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Controllability Robustness Against Cascading Failure for Complex Logistic Network Based on Dynamic Cascading Failure Model

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ABSTRACT Inspired by the empirical dynamic characteristics of the load of real logistics network, we propose a dynamic cascading failure model against cascading failure, which is more suitable for complex logistics network by adding dynamic factors based on the nonlinear load-capacity model under initial residual capacity load-redistribution strategy. The simulation is executed on the complex logistics network model and the results show that the controllability robustness and economy after cascading failure based on the dynamic cascading failure model is feasible and effective. It can effectively reduce the logistics cost and enhance controllability robustness against cascading failure by adjusting the network cost e and capacity parameter γ, so as to balance the controllability robustness and economy for the complex logistics network.

INDEX TERMS Complex logistics network, cascading failure, controllability robustness, dynamic cascading failure model.

I. INTRODUCTION

The operation of the logistics network is highly dependent on the external environment and is susceptible to the impact of emergencies. Emergencies include natural disasters, public health incidents and social security incidents, such as epidemic outbreak, natural disasters, terrorist attacks and the "out of space" in the shopping festival and so on. These "black swan" events lead to direct impact on the operation of the logistics network. For example, in January 2020, the new coronavirus epidemic broke out in Wuhan China, and spread rapidly across the country. China launched an emergency quarantine to prevent and control the epidemic. Traffic was blocked and logistics workers were making slow progress in returning to work. Therefore, a series of cascading failure occurred from Wuhan to all over the country. Figure 1 shows the logistics network of the provinces and global key manufacturing industries affected by the covid-19 outbreak which is from the Johns Hopkins University Center for Engineering and Systems Science on February 19, 2020 [1]. As can be seen from Figure 1, the red node is the failure node, that is, the epidemic event in Hubei province led to the involvement of Hunan, Anhui, Shanxi and other regions. The supply chain of key manufacturing industries in many provinces and cities was completely disrupted by the cascading failure, and the logistics network was largely paralyzed.

Thus, cascading failure is an extremely important problem for logistics network. It has become the key competitiveness of logistics industry about how to reduce cost, increase efficiency and improve the quality of logistics operation after cascading failure. Experts and scholars study the cascading failure for logistics network by applying complex network theory, so as to obtain a more robust and less cost logistics network, which has become a hot research direction in the field of logistics network. Complex logistics network is a complex network composed of nodes which carry logistics activities

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FIGURE 1. The logistics network of the provinces and global key manufacturing industries affected by the covid-19 outbreak.

such as storage, loading and unloading, handling, packaging and other logistics functions, and edges which connect these nodes. The nodes include logistics parks, logistics centers, distribution centers and storage centers, and the edges include transportation lines, transportation pipelines and communication lines. At present, some academic achievements have been made in cascading failure research based on complex logistics network [2].

A number of complex logistics network model have been intensively investigated in recent years [2]–[10]. Due to the characteristic of the power-law distribution of the logistics network, the construction of logistics network is simulated by experts based on complex network theory which considered the Baraba' si and Albert (BA) network for describing the agglomeration of economic benefits. Their rules for constructing complex logistics network are only adding nodes, and do not deleting them [3]–[6]. However, besides the agglomeration mechanism, logistics network also has the sprawl mechanism. Hessez and Feitelson *et al.* [7]–[10] proposed that logistics activities would have a long-distance layout, which reflected in the key logistics nodes being moved or deleted due to industrial characteristics such as the need to avoid traffic congestion, rigid requirements for logistics planning, trade organization authority, etc. In this case, logistics nodes will be removed or moved into areas where the cost is relatively low. So, the way to construct complex logistics network which only considering the increase of nodes without deleting nodes is inaccurate for simulating the evolution mechanism of real logistics network. Yue Yang *et al.* constructed a complex logistics network both considering the agglomeration and sprawl evolution mechanism based on the complex network, and confirmed it to the power-law distribution characteristic of complex networks [2]. This study lays a foundation for the follow-up cascading failure simulation for complex logistics network.

Based on the complex logistics network, some progress has been made in the research of constructing cascading failure model, which has been studied more deeply and applied to many different fields [11]–[20]. Among them, the load-capacity model is the most widely used one for complex logistics network to construct the cascading failure model for the load-capacity characteristics of the logistics network. The classical linear load-capacity model is adopted by scholars in order to simplify the cascading failure problem for complex logistics network, which defined the capacity and initial load of the logistics nodes as linear relationship [2], [4]–[6], [21]. However, Kim and Motter [22] demonstrated the feasibility of the nonlinear relationship of load-capacity. This breakthrough work was focused on the cascading failure problem of communication and transportation systems based on complex network theory, and proved that the capacity of the nodes of the four real-world networks of aviation, highway, power and Internet routers are nonlinear in their initial loads.

Given the above-mentioned circumstances, several authors have applied the nonlinear load-capacity model to study the controllability robustness against cascading failure and found that the nonlinear load-capacity model could tackle these difficulties and reduce the network cost by flexibly adjusting the minimum residual capacity of the nodes [23]–[26]. Especially, Chen and Dou [24], [25] proposed the nonlinear load-capacity model to study the processes and features of cascading failure based on complex network and proved that the nonlinear load-capacity model was helpful to improve the robustness of complex network. Although the research of controllability robustness of cascading failure based on the nonlinear load-capacity model has been expected to be feasible on some basic complex network model, but it hasn't frequently been used in the complex logistics network until Yang *et al.* [2] studied the empirical load-capacity characteristics of two different real logistics networks and proved the feasibility of the nonlinear load-capacity model. Then we proposed four different kinds of cascading failure models and proved the cascading failure model which adopting nonlinear load-capacity model with initial residual capacity load-redistribution strategy was the optimal cascading failure model by cascading failure simulation analysis on complex logistics network model. Since then, the nonlinear load-capacity model has been applied to the complex logistics network, and it was of great significance to the construction of cascading failure model.

The studies above are all based on the static network model, which assume that the load of the network is constant without considering the dynamic characteristics of the real logistics network. However, one of the special characteristics of the real logistics network is the flow of objects, so the dynamic characteristics of complex logistics network with load changes in real-time is an important influence factor influencing cascading failure research. When cascading failure occurs, the real-time load of logistics nodes and the residual capacity of the neighbor nodes of the failure node would change with time according to its dynamic characteristics. The distribution of load from failure node to the neighbor nodes after cascading failure is bound to be biased. So, the study of dynamic cascading failures problem based on complex network is also a hot topic. Duan *et al.* [27], [28] not only proposed a new cascading model based on a tunable load redistribution model with the linear load-capacity model, but also proved it for better robustness on scale-free network against cascading failure than the previous model by adjusting the redistribution range and heterogeneity. Schäfer *et al.* [29] proposed a model that incorporates the dynamical properties and the complex network topology of the Turkish power grid to investigate cascading failures. Jun *et al.* [30] proposed the load-redistribution strategy based on time-varying load against cascading failure for complex network and proved it can reduce the scale of cascading failure efficiently. It is a significant research for some basic complex network model, but there are some limitations that the model they proposed is based on the linear load-capacity model which cannot fit for the complex logistics network. It is because that the relationship between load and capacity of complex logistics network is nonlinear [2]. Moreover, the existing studies on cascading failure of complex logistics network do not consider the dynamic characteristics. So, the distribution of load after cascading failure which distributed from failure node to the neighbor nodes is bound to be biased. Therefore, the cascading failure model considering the dynamic characteristics and nonlinear characteristics of the real logistics network would improve the rationality of the stage of load distribution after cascading failure, reduce the scale of cascading failure, enhance the controllability robustness and economy of complex logistics network, so as to provide a better solution to the cascading failure problem for complex logistics network.

From previous discussions, according to the dynamic characteristics and nonlinear characteristics of real logistics network, we propose a dynamic cascading failure model by adding dynamic factors to the cascading failure model composed of nonlinear load-capacity model and initial residual capacity load-redistribution strategy. Based on complex logistics network model, the dynamic cascading failure model is compared with the cascading failure model without dynamic factors by detail cascading failure simulation analysis. Through the simulation analysis of controllability robustness and economy after cascading failure, we prove that the proposed dynamic cascading failure model is the optimal one for complex logistics networks. Furthermore, we provide the solution method to balance the controllability robustness and economy for complex logistics network by adjusting the network cost e and capacity parameter γ based on the dynamic cascading failure model.

In view of the above problem, the rest of this paper is organized as follows. The dynamic characteristic of real logistics network is demonstrated in Section II. The complex logistics network model is constructed In Section III. The dynamic cascading failure model is constructed in Section IV and simulated in Section V. Controllability robustness and economy of complex logistics network after cascading failure based on dynamic cascading failure model and cascading failure model without dynamic factors are simulated and analyzed in Section VI. Conclusions are drawn in Section VII.

II. EMPIRICAL STUDY ON DYNAMIC CHARACTERISTICS OF COMPLEX LOGISTICS NETWORK

One of the special characteristics of the complex logistics network is the flow of objects. However, the existing studies on cascading failures for complex logistics network are neglected to consider the dynamic characteristics. This will result in inaccurate residual load distribution after cascading failures. To consider the dynamic characteristics, we study the dynamic change of the load of logistics nodes in the real logistics network over time to reveal the operation law and structure characteristic of complex logistics network. In order to demonstrate the dynamic characteristics of the load of real logistics network, we take the logistics data of a fortune 500 enterprise (referred to as enterprise A) as an example, so as to provide the theoretical support for the dynamic cascading failure model for the complex logistics network. Figure 2 shows the real-time inventory data of the seven logistics distribution centers that we tracked in the logistics network of enterprise A during 20 consecutive days in January 2019. The daily inventory curve fluctuations are shown in Figure 2.

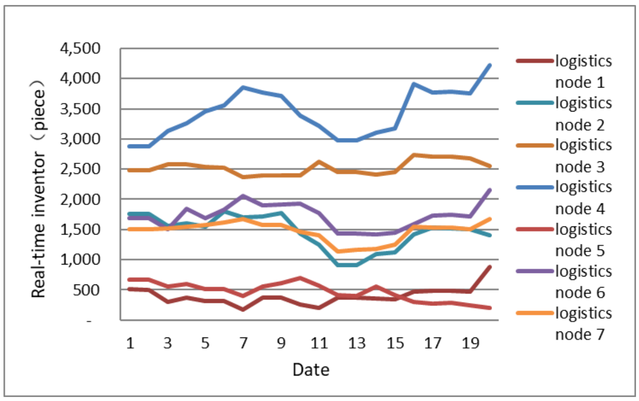

FIGURE 2. The real-time inventory data of the seven logistics distribution centers.

According to Figure 2, we can see the real-time load of logistics nodes in the complex logistics network become dynamic over time. Real-time inventory curves of logistics distribution center from 1 to 7 are all fluctuation curves. Among them, we can see that, for the logistics node 1, 3, 5 and 7, the inventory curve fluctuates relatively smoothly. For example, the inventory of logistics node 3 fluctuates from 2400 to 2750, the highest inventory is 2750 pieces on January 16th and the lowest inventory is 2400 pieces on January 7th to 10th. It is proved that the dynamic characteristics of the load of real logistics network. Similarly, there are other logistics node curves that can also prove this feature in Figure 2. For the logistics node 2, 4 and 6, the inventory curve fluctuates sharply in a relatively large range. It can be seen that the actual inventory of real logistics nodes are dynamic data with real-time changes, that is to say, the load of logistics nodes in complex logistics network presents dynamic characteristics. So, it can be inferred that when cascading failure occurs, the real-time load of the neighbor nodes of the failure node must also show dynamic characteristics. Under the background of such dynamic characteristics as verified in Figure 2, the cascading failure problem should consider the dynamic characteristics for accuracy and reality, which carried out in the topic of our innovation study for dynamic cascading failure model. Therefore, in this paper, we propose a cascading failure model with the real-time load for complex logistics network, which is defined as a dynamic cascading failure model for complex logistics network.

III. COMPLEX LOGISTICS NETWORK

From the above, we construct a complex logistics network for experimental purpose, which include the agglomeration and sprawl mechanism and the complex features of logistics network. We define the complex logistics network as a logistics infrastructure network $G = (V, E)$. The V is the nodes that realize all of the functions in real logistics network, such as package sending and receiving, transit and circulation, warehousing and information processing, etc., which include logistics parks, logistics centers, distribution centers and storage centers. The E is the edges that realize the functions of goods transportation and information transmission, which include facilities such as roads, transportation pipelines and communication lines required for logistics operations. Each node and edge has a different weight related to its service capabilities. Therefore, the traffic flow generated by each node and edge is defined as the node weight and edge weight respectively. Since the flow of goods between adjacent nodes in the logistics infrastructure network can move in both directions, the micro flow direction of the material flow is not considered in this paper. Therefore, the complex logistics network can be abstracted into an extend BA network model, whose generation algorithm is given as follows:

(1) The network starts with m_0 nodes and adds a new node at every equal time interval. The new node is connected with $m(m \leq m_0)$ different old nodes that already exist in the network to generate m new edges.

(2) According to the aggregation mechanism of the logistics network, the newly added node and edges are connected according to the preferred connection rules. It is assumed that the probability that the new node j is connected to the existing node i is $P(k_i)$, and the degree of the node i is k_i, as shown in formula (1):

$$P(k_i) = \frac{k_i}{\sum_j k_j} \tag{1}$$

(3) Let s_i be the node strength, which represents the capability of the logistics flow processing of node i as follows:

$$s_i = \sum_j a_{ij} f_{ij} \tag{2}$$

where a_{ij} is the neighbor matrix of the failed node i, and f_{ij} is the edge weight, that is, the scale of the logistics flow between nodes i and j.

(4) According to the sprawl mechanism of the complex logistics network, all the nodes in $s_i > s_0$ case of the network are selected, and the partial nodes and all edges connected to these nodes are deleted with probability P.

After t time intervals, the model evolves into an extended BA model with N nodes, simulating the agglomeration and sprawl evolution of the logistics infrastructure network.

Based on the generation algorithm of the complex logistics network, the extended BA network is generated using a simulation tool called Python. As shown in Figure 3, the number of initialization network nodes is 1000, and the average degree is 4.

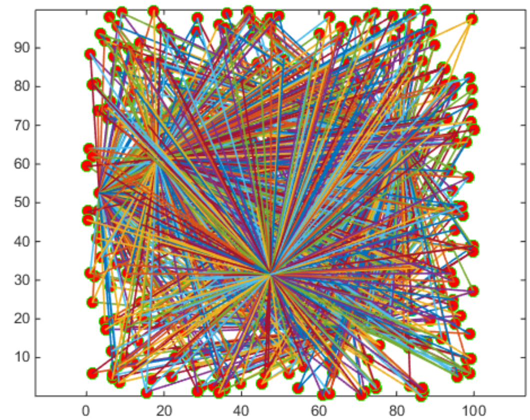

FIGURE 3. Extended BA network.

IV. MODELING OF DYNAMIC CASCADING FAILURE MODEL

A. CASCADING FAILURE MODEL

Based on the complex network theory, the cascading failure process of a complex logistics network is described as follows: we delete the node with the largest degree to simulate the phenomenon of logistics node failure due to some force majeure emergencies. Then the service coupling relationship between the failed logistics node and its adjacent nodes is disrupted, and the load of the failed logistics node is redistributed to its adjacent nodes, the load-redistribution process may cause a chain reaction of successive failures in adjacent nodes, because they also could surpass their own load capacities. The above phenomenon is called the cascading failure of the complex logistics network.

To measure the robustness against cascading failure for complex logistics network, we use the relative size G of the giant component to measure the extent of disconnection of the network as follows:

$$G = \frac{N'}{N} \tag{3}$$

where N' is the size of the giant component after cascading failure and N is the initial network size. High G values correspond to robust network, while low G values represent vulnerable networks [31], [32].

Many previous studies have shown that the cascading failure model of complex logistics networks covers the following: the definition of the initial load of the node, the load-capacity model and the load-redistribution strategy. Among these, the initial load L_i^0 of node i is defined as a function of the degree of the node [4], [30], [32], [35], [36]. If the number of adjacent nodes connected to logistics node i is k_i, then the degree of logistics node i is k_i. The initial load L_i^0 of node i is defined as follows:

$$L_i^0 = (k_i \sum_{m \in \Gamma_i} k_m)^\alpha, \quad i = 1, 2, \ldots, N \tag{4}$$

where Γ_i is the set of adjacent nodes of logistics node i, α is the load parameter which is used to control the strength of the initial load, with $\alpha > 0$, N is the total number of nodes in the network.

The load capacity model includes linear load capacity model and nonlinear load capacity model, as shown below. The linear load-capacity model is adopted to define node capacity in complex logistics networks [25], [33] as follows::

$$C_i = (1 + \beta) L_i^0, \quad i = 1, 2, \ldots, N \tag{5}$$

where C_i is the capacity of node i, β is the tolerance parameters, with $\beta \geq 0$. The capacity of a complex logistics network is defined based on the nonlinear load-capacity model [5], [6], as follows:

$$C_i = L_i^0 + \beta (L_i^0)^\gamma \tag{6}$$

where C_i is the capacity of node i, β, γ are the tolerance parameters, with $\beta \geq 0, \gamma > 0$. Note that, if $\gamma = 1$, the nonlinear load-capacity model degenerates to the linear load-capacity model (5).

Let C_j denotes the capacity of the adjacent node j of node i. The additional load ΔL_{ji} of the adjacent node j, moved from the failed node i under the initial residual capacity load-redistribution strategy, is defined as follows:

$$\Delta L_{ji} = L_i \times \frac{C_j - L_j^0}{\sum_{n \in \Gamma_i} (C_n - L_n^0)} \tag{7}$$

Among them, L_i is the load of the failed node i, L_j^0 is the initial load of the adjacent node j, L_n^0 is the initial load of the adjacent node n, Γ_i is the set of adjacent nodes of node i. It is worth explaining that the difference between L_i^0 and L_i is that L_i^0 is the initial load of node i which is set before cascading failure, while L_i is the load of node i after cascading failure. Except this, the load of the first attacked node in the cascading failure experiment is equal to its initial load, the load of the other failed nodes is not the initial load, but the sum of the initial load and the load of the assigned failed node.

In order to analyze the different effect on the robustness against cascading failure between linear load-capacity model and nonlinear load-capacity model, we simulate the two model based on the complex logistics network model respectively. Since the probability of multiple nodes failing simultaneously in a real logistics network is small, this paper assumes that only one node is attacked when emergencies at a time, and the failed node cannot automatically renew to its normal state. Based on the complex logistics network constructed in Section III as shown in Figure 3, the cascading failure simulation process under the above two cascading failure models is given as follows:

Step 1: Select linear load-capacity model or nonlinear load-capacity model to define the relationship between the initial load and capacity of the network.

Step 2: Let the most efficient logistics node i fails, such as $k_i = k_{\max}$.

Step 3: The load of failed node i is redistributed to the adjacent node j in accordance with the load-redistribution strategy as equation (7). The extra load of node j is ΔL_{ji}.

Step 4: Determine whether node j fails. If $\Delta L_{ji} > C_j$, node j fails, then return to step 3. If $\Delta L_{ji} \leq C_j$, node j does not fail, then go to step 5.

Step 5: When there is no failed node appear, calculate the robustness G of the complex logistics network.

The cascading failure simulation results are shown as follows:

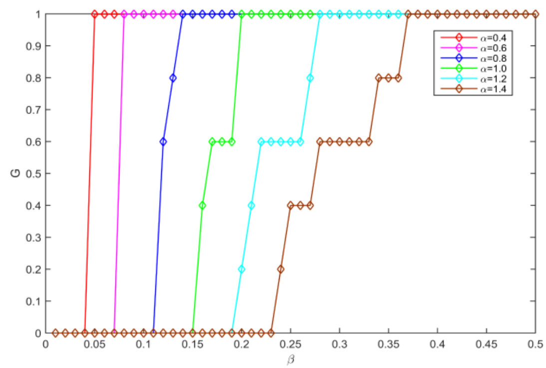

FIGURE 4. **The relation between β and G for linear load-capacity model.**

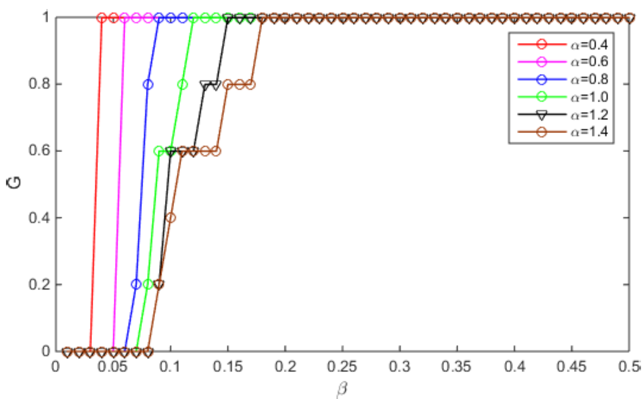

FIGURE 5. **The relation between β and G for nonlinear load-capacity model.**

Figure 4 is the cascading failure simulation diagram under the linear load-capacity model. Figure 5 is the cascading failure simulation diagram under the nonlinear load-capacity model. To analyze the relation between β and G in the simulation results analysis, we conclude from Figure 4 and Figure 5 that, with the increase of β, the value of G presents three states: firstly, with the increase of β, the value of G remains unchanged as 0, which means no cascading failure occurs; secondly, with the increase of β, the value of G increases, which means cascading failure occurs. Finally, with the increase of β, the value of G remains the same as 1, that is, all nodes are failed. It can be seen that, under the same α, the cascading failure threshold of β in Figure 4 is larger than that in Figure 5. For example, when $\alpha = 0.4$, β is $\beta = 0.05$ in Figure 4, while β is $\beta = 0.04$ in Figure 5; when $\alpha = 0.4$, β is $\beta = 0.08$ in Figure 4, while β is $\beta = 0.06$ in Figure 5. It means that the cascading failure threshold based on nonlinear load-capacity model is smaller than that based on linear load-capacity model. Based on the above, it can be concluded that the cascading failure model of complex logistics network based on the nonlinear load-capacity model is superior, and the complex logistics network after cascading failure is more robust. Therefore, we will establish a dynamic cascading failure model based on nonlinear load-capacity model by adding dynamic factors.

B. DYNAMIC CASCADING FAILURE MODEL

Based on the above research results, we establish a dynamic cascading failure model based on nonlinear load-capacity model by adding dynamic factors. First, the initial load L_i^0 of node i is defined as equation (4). The dynamic load of the logistics node ΔL_i is defined as follows:

$$\Delta L_i = \eta L_i^0 \delta \tag{8}$$

where ΔL_i is the dynamic load of the logistics node. Based on the initial load, the dynamic real-time load of logistics node is dependent on the dynamically adjustable parameters η and δ, $\eta \in [-1, 1]$, $\delta \in [0, 1]$. The dynamic real-time load L_i of logistics node i is defined as follows:

$$L_i = L_i^0 + \Delta L_i \tag{9}$$

Obviously, the real-time load of the logistics node L_i is a dynamic variable. According to the nonlinear load-capacity model as equation (6), the load-capacity model for dynamic cascading failure model is defined as follows:

$$C_i = L_i^0 + \beta (L_i^0)^\gamma \tag{10}$$

where C_i is the capacity of node i, and β, γ are the tolerance parameters, with $\beta \geq 0, \gamma > 0$.

Let C_j denotes the capacity of the adjacent node j of node i. The additional load $\Delta \tilde{L}_{ji}$ of the adjacent node j, which is moved from the failed node i under the initial residual capacity load-redistribution strategy, is defined as follows:

$$\begin{aligned}\Delta \tilde{L}_{ji} &= L_i \times \frac{C_j - L_j^0}{\sum_{m\in\Gamma_i}(C_m - L_m^0)} \\ &= L_i \times \frac{L_j^0 + \beta (L_j^0)^\gamma - L_j^0}{\sum_{m\in\Gamma_i}(L_m^0 + \beta (L_m^0)^\gamma - L_m^0)} \\ &= L_i \times \frac{(L_j^0)^\gamma}{\sum_{m\in\Gamma_i}(L_m^0)^\gamma}\end{aligned} \tag{11}$$

Among them, L_i is the load of the failed node i, L_j^0 is the initial load of the adjacent node j, L_m^0 is the initial load of the adjacent node m, Γ_i is the set of adjacent nodes of node i. C_j is the capacity of the adjacent node j. Considering the change of the dynamic load of logistics node, the load of the failure node i is distributed to its neighbor node j in proportion to $\prod_j$ which is based on the differential redistribution strategy. Among them, the $\prod_j$ is defined as follows:

$$\prod\nolimits_j = \frac{C_j - L_j(t)}{\sum_{m\in\Gamma_i}(C_m - L_m(t))}, \quad t = 0, 1, 2, \ldots q \tag{12}$$

where t is the time interval, q is the number of time intervals from the initial state to the end of cascading failure, C_j is the capacity of the adjacent node j, $L_j(t)$ is the real-time load of the adjacent node j at time t, Γ_i is the set of adjacent nodes of node i.

Then, under the dynamic load distribution strategy, the additional load $\Delta \hat{L}_{ji}$ of the adjacent node j is defined as follows:

$$\begin{aligned}\Delta \hat{L}_{ji} &= L_i \times \frac{C_j - L_j(t)}{\sum_{m\in\Gamma_i}(C_m - L_m(t))} \\ &= L_i \times \frac{(L_j^0 + \beta (L_j^0)^\gamma) - (L_j^0 + \eta L_j^0 \delta)}{\sum_{m\in\Gamma_i}((L_m^0 + \beta (L_m^0)^\gamma) - (L_m^0 + \eta L_m^0 \delta))} \\ &= L_i \times \frac{\beta (L_j^0)^\gamma + \eta L_j^0 \delta}{\sum_{m\in\Gamma_i}(\beta (L_m^0)^\gamma + \eta L_m^0 \delta)}\end{aligned} \tag{13}$$

According to equation (13), we can know that the load distribution results after cascading failure can be adjusted by the dynamically adjustable parameters η and δ, so as to obtain more accurate cascading failure redistribution results and improve the robustness of the complex logistics network.

V. SIMULATION RESULTS AND DISCUSSION

Based on the above dynamic cascading failure model with dynamic factors, we carry out cascading failure simulation for the complex logistics model constructed in Section II. Since the probability of multiple nodes failing simultaneously in a real logistics network is small, we still assume that only one node fails at a time, and the failed node cannot automatically renew to its normal state. The cascading failure simulation process under the dynamic cascading failure models is given as follows:

Step 1: Select nonlinear load-capacity model to define the relationship between the initial load and capacity of the network.

Step 2: Let the most efficient logistics node i fail, such that $k_i = k_{\max}$.

Step 3: The load of failed node i is redistributed to the adjacent node j in accordance with the load-redistribution strategy as equation (13). The additional load of node j is $\Delta \tilde{L}_{ji}$.

Step 4: It is assumed that the node is directly removed from the network after its failure. Therefore, the value of the failed node i in the neighbor matrix network is set to 0 and it is no longer connected with other nodes.

Step 5: After the load of the failed node is redistributed, check if any nodes in the neighbor node set have failed. When the neighbor node is failed, classify the failed node into the failed node set and update the dynamic load of all nodes, then return to Step 3; otherwise, go to Step 6.

Step 6: Until no logistics node fails, calculate the robustness G of the complex logistics network, and the whole dynamic cascading failure simulation process is finished.

Compared the dynamic cascading failure model with the one without dynamic factors, we assume the tolerance parameters as $\gamma = 1.3$, $\gamma = 1.1$, $\gamma = 0.9$, $\gamma = 0.7$ and $\gamma = 0.5$, and the simulation results are shown as Figure 6 to Figure1.

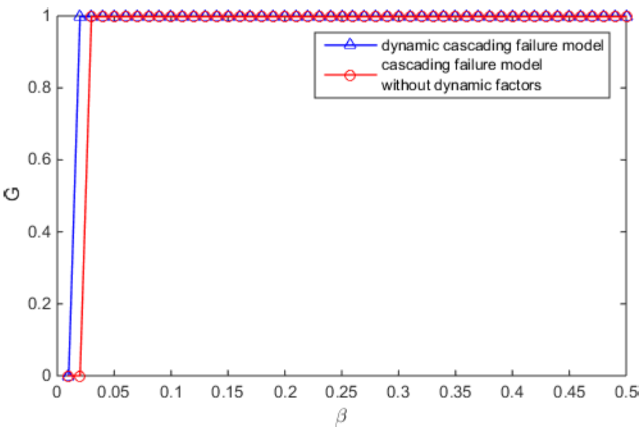

FIGURE 6. The relation between β and G for the dynamic cascading failure model and the cascading failure model without dynamic factors when $\gamma = 1.3$.

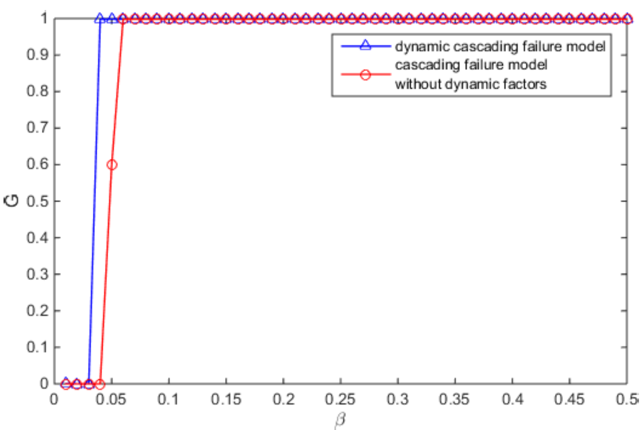

FIGURE 7. The relation between β and G for the dynamic cascading failure model and the cascading failure model without dynamic factors when $\gamma = 1.1$.

Figure 6-10 are the relation between β and robustness G for the dynamic cascading failure model and the cascading failure model without dynamic factors when $\gamma = 1.3$, $\gamma = 1.1$, $\gamma = 0.9$, $\gamma = 0.7$, and $\gamma = 0.5$ respectively. The blue lines represent the simulation value of the robustness G after cascading failure for complex logistics network based on the dynamic cascading failure model; The red lines represent the simulation value of the robustness G after cascading failure for complex logistics network based on the cascading

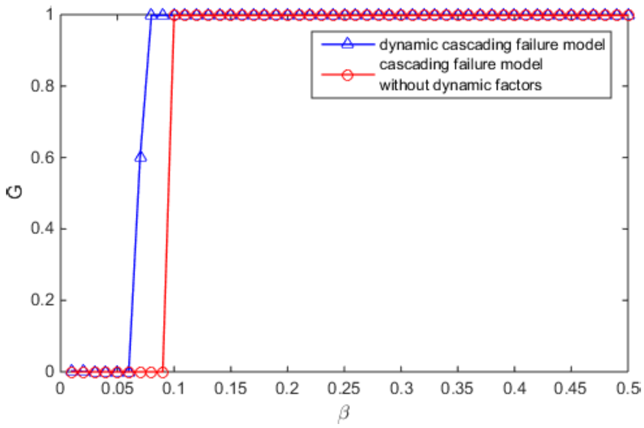

FIGURE 8. The relation between β and G for the dynamic cascading failure model and the cascading failure model without dynamic factors when $\gamma = 0.9$.

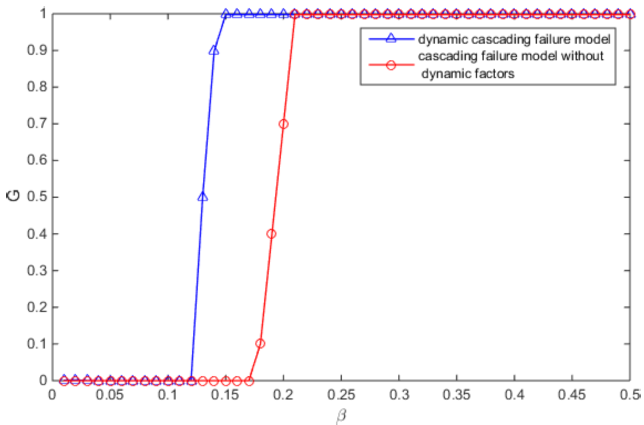

FIGURE 9. The relation between β and G for the dynamic cascading failure model and the cascading failure model without dynamic factors when $\gamma = 0.7$.

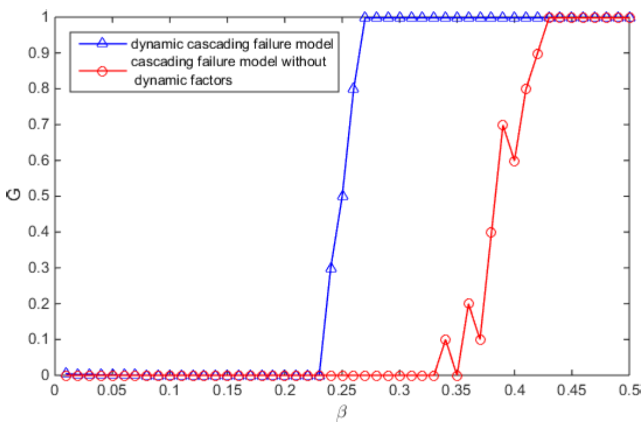

FIGURE 10. The relation between β and G for the dynamic cascading failure model and the cascading failure model without dynamic factors when $\gamma = 0.5$.

failure model without dynamic factors. From figure 6, one can see that, when $\gamma = 1.3$, the cascading failure threshold β for the dynamic cascading failure model is $\beta = 0.02$, and the cascading failure threshold β for the cascading failure model without dynamic factors is $\beta = 0.03$. In a similar way, from figure 7, we can see that, when $\gamma = 1.1$, the cascading failure threshold of β for the dynamic cascading failure model is $\beta = 0.04$, and the cascading failure threshold β for the cascading failure model without dynamic factors is $\beta = 0.06$. From figure 8, we can see that, when $\gamma = 0.9$, the cascading failure threshold β for the dynamic cascading failure model is $\beta = 0.08$, and the cascading failure threshold β for the cascading failure model without dynamic factors is $\beta = 0.1$. From figure 9, we can see that, when $\gamma = 0.7$, the cascading failure threshold β for the dynamic cascading failure model is $\beta = 0.15$, and the cascading failure threshold β for the cascading failure model without dynamic factors is $\beta = 0.21$. From figure 10, we can see that, when $\gamma = 0.5$, the cascading failure threshold β for the dynamic cascading failure model is $\beta = 0.27$, and the cascading failure threshold β for the cascading failure model without dynamic factors is $\beta = 0.43$. By comparing the five groups of simulation results, the following conclusions can be proved: 1)the larger the capacity parameter γ is, the smaller the cascading failure threshold β is, the more robust the network is. 2) When the capacity parameter γ is fixed, the cascading failure threshold β based on dynamic cascading failure model is smaller than the cascading failure model without dynamic factors. It means that the cascading failure threshold based on the dynamic cascading failure model is smaller than that based on the cascading failure model without dynamic factors. So, the dynamic cascading failure model for complex logistics network after cascading failure is the optimization model which has the strongest robustness and can provide a better solution to the cascading failure problem for complex logistics network.

VI. SIMULATION ANALYSIS OF CONTROLLABILITY ROBUSTNESS AND ECONOMY OF COMPLEX LOGISTICS NETWORK UNDER CASCADING FAILURE

Logistics cost is the core of logistics economy. The actual logistics network not only focuses on the robustness of the network, but also considers the cost of the logistics network. Cascading failure for complex logistics network would cause economic losses. So, it is of great significance to control the robustness and economy for complex logistics network, which can greatly improve network performance and create great economic value. In this section, we study the relationship between the controllability robustness and economy for complex logistics network after cascading failure, so as to achieve the method for getting the strongest robustness when the logistics cost is lowest in the same time.

We use the controllability robustness P_i and cost e to measure the controllability robustness and economy of complex logistics network [24], [32]. The controllability robustness P_i is defined as follows:

$$P_i = \frac{F_i}{N} \tag{14}$$

where F_i is the number of failed nodes in the complex logistics network after the failure of node i, N is the initial network size. The cost e is defined as follows:

$$e = \frac{\sum_{i=1}^{N} C_i}{\sum_{i=1}^{N} L_i^0} = \frac{\sum_{i=1}^{N} L_i^0 + \beta (L_i^0)^\gamma}{\sum_{i=1}^{N} L_i^0} \tag{15}$$

where $\sum_{i=1}^{N} C_i$ is the total capacity of the network that indicates the total cost of complex logistics network, $\sum_{i=1}^{N} L_i(0)$ is the total initial load of the network that indicates the initial cost of complex logistics network. Compared the dynamic cascading failure model with the cascading failure model without dynamic factors, the three-dimensional simulation results considering the controllability robustness P_i, cost e and capacity parameters γ simultaneously are shown in Figure 11 and Figure 12.

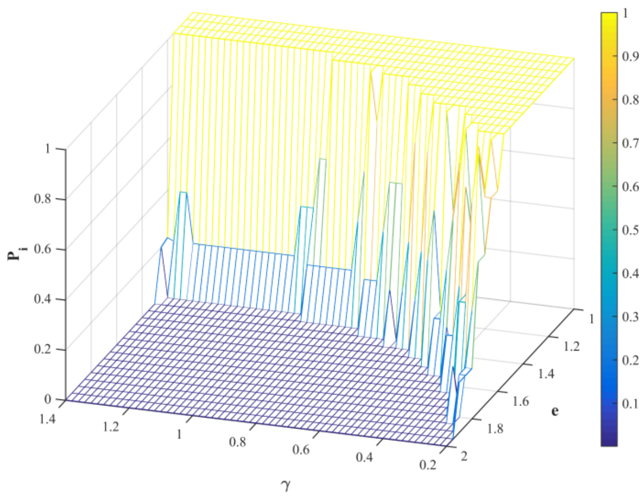

FIGURE 11. Relationship among P_i, γ and e under cascading failure model without dynamic factors.

Based on the cascading failure model without dynamic factors in the complex logistics network, the relationship among P_i, γ and e is shown in Figure 11. Based on the dynamic cascading failure model in the complex logistics network, the relationship among P_i, γ and e is shown in Figure 12. As can be seen from Figure 11 and Figure 12, the yellow region indicates that the value of controllability robustness P_i approaches 1 under different value of capacity parameters γ and cost e.The closer the color is to yellow, the closer the value of controllability robustness P_i is to 1; The blue region indicates that the value of controllability robustness approaches 0 under different value of capacity parameters γ and cost e. The darker the blue color is, the closer the value of controllability robustness P_i is to 0. By comparing Figure 11 and Figure 12, it can be seen that the blue region

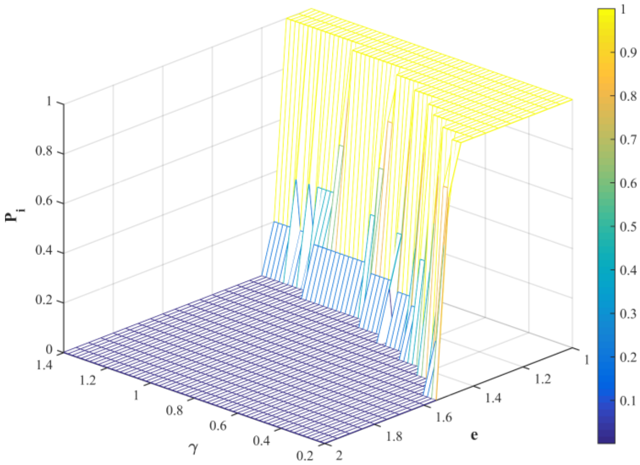

FIGURE 12. Relationship among P_i, γ and e under dynamic cascading failure model.

in Figure 11 is smaller than the blue region in Figure 12, which is means that in the dynamic cascading failure model, the smaller the cost threshold is, the bigger the blue region is. Moreover, in order to get better comparisons and conclusions for the results of the two experiments, we make a detailed comparative analysis of the plane view and side view of the two three-dimensional figures respectively which are shown in Figure 13 and Figure14.

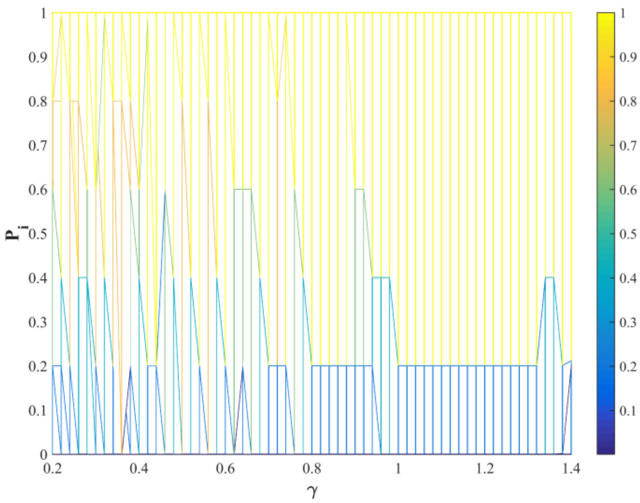

FIGURE 13. Relationship between P_i and γ under cascading failure model without dynamic factors.

Figure 13 is the side view in controllability robustness P_i and capacity parameter γ directions of Figure 11, it shows the relationship between P_i and γ based on the cascading failure model without dynamic factors in the complex logistics network. Figures 13 is the side view in controllability robustness P_i and capacity parameter γ directions of Figure 12, it shows the relationship between P_i and γ based on the dynamic cascading failure model in the complex logistics network. In Figure 13, the controllability robustness of the complex logistics network is not stable in the interval of $0 < \gamma \leq 0.8$, and very monotonous in the interval of $\gamma > 0.8$. It is hard to optimize the controllability robustness

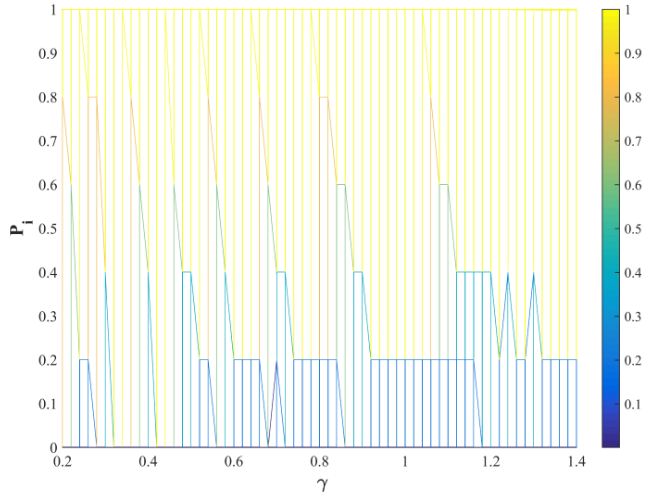

FIGURE 14. Relationship between P_i and γ under dynamic cascading failure model.

by controlling γ to fit the actual economic requirements of the logistics cost e according to Figure 12. However, comparing Figure 13 with Figure 14, the controllability robustness of the complex logistics network in Figure 14 is much more stable in the interval of $0 < \gamma \leq 0.8$, and much more clearly and multiply controllability robustness selection intervals of all the interval of γ. So, a conclusion can be drawn by comparison is that comparing with the cascading failure model without dynamic factors, the dynamic cascading failure model can be optimized more efficiency by adjusting capacity parameter γ to control the controllability robustness P_i more flexibly and accurately under a fit cost e. Thus, under the premise of limited economic cost, the performance of complex logistics network can be better controlled by the dynamic cascading failure model.

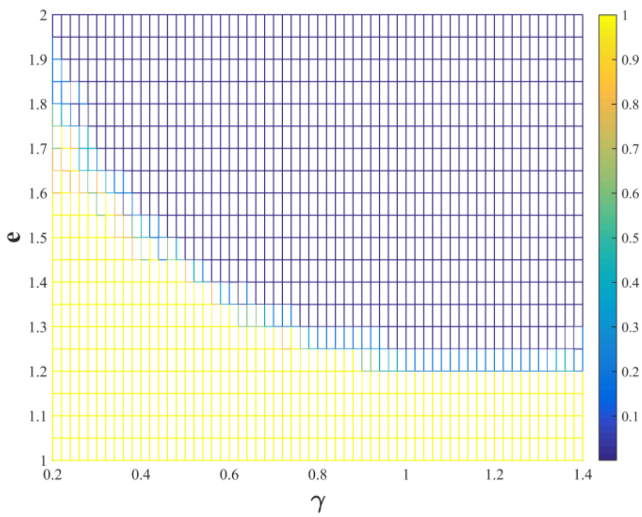

FIGURE 15. Relationship between e and γ under cascading failure model without dynamic factors.

Figure 15 is the plane view in cost e and capacity parameter γ directions of Figure 11, it shows the relationship between e and γ based on the cascading failure model without dynamic

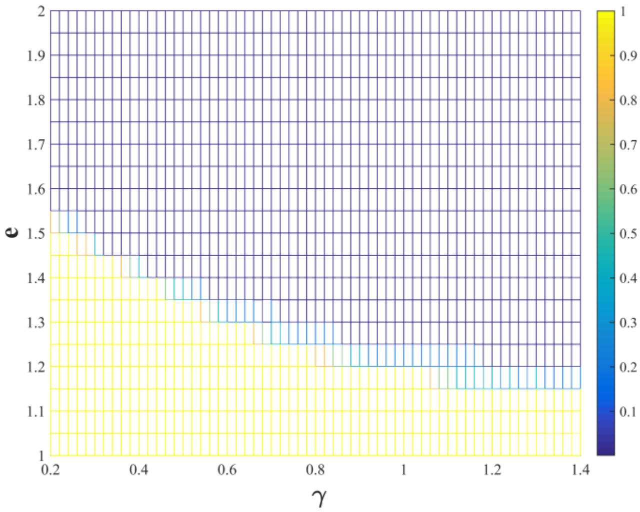

FIGURE 16. Relationship between e and γ under dynamic cascading failure model.

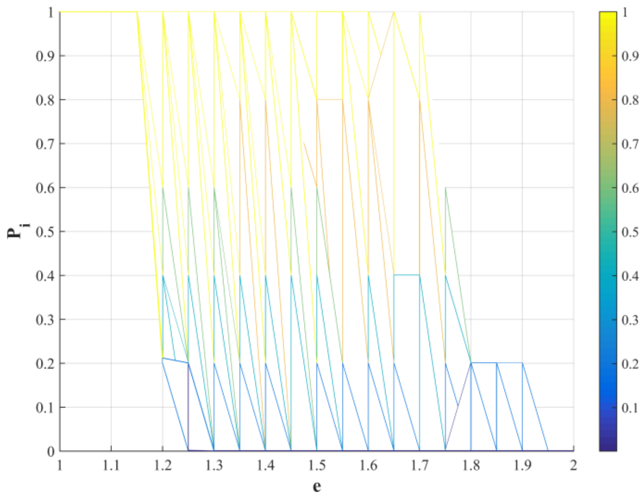

FIGURE 17. Relationship between P_i and e under cascading failure model without dynamic factors.

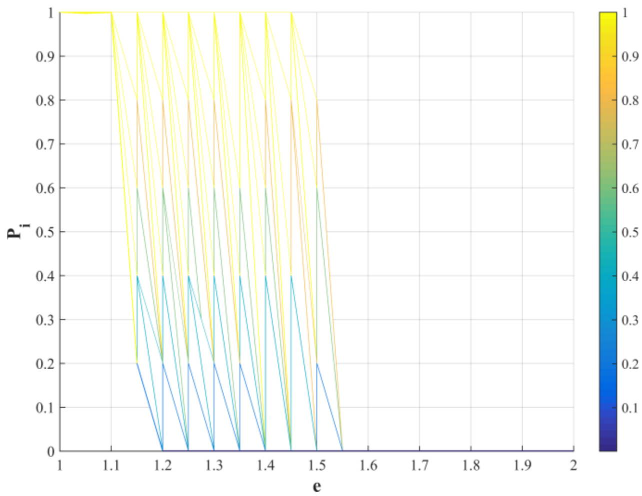

FIGURE 18. Relationship between P_i and e under dynamic cascading failure model.

factors in the complex logistics network; Figures 16 is the plane view in cost e and capacity parameter γ directions of Figure 12, it shows the relationship between e and γ based on the dynamic cascading failure model in the complex logistics network. From Figure 15 and Figure 16, we can see that the controllability robustness distribution under the influence of network cost and capacity parameters. The blue area is for the controllability robustness P_i with $P_i \neq 1$, the yellow areas is for the controllability robustness P_i with $P_i = 1$. The blue area is the best choice for balancing the optimal combination of the cost e and capacity parameter γ. Obviously, the blue area in Figure 15 is smaller than the blue area in Figure 16, which means that the optional area under cascading failure model without dynamic factors is smaller than that under dynamic cascading failure model. So, the dynamic cascading failure model is a more intelligent model to control the cost e and capacity parameters γ synchronously to achieve a better controllability robustness for complex logistics network. According to the specific requirements of logistics cost range, we can control the capacity parameters γ under dynamic cascading failure model in the blue area to improve the controllability robustness for complex logistics network. When the cost e is fixed, the bigger capacity parameter γ is, the stronger controllability robustness is.

Figure 17 is another side view in controllability robustness P_i and cost e directions of Figure 11, it shows the relationship between P_i and e based on the cascading failure model without dynamic factors in the complex logistics network. Figure 18 is another side view in controllability robustness P_i and cost e directions of Figure 12, it shows the relationship between P_i and e based on the dynamic cascading failure model in the complex logistics network. From Figure 17 and Figure 18, we can see that the controllability robustness for complex logistics network increases with the increasing cost. On the premise of not considering the limitation of cost e, the controllability robustness against cascading failure for logistics network can be controlled to a stronger state by increasing the construction cost of logistics network. Furthermore, we can know from the data in Figure16 and Figure17 that the controllability robustness P_i approaches to stable as $P_i = 0$ with the cost $e = 1.95$ in Figure 16, and with the cost $e = 1.55$ in Figure 18. It means that, for the same controllability robustness for complex logistics network, the cost e in Figure 18 can be much lower than Figure 17. So, a conclusion can be drawn by comparison is that the dynamic cascading failure model is more intelligent than the cascading failure model without dynamic factors for controlling the cost e and controllability robustness P_i synchronously, which can achieve a better economy for complex logistics network after cascading failure. So, we can control the controllability robustness P_i with a lower cost e under dynamic cascading failure model to improve the economy for complex logistics network.

From the above, the dynamic cascading failure model with dynamic factors is an optimized model. It can effectively control the controllability robustness and economy of the complex logistics network by adjusting the cost e and capacity parameters γ, so as to reduce the cost and enhance the controllability against cascading failure.

VII. CONCLUSION

In conclusion, according to the empirical dynamic characteristics of the load of real logistics network, we propose a dynamic cascading failure model which adds dynamic factors to the cascading failure model based on nonlinear load-capacity model under initial residual capacity load-redistribution strategy. Based on the complex logistics network model, we compare the dynamic cascading failure model with the cascading failure model without dynamic factors by cascading failure simulation. Through the simulation analysis of controllability robustness and economy after cascading failure, we find that the dynamic cascading failure model we proposed has better performance for complex logistics network. It can more effectively reduce the logistics cost and enhance controllability robustness against cascading failure by adjusting the network cost e and capacity parameter γ, so as to balance the controllability robustness and economy of the complex logistics network.

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