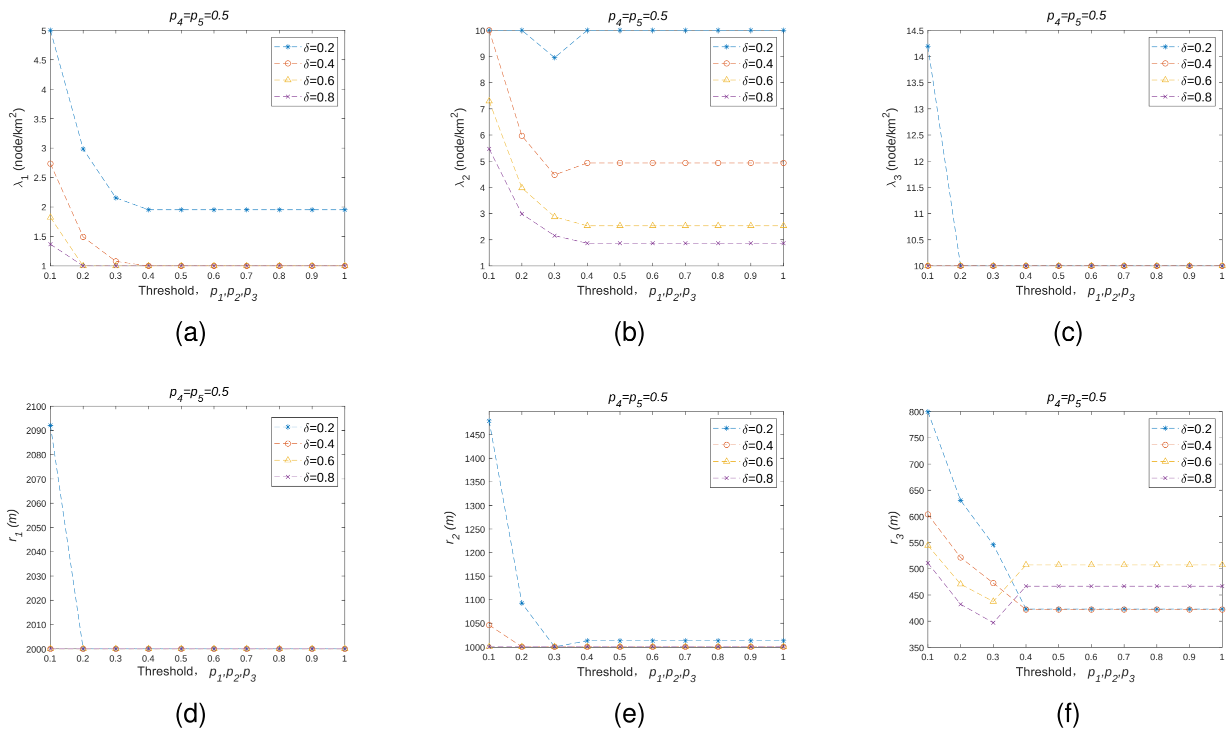

Fig. 8. Optimizing the parameters with respect to Different single information dissemination thresholds. (a) Optimize λ_1. (b) Optimize λ_2. (c) Optimize λ_3. (d) Optimize r_1. (e) Optimize r_2. (f) Optimize r_3.

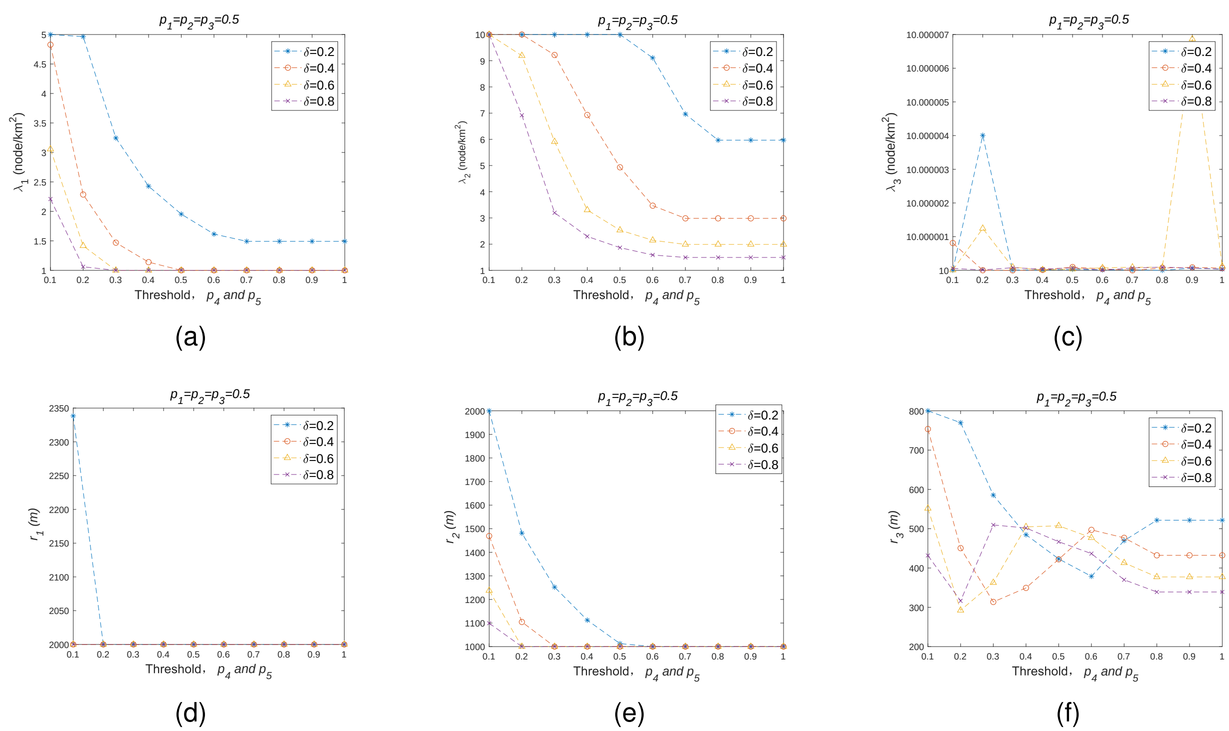

Fig. 9. Optimizing parameters with respect to different multi-information dissemination thresholds. (a) Optimize λ_1. (b) Optimize λ_2. (c) Optimize λ_3. (d) Optimize r_1. (e) Optimize r_2. (f) Optimize r_3.

with the increase of p_4 and p_5, the curve of λ_1 in subgraph (a) and the curve of λ_2 in subgraph (b) gradually decrease, and the larger δ, the smaller their values. Because the increase of p_4 , p_5 and δ reduces the difficulty of information dissemination, the interference optimization algorithm for the MMND will reduce the density of nodes to reduce cost. The curve of λ_3 in subgraph (c) is stable at a minimum value of 10 because the UAV and vehicle nodes are enough to complete the

information dissemination. In order to reduce cost, the density λ_3 of the rescuer nodes is kept at a minimum value. For the same reason as in (a) and (b), the curves of r_1 in subgraph (d) and r_2 in subgraph (e) also decrease to the minimum value with the increase of multi-message propagation threshold. The curve of r_3 in subgraph (f) rebounds due to the decrease of the UAV and vehicle node density, but it shows a downward trend as a whole.

VI. CONCLUSION

This paper establishes a MMND which analyzes the information dissemination process in the CNDA. In addition, an interference optimization algorithm for the MMND is proposed. The algorithm takes into account the interference from the environment and the deployment and running cost of all nodes, and provides parameters optimization for the CNDA. Numerical results demonstrate that the results of information dissemination are consistent with the theoretical analysis. By changing the density and communication range of nodes in the CNDA, the information dissemination requirements of the network can be met. Under different information dissemination thresholds, the optimal node density and the optimal communication range show a decreasing trend, and the deployment cost of the network is also monotonically decreasing.

APPENDIX A

For the layer II network, the degree distribution of its nodes is given by

$$\begin{aligned} p\left(K_2=l\right)=p\left(K_2=l \mid T_i=1\right) p\left(T_i=1\right) \\ +p\left(K_2=l \mid T_i=2\right) p\left(T_i=2\right), \end{aligned} \tag{55}$$

where $T_i \in \{1,2,3\}$ denotes the type of the i-th node. If $T_i=2$, the node is a vehicle node and can communicate with nodes on the same network layer within the communication range r_2. At this time, its degree obeys the Poisson distribution with strength $\pi\left(\lambda_2+\lambda_3\right) r_2^2$, i.e.,

$$p\left(K_2=l \mid T_i=2\right)=e^{-\pi\left(\lambda_2+\lambda_3\right) r_2^2} \frac{\left[-\pi\left(\lambda_2+\lambda_3\right) r_2^2\right]^l}{l!}. \tag{56}$$

If $T_i=1$, vehicle nodes within r_2 and UAV nodes within r_1 need to be considered. The UAV and vehicle nodes are distributed independently in the network. Therefore, the degree distribution of the node is given by

$$p\left(K_2=l \mid T_i=1\right)=e^{-\pi\left(\lambda_1 r_1^2+\lambda_2 r_2^2\right)} \frac{\left[\pi\left(\lambda_1 r_1^2+\lambda_2 r_2^2\right)\right]^l}{l!}. \tag{57}$$

The average degree of layer II network nodes is obtained from (56) and (57), i.e.,

$$\begin{aligned} E\left(K_2\right)=\sum_{l \geq 0} l p\left(K_2=l\right) \\ =p\left(T_i=1\right) \sum_{l \geq 0} l p\left(K_2=l \mid T_i=1\right) \\ +p\left(T_i=2\right) \sum_{l \geq 0} l p\left(K_2=l \mid T_i=2\right) \\ =\pi \frac{\lambda_1^2 r_1^2+2 \lambda_1 \lambda_2 r_2^2+\lambda_2^2 r_2^2}{\lambda_1+\lambda_2}. \end{aligned} \tag{58}$$

APPENDIX B

For the existence of the solution in (25), it is set to

$$\begin{aligned} F\left(\theta_1\right)=\frac{1}{E\left(K_1\right)} \sum_{k \geq 0} \frac{k^2 \theta_1 \delta \gamma p\left(K_1=k\right)}{(1+\gamma) k \theta_1 \delta+1} \\ =\frac{E\left(\frac{k^2 \theta_1 \delta \gamma}{(1+\gamma) k \theta_1 \delta+1}\right)}{E\left(K_1\right)}. \end{aligned} \tag{59}$$

According to contraction mapping theorem, for any $\theta_{1a}, \theta_{1b} \in (0,1)$, if $\left|F\left(\theta_{1a}\right)-F\left(\theta_{1b}\right)\right|<\left|\theta_{1a}-\theta_{1b}\right|$ holds, (25) has a unique solution, i.e.,

$$\begin{aligned} &\left|F\left(\theta_{1a}\right)-F\left(\theta_{1b}\right)\right| \\ &=\left|\frac{E\left(\frac{k^2 \theta_{1a} \delta \gamma}{(1+\gamma) k \theta_{1a} \delta+1}\right)}{E\left(K_1\right)}-\frac{E\left(\frac{k^2 \theta_{1b} \delta \gamma}{(1+\gamma) k \theta_{1b} \delta+1}\right)}{E\left(K_1\right)}\right| \\ &=\frac{1}{E\left(K_1\right)} \cdot \\ &\left|E\left(k^2 \delta \gamma\left[\frac{\theta_{1a}}{(1+\gamma) k \theta_{1a} \delta+1}-\frac{\theta_{1b}}{\left(1+\gamma_k\right) k \theta_{1b} \delta+1}\right]\right)\right| \\ &=\frac{1}{E\left(K_1\right)}\left|E\left(\frac{k^2 \delta \gamma\left(\theta_{1a}-\theta_{1b}\right)}{\left[(1+\gamma) k \theta_{1a} \delta+1\right]\left[(1+\gamma) k \theta_{1b} \delta+1\right]}\right)\right| \\ &=\frac{\left|\theta_{1a}-\theta_{1b}\right|}{E\left(K_1\right)} E\left(\frac{k^2 \delta \gamma}{\left[(1+\gamma) k \theta_{1a} \delta+1\right]\left[(1+\gamma) k \theta_{1b} \delta+1\right]}\right). \end{aligned} \tag{60}$$

Therefore, to prove that (25) has a unique solution, only need to prove that

$$\frac{1}{E\left(K_1\right)} E\left(\frac{k^2 \delta \gamma}{\left[(1+\gamma) k \theta_{1a} \delta+1\right]\left[(1+\gamma) k \theta_{1b} \delta+1\right]}\right)<1. \tag{61}$$

Assume that

$$f\left(K_1\right)=\frac{{K_1}^2 \delta \gamma}{\left[(1+\gamma) K_1 \theta_{1a} \delta+1\right]\left[(1+\gamma) K_1 \theta_{1b} \delta+1\right]}. \tag{62}$$

The function $f\left(K_1\right)$ is concave, so from Jensen inequality, we have

$$\begin{aligned} &\frac{1}{E\left(K_1\right)} E\left(\frac{k^2 \delta \gamma}{\left[(1+\gamma) k \theta_{1a} \delta+1\right]\left[(1+\gamma) k \theta_{1b} \delta+1\right]}\right) \\ &\leq \frac{E\left(K_1\right) \delta \gamma}{\left[(1+\gamma) E\left(K_1\right) \theta_{1a} \delta+1\right]\left[(1+\gamma) E\left(K_1\right) \theta_{1b} \delta+1\right]} \\ &=1/((1+\frac{1}{\gamma})^2 \gamma E(K_1) \theta_{1a} \theta_{1b} \delta \\ &+(1+\frac{1}{\gamma})(\theta_{1a}+\theta_{1b})+\frac{1}{\gamma E(K_1) \delta}). \end{aligned} \tag{63}$$

Obviously, when θ_1 is not close to 0 and satisfies the condition of (63), (25) has a unique solution. The proof that the solution

is between (0, 1) is as follows: Solve (25), which is equivalent to solving

$$\frac{E\left(\frac{{K_1}^2\delta\gamma}{(1+\gamma)K_1\theta_1\delta+1}\right)}{E(K_1)}=1. \tag{64}$$

Assume that

$$g(\theta_1)=\frac{E\left(\frac{{K_1}^2\delta\gamma}{(1+\gamma)K_1\theta_1\delta+1}\right)}{E(K_1)}. \tag{65}$$

The function $g(\theta_1)$ is monotonically decreasing with respect to θ_1 , and its values at 0 and 1 are

$$g(0)=\frac{\delta\gamma E\left({K_1}^2\right)}{E(K_1)}, \tag{66}$$

$$\begin{aligned} g(1)&=\frac{E\left(\frac{{K_1}^2\delta\gamma}{(1+\gamma)K_1\delta+1}\right)}{E(K_1)} \\ &<\frac{E\left(\frac{{K_1}^2\delta\gamma}{(1+\gamma)K_1\delta}\right)}{E(K_1)}=\frac{\gamma}{\gamma+1}<1. \end{aligned} \tag{67}$$

According to the intermediate value theorem, if $g(\theta_1)=1$ has a solution on $(0,1)$, it must satisfy $g(0)>1$, i.e.,$\delta\gamma > E(K_1)/E\left({K_1}^2\right)$. Relax it, we have

$$\frac{E(K_1)}{E\left({K_1}^2\right)}=\frac{1}{E(K_1)+\frac{D(K_1)}{E(K_1)}}<\frac{1}{E(K_1)}\leq\delta\gamma \tag{68}$$

It can be obtained from (68) that when $\delta\gamma\geq 1/E(K_1)$, (25) has a unique solution on (0, 1).

Appendix C

Define a function according to (64)

$$G(K_1)=\frac{{K_1}^2\delta\gamma}{(1+\gamma)K_1\theta_1\delta+1}. \tag{69}$$

The function $G(K_1)$ is convex, so $E[G(K_1)]\geq G(E[K_1])$ can be derived from Jensen inequality. Substitute it into (64) (69), we have

$$\begin{aligned} 1&=\frac{E\left(\frac{k^2\delta\gamma}{(1+\gamma)k\theta_1\delta+1}\right)}{E(K_1)} \\ &\geq\frac{E(K_1)\delta\gamma}{(1+\gamma)E(K_1)\theta_1\delta+1}. \end{aligned} \tag{70}$$

Reorganize equation (70), equation (71) can be given by

$$\theta_1\geq\frac{\gamma}{1+\gamma}-\frac{1}{(1+\gamma)E(K_1)\delta}. \tag{71}$$

Take the right side of (71) as the approximate solution of θ_1, i.e.,

$$\theta_1=\frac{\gamma}{1+\gamma}-\frac{1}{(1+\gamma)E(K_1)\delta}. \tag{72}$$

Fig.10 shows the approximate solution obtained by (72) and the exact solution obtained by computer at different averages degree of nodes. After comparison, it can be found that the greater the average degree of nodes, the closer the approximate solution is to the exact solution.

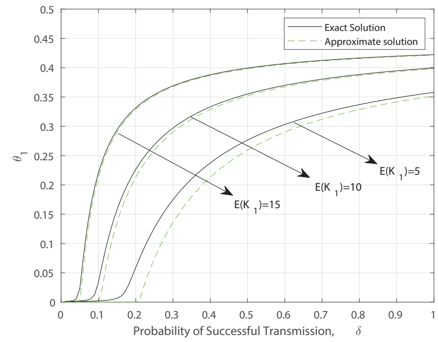

Fig. 10. Solution of θ_1.

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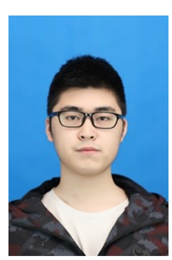

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