Research Article
Study on Invulnerability of Material Emergency Transportation System Based on Three-Layer Interdependent Network

Boyu Feng, Lin Zhou, Zhihao Zhang, and Yuhui Wang

1 Equipment Management and UAV Engineering College, Airforce Engineering University, Xian 710051, China
2 Air and Missile Defense College, Airforce Engineering University, Xian 710051, China
3 Air Traffic Control and Navigation College, Airforce Engineering University, Xian 710051, China

Correspondence should be addressed to Boyu Feng; 2690217726@qq.com

Received 29 December 2021; Revised 13 April 2022; Accepted 29 April 2022; Published 10 June 2022

1. Introduction

The outbreak of COVID-19 at the beginning of 2020 is a test for the modern governance systems and capabilities of countries worldwide. Due to the rapid increase of demand for some materials and the shutdown of production, logistics transportation has suffered a great impact, and the materials cannot be transported or equipped in time. This has greatly reduced the speed with which the state can deal with emergencies. Globally, the novel coronavirus pneumonia has brought serious problems to the material transportation system in many countries. In China, for example, the investment in the transportation industry declined by 22.5% in the first quarter of 2020 than that in the same period time of previous years. The total volume of domestic business transportation declined by ~60% and ~50% in April and May, respectively [1]. In fact, the impact of major infectious diseases and wars on the transportation industry is severe in all countries. The Ebola outbreak in early 2014 led to a decrease in material transport between countries around the world and African countries, which did not ease until 2016. Brazil’s Zika virus epidemic ended in November 2016, which resulted in a decrease of over 40% of the total domestic material transportation in Brazil in 2016. During the war between Armenia and Azerbaijan in 2020, many important transportation nodes in Armenia were destroyed, and the national transportation network of equipment and materials was almost completely paralyzed, which led to a severe shortage of living supplies such as food and drugs, and military equipment. Therefore, it is very important to establish a complete national emergency transportation network that can resist the impact of pandemics.

The single network was widely studied for a long time, and scholars have obtained many valuable research findings. But this kind of isolated network cannot describe the relationship between multiple systems [2]. However, in practice, many systems interact and relate with each other [3, 4]. The communication system and the power system are taken as examples. The successful operation of the power system must be controlled by the communication system [5],
while the successful operation of the communication system also requires power support from the power system. Another example is the railway transportation system and the power system. The power system provides electricity for the railway transportation system, while the railway transportation system supplies energy sources, such as coal, for the power system to generate electricity. These systems highly depend on each other in a complex way. The interdependence between network systems enhances the performance of the network in some ways, but at the same time, it also makes the dependent network system more vulnerable. Because of the interaction between different network nodes, failure of nodes or edges may harm the performance of other network nodes or edges, which can lead to cascading failure between networks and result to complete collapse of the whole interdependent network. The risk of cascading failure can increase when the correlation among the systems becomes complicated. Different from a single network, the interdependent network can take into account the correlation among multiple systems and is more practical in the study of material emergency transportation networks [6–8].

The aggregate of several similar nodes in a material emergency transportation network can be considered as one complex subnetwork, and the whole of several coupled subnetworks is an interdependent network. It is found that the interdependent network is more practical than a single-layer complex network. This kind of network was first studied by Buldyrev et al. [9]. Parshani et al. [10] studied the robustness of partially interdependent networks. Gao et al. [11] extended the two interdependent network models to more common multiple networks and summarized the “network of networks” model and related developments under interdependence [12]. Huang et al. [13] studied the robustness of completely interdependent networks under deliberate attacks. Quill et al. [14] pointed out that the study of interdependent networks is one of the major breakthroughs in the field of complex network research. However, these approaches did not consider the influence of the load in the network. There are few studies on the propagation of cascading faults under the condition of load in interdependent networks. Brummitt et al. [15] used the sand pile model to study the cascading failures in an interdependent network. Tan et al. [16] studied the cascading failure of dependent networks when there is a load under different coupling ratios. Yang and Sun studied the robustness of network controllability [17]. Jia et al. [18] studied cascading failure in congested urban road networks with self-organization. Wang [19] used data analysis methods to identify critical nodes that affect the robustness of the network. Dong et al. [20] established a new model to characterize the cascading failures and network vulnerability assessment. An and Gao detected the significant nodes in two-layer flow networks [21]. To study the influence of different parameters on the invulnerability of the network cascading failure, researchers conducted a lot of experiments and discovered the influence of degree distribution, network flow, and attack type on the robustness of the network [22–29].

In addition to theoretical research, there are many literature applying complex network cascading failures to a real-life complex system [30–38]. Fu applied the theoretical results of predecessors to study the cascading failure model and optimal control of the wireless sensor networks [39–42]. Hamzelou et al. [43] and Yokoi et al. [44] analyzed the main characteristics of social networks and studied methods to prevent cascading effects of the network. Ke and Cao established a functional network model and applied the network cascading failure theory to the treatment of neurological patients [45]. Jiang applied complex network theory to study indoor navigation systems and location-based services [46, 47]. Liu studied low-power wireless networks using network transmission theory. To avoid the potential ACK collision in CT, this article proposed an aligner which develops a new transmission pattern to coordinate concurrent senders in a distributed manner [48]. Xiao and Li studied the data of transportation networks and inferred a cooperative relationship between various vehicles and social network information [49, 50].

Researching various systems in material transportation based on complex network theory is also a new perspective, which is more realistic and valuable. Some recent scholars regard the units in the emergency transportation system as the nodes in the network and regard the information flows between the units as edges between them. This network can realize the coordinated actions of the emergency material transportation network through the effective connection and collaborative work of each unit, thereby improving the efficiency of the emergency transportation system. However, the existing network model still has some shortcomings, mainly in the following three aspects:

1. Most of the existing interdependent network models are two-layer networks, so the number of levels and complexity cannot meet the requirements of the emergency transportation network.

2. The dependence mode of interdependent networks is mostly full dependence; that is, the dependence mode is one-to-one between nodes in multilayer networks. However, in reality, things like one-to-many coupling among nodes or some nodes having no cross-layer coupling are quite common. There is a deviation between the existing research and the actual emergency transportation network.

3. Most scholars ignore the problem of transportation flow between nodes and networks when they build interdependent network models. Therefore, these models cannot truly reflect the impact of material flow changes in the emergency transportation network performance.

Due to the dual attributes of the information transmission network and military emergency network, the study of material emergency transportation network should focus on the sensitivity of its response to attacks and the robustness of the network. In this article, we propose a three-layer resource and transport and user (RTU) interdependent network model that treats the units in an emergency transportation system as the nodes in the network and considers information flows between the units as the edges.
between the nodes. This network can realize the coordinated actions of the emergency material transportation network through the effective connection and collaborative work of each unit and thereby improves the efficiency of the emergency transportation system.

Based on analyzing the characteristics of the system, this article builds a three-layer interdependent network model and uses the improved M-L model to describe the cascading failure propagation of node damage in the three-layer network. Then, the network model is attacked randomly, and the relationship between the invulnerability of the three-layer network and the three main indexes of network flow, average degree, and probability of interdependence are studied. And then, the propagation of cascading failure among the three subnetworks is analyzed and compared.

Through the simulation experiment, we get four main conclusions. Firstly, when the tolerance coefficient is fixed, the cascading robustness decreases gradually with the increase of network traffic. Secondly, when the tolerance coefficient is fixed, the cascading robustness increases gradually with the increase of the average degree of the network. Thirdly, when the tolerance coefficient is fixed, the cascading robustness decreases gradually with the increase of the connection probability between network layers. Fourthly, under the same parameter configuration, the robustness of the three subnetworks becomes stronger with the increase of the network layer. To sum up, this article provides a theoretical basis for building an efficient and robust emergency material transportation system.

2. Material Emergency Transportation Network Modeling

In the previous research on the invulnerability of the material transportation system, scholars often establish a single-layer complex network model only containing transportation system nodes or a double-layer complex network model containing transportation system nodes and material nodes. However, the above models are not complete and cannot accurately describe the material emergency transportation system in reality. In the practical material emergency transportation system, the relationship among resources, transportation system, and users must be comprehensively considered, so it is more appropriate to use a three-tier network to describe it.

According to the demand for material emergency transportation, aiming at the problems of the changeable situation in emergency or wartime, diversified resource demand, urgent demand for transportation speed, and the wide application of emerging technologies in an emergency situation, a resource and transport and user (RTU) three-layer interdependent network model is constructed [51]. The three subnetworks in the model do not exist independently and depend on the dependence of nodes in each layer to form interdependent networks.

2.1. Interdependent Network Model. There is unidirectional coupling between the networks of each layer of the RTU network model. The main characteristics of the network are extracted, and the RTU network model is constructed as shown in Figure 1.

In Figure 1, \( u_i \) \( (i = 1, 2, 3 \ldots n) \) and \( w_j \) \( (j = 1, 2, 3 \ldots m) \) are the interlayer dependence connecting nodes in networks of resources and transportation and nodes in transportation and users, respectively. Values of \( u_i \) and \( w_j \) indicate the dependence of the link between two layers. When \( u_i \in [0, 1] \) and \( w_j \in [0, 1] \), there is no interlayer dependence between the two nodes linked by \( u_i \) and \( w_j \). When \( u_i = 0 \) or \( w_j = 0 \), then the link can be deleted. When \( u_i = 1 \) or \( w_j = 1 \), the dependence between the two layers connected by the link of \( u_i \) and \( w_j \) is the strongest, and the failure of a certain point can cause the complete failure of the connecting point.

The network model can be described by setting \( G(N, L, W) \), and \( N \) is the total number of RTU network nodes; \( L \) is the set of inner and outer coupling links in the dependent network; and \( W \) is the coupling matrix. The mathematical expression of the above relationship is shown in equations (1)–(3).

\[
N = N^A \cup N^B \cup N^C = \{ n^A_i, n^B_j, n^C_k | i = 1, 2, \ldots, N^A_a, j = 1, 2, \ldots, N^B_b, k = 1, 2, \ldots, N^C_c \}, \quad (1) 
\]

where \( N^A \) is the set of all nodes in the first layer subnet, \( N^A_a \) is the total number of nodes in the subnet, \( N^B \) is the set of all nodes in the second layer subnet, \( N^B_b \) is the total number of nodes in the subnet, \( N^C \) is the set of all nodes in the third layer subnet, \( N^C_c \) is the total number of nodes in the subnet, and \( n^r_j(n^r_j, n^r_k) \) stands for a node in a subnet.

\[
L = L_A \cup L_B \cup L_C \cup L_{AB} \cup L_{BC} = \{ l_i | l_i = (n^r_i, n^r_j), l = 1, 2, \ldots, M \}, \quad (2) 
\]

where \( L_A, L_B, \) and \( L_C \) are the internal links of the first, second, and third layer subnets, respectively; \( L_{AB} \) and \( L_{BC} \) are the dependent links between the first and second layer subnets and between the second and third layer subnets, respectively; and \( li \) is the connection link between any two nodes and outer connecting links.

\[
W = (w_{ij})_{N \times N} \cup (w_{jk})_{N \times N} = \left[ \begin{array}{cc} W_A & W_{AB} \\ W_{BA} & W_B \\ \end{array} \right] \cup \left[ \begin{array}{cc} W_B & W_{BC} \\ \end{array} \right], \quad (3) 
\]

where \( w_{ij} \) is the weight of the link, \( w_{ij} \in [0, \infty) \); when \( w_{ij} = 0 \), it means that the two nodes have no coupling relationship. The elements \( W_A, W_B, \) and \( W_C \) in the block matrix represent the internal coupling of the first, second, and third layer subnets, respectively. \( W_{AB} \) and \( W_{BC} \) represent the dependent coupling between the first and second layer and between the second and third layer, respectively, where \( W_{AB} = W_{BA}, W_{BC} = W_{CB}, w_{ij} = w_{ji}, \) and \( w_{jk} = w_{kj} \).

2.2. Description of Subnets. The three subnets in the RTU network are all physical networks of social organizations. The internal coupling of each layer is different from that of the regular network, ER random network, and small-world
network. However, they have common characteristics similar to the Internet and the Internet of things; that is, some nodes have a large number of links, most nodes have only a few connections, and their degree distribution presents a power-law form, which is generally expressed as

\[ P(k) \sim k^{-\gamma} , \]  

(4)

where \( P(k) \) is a random node in the network, whose value of degree is \( k \), and the power-law exponent is \( \gamma \) [52]. We build an aircraft swarm network including \( N \) isolated nodes, number them from 1 to \( N \), and weighting the \( i \)th node \( P_i \) as

\[ P_i = i^{-a} \quad (i = 1, 2, \cdots, N), \]  

(5)

where \( a \in [0, 1) \) is a variable parameter. After all weights are normalized, we can obtain the following equation:

\[ P_i^* = \frac{P_j}{\sum_k P_k}. \]  

(6)

Obviously,

\[ \sum_{i=1}^{N} P_i^* = 1. \]  

(7)

Then, add links to the network model following the rule below: the probability of link between node \( i \) and node \( j \) is expressed by the weighted value between \( P_i^* \) and \( P_j^* \). All links are constructed in this way until the total reaches \( qN \). Therefore, the average degree of the network can be calculated as follows:

**Figure 1: RTU network structure.**

**Figure 2: Degree distribution when \( \gamma = 2.1 \). (In this graph, the directivity of degree is considered, \( \star \) denotes incoming degree, and \( \diamond \) denotes outgoing degree. For the network model studied in this article, incoming and outgoing degrees are consistent.)**
$$K = 2q.$$  

(8)

In (4), $\gamma$ satisfies the following equation:

$$\gamma = 1 + \frac{1}{\alpha}$$  

(9)

Since $\alpha \in [0, 1)$, we can adjust $\alpha$ to create a scale-free network with a power-law index $\gamma$ ranging from 2 to infinity.

The network established according to the above rules is called a scale-free network. Before the invulnerability research, we build three scale-free network models to simulate each layer subnet of the RTU network. Among them, the number of nodes in each subnet is 200, set $\gamma = 2.1$, simulate the network degree distribution, and then we obtain Figure 2. As can be seen from Figure 2, the degree of the subnet follows the power-law distribution.

When generating the interdependent network, we follow three principles:

(1) For the convenience of comparison, the node size of the three-layer subnet is the same, that is, $N^A = N^B = N^C$.

(2) The network growth mechanism is used to establish the subnet; that is, $n_0$ nodes are set in the initial state, and then a new node is added in each step. Each time the new node is randomly connected to the original $n$ nodes, where $n \in [0, n_0]$.

(3) According to the priority connection mechanism, the connection probability between a new node and an existing node $i$ satisfies the following formula:

$$\Pi_i = \frac{k_i + 1}{\sum j k_j + 1}$$  

(10)

3. Cascading Failure Model of RTU Network

3.1. M-L Model. The classic M-L model (load and capacity model) that was proposed by Motter and Lai is a classic model to study cascading failure of complex networks, and the model defines the capacity $C_i$ of node $i$ as follows:

$$C_i = (1 + \beta)L_i(0),$$  

(11)

where $\beta \geq 0$ is the tolerance coefficient, and the larger the value is, the stronger the ability of the network to resist cascading failure is [52]. But in practice, the increase of node tolerance load will greatly increase the cost of system operation, so the value of $\beta$ should be controlled within a certain range. Comparing the network invulnerability of a certain value of $\beta$ is a meaningful research to improve the resistance of emergency transportation networks to external attacks.

In (10), $L_i(0)$ is the initial load of the network, which can be expressed as a function of node degree. According to Wang's improvement work on the "load capacity" model, combined with the particularity of the three-layer dependent network, the initial load $L_i(0)$ of node $i$ is described as follows:

$$L_i(0) = r k_i^\alpha.$$  

(12)

In the above formula, $r, \alpha > 0$, their change can control the initial load distribution.

3.2. Cascading Failure Model

3.2.1. Failure Propagation in Subnet. Suppose that a node in the first layer subnet (resource supply network, network $A$) of RTU network is attacked and fails, $j$ is its neighbor node in network $A$, and the original load on node $i$ will be transferred to node $j$ according to the following formula [53]:

$$\eta_j = \frac{C_j^A}{\sum_{n \in \Gamma_j} C_n^A},$$  

(13)

where $\Gamma_j$ is the set of neighbor nodes and $n \in \Gamma_j$ is any neighbor node of the node $i$. When node $j$ receives the load from the node, and the sum of the load and the original load exceeds the node capacity ($L_j + \eta_j L_i > C_j$), the node $j$ fails, and then the node is deleted from the network. Its load continues to be distributed to the neighboring nodes according to (13), and the cascading failure propagates in network $A$ according to this rule [54].

3.2.2. Failure Propagation in Subnetworks. If node $l$ in network $B$ is connected with some nodes in network $A$ to form a dependent link, then according to the characteristics of a real logistics network, the following principles should be followed when cascading failures propagate between two layers of networks.

When the node $i$ connected with node $l$ in network $A$ fails, the load of node $i$ only transfers in network $A$, not to node $l$.

When all the dependent nodes of node $l$ in network $A$ failed, node $l$ fails immediately, and its load is transferred to the dependent node $m$ of node $l$ in network $B$ according to the following formula:

$$\eta_{lm} = \frac{C_m^B}{\sum_{n \in \Gamma_l} C_n^B},$$  

(14)

When the load of the node $m$ exceeds the capacity ($L_m + \eta_{lm} L_l > C_m$), the node $m$ fails and the cascading failure propagates in network $B$.

In the material emergency transportation network studied in this article, the failure propagation mechanism from network $B$ to network $C$ is the same as that from network $A$ to network $B$, and the failure only propagates in one direction ($A \rightarrow B \rightarrow C$) between three layers of the network. In particular, when the node $m$ in network $B$ is a dependent node between networks $A$ and $B$ and between networks $B$ and $C$, and node $t$ in network $C$ has only one dependent node $m$ in network $B$, the failure of node $m$ and node $t$ occurs simultaneously, and the cascading failure caused by the failure of node $m$ and node $t$ in networks $B$ and $C$ begins to propagate at the same time.
3.3. Invulnerability Measurement of Three-Layer Interdependent Networks. To evaluate the robustness of the three-layer dependent network, we can observe the proportion of the remaining nodes after cascading failure, which is represented by $F$.

$$F = \frac{N_A^f + N_B^f + N_C^f}{N_A + N_B + N_C}$$

(15)

In (15), $N_A^f$, $N_B^f$, and $N_C^f$ are the number of failed nodes in networks $A$, $B$, and $C$, respectively. After being attacked, the smaller the value of $F$, the stronger the invulnerability of the three-layer dependent network. In addition, the largest connected subgraph ratio is also an important invulnerability measure of dependent complex networks.

$$G = \frac{N_A^g + N_B^g + N_C^g}{N_A + N_B + N_C}$$

(16)

where $N_A^g$, $N_B^g$, and $N_C^g$ are the number of nodes of the largest connected subgraph in each single-layer network after cascading failure of network $A$, $B$, and $C$. When attacked, the larger the value of $G$, the stronger the invulnerability of the three-layer dependent network.

4. Invulnerability Experiment and Analysis under Random Attack

According to the network generation mechanism introduced above and the improved M-L model between layers of the interdependent network, a cascading failure model of a three-layer interdependent network is established, and then random attacks are carried out on the interdependent network to cause a cascading failure. The effects of network flow, average degree, and interlayer connection probability on the invulnerability of three-layer interdependent networks are observed.

Generally speaking, the invulnerability analysis of complex networks follows the process of Figure 3. The three-layer dependent networks studied in this article also follow this process for invulnerability analysis [55].

According to the flow chart above, we change some parameters of the three-layer dependent network for the simulation experiment, observe the changes in network invulnerability, and analyze the simulation results.

Based on the improved M-L model, we establish a three-layer interdependent complex network model. To make the model more realistic when simulating real RTU network, the fault propagation in this model is directional. When we set up attacks, we only target the first layer network, that is, the resource network. The resource network transfers the damage to the next two layers of networks in turn. To ensure scientificity, we set 200 nodes in each subnetwork, and the number of nodes is enough. The following simulations are the invulnerability test results on this three-layer interdependent network.

As can be seen from the curves in Figure 4, with the increase of tolerance coefficient $\beta$, the four curves in the figure show a downward trend, which means that the network damage degree $F$ gradually decreases; that is, the network invulnerability gradually increases. When the network flow $P_f$ is set to 0.1, 0.3, 0.6, and 1, the invulnerability of the network gradually weakens with the
increase of $P_f$, which indicates that the larger the network flow is, the more likely the three-layer dependent network is to have cascading failure. In Figure 5, the network invulnerability is represented by the largest connected subgraph size, and the conclusion is consistent with that in Figure 4.

However, it is worth noting that the network invulnerability does not change significantly when the network traffic changes by 10 times, especially when the tolerance coefficient $\beta < 0.25$, the invulnerability of dependent networks is basically the same under different flow. Therefore, when the

Figure 5: The proportion of the largest subgraph size after the network attack under different network flow.

Figure 6: The proportion of failure nodes after network attack under different average degrees.

Figure 7: The proportion of the largest subgraph size after the network attack under different average degrees.

Figure 8: The proportion of failure nodes after network attack under different connection probabilities.
network node capacity coefficient is small, the network traffic cannot be taken as the key index to improve the invulnerability, it can increase the flow as much as possible within the bearing range of each node to ensure the transportation efficiency to meet the material transportation demand in an emergency situation.

Figure 6 shows that, after the RTU network is attacked and cascading failure occurred under different average degrees, the invulnerability of the three-layer dependent network gradually becomes stronger when the average degree increase. In addition, we can also find that when the tolerance coefficient of the node increases, the invulnerability of the RTU network increases gradually.

Figure 7 shows the relationship between the maximum connectivity subgraph size and the tolerance coefficient $\beta$ after the network is attacked after the average degree is appropriately expanded. It can also be observed in Figure 7 that with the increase of the average degree of the network, the invulnerability of the RTU network increases gradually.

The interlayer connection probability of the interdependent network is an important factor that affects the propagation of cascading failure. As shown in Figures 8 and 9, with the increase of the interlayer connection probability of the network from 0.01 to 0.5, the propagation of cascading failure in the interdependent network becomes more and more severe. However, it is worth noting that the cascading failure of interdependent networks is still significant even if the probability of interlayer connection is only 0.01. Because the nodes are randomly connected in the network model, the invulnerability of the network changes when the nodes with different degrees are interlayer coupling nodes. Therefore, the curve in the graph will appear an unsmooth stage.

Based on the investigation of all network nodes, the invulnerability of three subnets of dependent networks with the variation of tolerance coefficient is observed. In the simulation, the network flow is set to 0.5, and the results are shown in Figures 10 and 11. With the increase of the tolerance coefficient $\beta$, the invulnerability of the three subnetworks is gradually enhanced. In contrast, the invulnerability of the first layer network (network A) is significantly better than that of the second layer network.
Zhihao Zhang; data collection by performed by Zhihao

Study conception and design was done by Boyu Feng and the authors declare that they have no conflicts of interest.

Conflicts of Interest

Supplemental Files.

The simulation data of this manuscript can be found in the Data Availability.

5. Conclusion

By analyzing the importance of the national logistics transportation system under emergency conditions, this article extracts the main characteristics of the material emergency transportation network and establishes a three-layer interdependent network model. The improved M-L cascading failure model of a single-layer network is extended to a three-layer interdependent network. Through simulations, we found that the overall invulnerability of the three-layer interdependent network had a weakening trend when the average degree of the network or the coupling probability of the network layers was increased, with the other variables being the same. Therefore, to improve the invulnerability of the network, we recommend reducing the average degree of the network or the number of coupling layers while ensuring the normal function of the system.

It is also found that the flow between nodes and networks had little effect on the invulnerability of the three-layer interdependent network, and network flow was related to the efficiency of material transportation. Therefore, network flow is not a critical factor of invulnerability in the actual construction of a material emergency transportation system. We suggest increasing network flow as much as possible within the scope of transportation capacity to enhance the transportation capacity of the emergency transportation system.

When the three subnetworks were observed separately, their cascading failures were gradually serious from the first layer network to the third layer network, which indicates that the downstream network was substantially affected by the failure of the upstream network. Therefore, when constructing a material emergency transportation network in practice, we recommend building the upstream network as strong as possible, so that the impact of cascading failure transferred to the downstream network can be reduced to the minimum and large-scale failure on the user side can be avoided.

Data Availability

The simulation data of this manuscript can be found in the Supplemental Files.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors’ Contributions

Study conception and design was done by Boyu Feng and Zhihao Zhang; data collection by performed by Zhihao Zhang. Analysis and interpretation of results was performed by Lin Zhou and Boyu Feng. Draft manuscript was prepared by Lin Zhou and Yuhui Wang. All authors reviewed the results and approved the final version of the manuscript.

Acknowledgments

This work was supported in part by the National Natural Science Foundation of China under Grant nos. 20171101 and 71901216.

Supplementary Materials

The supplementary material file mainly contains the data used in the simulation and the simulation result data.

(Supplementary Materials)

References


[44] H. Yokoi and T. Tachibana, “Autonomous relay device placement algorithm for avoiding cascading failure in d2d-


