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Controllability Robustness Against Cascading Failure for Complex Logistics Networks Based on Nonlinear Load-Capacity Model

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ABSTRACT In order to achieve good connectivity after the cascading failure of a logistics network, this paper studies the controllability robustness of complex logistics network based on the nonlinear load-capacity (NLC) model. Firstly, the extended Baraba' si and Albert (BA) network is constructed as a complex logistics network for experiments, based on the power law distribution and the agglomeration and sprawl evolution mechanism. Secondly, the existence of the NLC relationship of the real logistics network is proved, and then the NLC model of complex logistics networks is proposed. Furthermore, a simulation analysis of the controllability robustness and influencing factors of the complex logistics network is carried out under four different cascading failure models. In those models, different scenarios of the NLC and the classical linear load-capacity (LLC) model with initial load (IL)/initial residual capacity (IRC) load-redistribution strategies are combined. The research results show that the main influencing factors of the cascading failure of complex logistics networks for the controllability robustness P_i are the tolerance parameters β and γ. Moreover, the effect of γ on the load-capacity relationship under the NLC model is more significant than that of β. Among the four cascading failure models, the one based on the NLC model with IRC strategy is the optimal for controllability robustness. Based on the optimal model, the simulation considering the perspective of the logistics economy shows that the relationship among the network cost e, P_i and γ is as follows: under a fixed cost, the greater is γ, the stronger is P_i. Also, when $2 < \gamma \leq 9$, the robustness of the network is controllable. According to the requirements of real logistics networks, both controllability robustness and the logistics cost can be controlled, and a solution that against cascading failure can be obtained by adjusting the minimum residual load.

INDEX TERMS Complex logistics network, cascading failure, controllability robustness, nonlinear load-capacity model.

I. INTRODUCTION

Complex logistics networks represent one of the most important fields of the interdisciplinary application of complex network theory [1]–[4]. Complex network theory can reveal the essence, characteristics and operational rules of real logistics network activities [5]–[7]. A complex logistics network is a complex network composed of nodes which carry logistics activities such as storage, loading and unloading, handling, packaging and other logistics functions, and edges which connect these nodes. Nodes include logistics parks, logistics centers, distribution centers and storage centers, while edges include transportation lines, transportation pipelines and communication lines. Therefore, complex logistics networks have the agglomeration and sprawl characteristics of real logistics networks, and feature the power law distribution of complex network theory. The realization of the function of a complex logistics network depends on the efficient

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operation of the nodes and the just-in-time transportation of the edges between any two nodes, which are highly dependent on real-world situations. In real logistics situations, force-majeure accident situations may occur, such as extreme weather, political factors, workers taking vacations at the same time for the Spring Festival, workers' strikes, etc., and can lead to the function failure of a given node in the network [8], [9]. When a failure occurs, the load of the failed node needs to be redistributed to the adjacent nodes. Because of the limitations of real logistics node capacity, the adjacent nodes will probably surpass their capacity and this will lead to further failures. The mutual coupling relationship between nodes will ultimately bring about the collapse of the whole logistics network. This dynamic process is called the cascading failure of the complex logistics network, which affects the normal operation of the logistics network and causes economic losses. Therefore, figuring out how to make logistics networks achieve better connectivity after cascading failure, i.e. achieving controllability robustness against cascading failure, has become a hot topic for logistics enterprises and scholars. In this paper, we study controllability robustness against the cascading failure of a complex logistics network based on complex network theory and the cascading failure load-capacity model, considering the agglomeration and sprawl evolution mechanism of a real logistics network. The relationship between the logistics network cost, controllability robustness and the residual load of the node is revealed, providing a solution that lowers the logistics network cost by flexibly adjusting the minimum residual capacity of the nodes and ensuring that the robustness of the complex logistics network is controlled.

To construct a complex logistics network, we first need to consider the agglomeration and sprawl characteristics of the real logistics network. The logistics agglomeration is the phenomenon of logistics activities and facilities being concentrated in specific areas; the logistics sprawl is the phenomenon whereby logistics activities and facilities move from central urban areas to peripheral suburbs [10], [11]. The reason for the logistics agglomeration is that logistics activity is limited by different factors, such as the economic environment, political conditions and geographical position. The key nodes in some specific areas are differ greatly from the general nodes in the geographic economy. Thus, the evolution of the logistics network presents the power-law distribution characteristic of "the rich people get richer", which is the Baraba' si and Albert (BA) network, and this generates agglomeration-based economic benefits. To construct a logistics network based on complex network theory, the BA network is used by authors to simulate a logistics network based on the logistics network characteristic of the power law distribution to generate the agglomeration of economic benefits. The rules by which they construct the complex logistics network only add nodes, and do not delete or move them [4], [12]–[14]. However, when the agglomeration was evolved to a certain scale, the economic benefits may no longer increase, or may even decrease. Dablanc demonstrates that the suburbs and remote suburbs are more attractive than the city center for logistics hubs, because of the land availability, lower costs and better connections to other regions or countries [11], [15]; Hesse and Rodrigue [16], Hesse [17] and [18], and Feitelson and Salomon [19] proposed that logistics activities would have a long-distance layout, 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. Therefore, the BA network cannot accurately describe real logistics networks because of the nodes without removed or moved for the logistics sprawl. This paper intends to extended the BA network into a complex logistics network considering both agglomeration and sprawl evolution mechanism.

In order to control the risk of complex logistics network in the operation process, the controllability robustness of the network against cascading failure is a crucial problem to consider. In recent years, the cascade failure analysis of complex networks has been studied more deeply [20]–[25] and many kinds of cascading failure model is adopted in different field [3], [7], [10], [12]–[14], [16], [26]. In the field of complex logistics networks, the load-capacity model is the most widely used because of the load capacity characteristics of the logistics system. Moreover, the classical linear load-capacity (LLC) model is adopt by scholars in order to simplify the problem, in which the capacity and initial load of the nodes are defined to have a linear relationship [1], [11]–[14]. The LLC model is proposed to study cascading failure by A. E. Motter in 2002 [27] and widely used by later scholars in logistics, communications and many other different fields [7], [12]–[14], [21], [28]. However, Kim and Motter [5] and indicated 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 is nonlinear in their initial loads. In addition, network nodes with small capacity have large proportions of residual capacity, which provides a research reference for the wide application of the nonlinear load-capacity (NLC) model. Given the above-mentioned circumstances, several authors have proposed to apply the NLC model to study the controllability robustness of cascading failures and found that the NLC model could tackle these difficulties and reduce the network cost by flexibly adjusting the minimum residual capacity of the nodes [29]–[32]. Especially, Chen *et al.* [30] and Dou *et al.* [31] proposed the NLC model to research on the processes and features of cascading failure on complex networks and proved that the NLC model is helpful to guide system construction and improve its robustness. But although the study of controllability robustness of cascading failure based on the NLC model can be expected to be feasible, it is less frequently used in the complex logistics networks. So, this paper attempts to analyze the load-capacity characteristics of two different real logistics networks and thereby proves the feasibility of the NLC model.

In addition to the load-capacity model, different load redistribution strategies may also have a significant impact on the controllability robustness of a complex logistics network against cascading failure [12]–[14], [33]–[35]. The load redistribution strategy involves distributing the load of the failed node to its adjacent nodes according to a certain redistribution mechanism, so as to realize the logistics function of the complex logistics network under cascading failure. The cascading failure load redistribution strategy of a complex network is based on the number of adjacent nodes [30], the ratio of the capacities of the adjacent nodes [14], the initial load (IL) [12], [13], the initial residual capacity (IRC) [34], [35], and various other strategies. Among them, the research in the complex logistics network field mostly adopts the IL and IRC redistribution strategies [12], [30]. The IL redistribution strategy is a redistribution rule whereby the load of the failed node is redistributed to its adjacent nodes according to the initial load. Under the IRC redistribution strategy, the load of the failed node is redistributed to its adjacent nodes according to the difference between the capacity and the initial load. This paper attempts to explore in depth the influence of the IL and IRC redistribution strategies on the controllability robustness of complex logistics networks, based on the LLC and NLC models.

In view of the above problem, the rest of this paper is organized as follows: the complex logistics network is defined and described based on the extended BA network model in Section 2. In Section 3, the complex logistics network cascading failure model is constructed, based on the NLC model, and the results of applying the model are compared with those of the LLC model under the IL and IRC redistribution strategies. Conclusions are drawn in Section 5.

II. COMPLEX LOGISTICS NETWORK

A. DESCRIPTION OF PROBLEM

From the above, we construct a complex logistics network for experimental purposes, which includes the agglomeration and sprawl mechanisms and the complex features of logistics networks. The evolution mechanism characteristics of the BA network, namely growth and preferential connections, are adopted [3]. Moreover, the agglomeration and sprawl mechanisms of the logistics network are considered at the same time. Thus, an extended BA network model is established for constructing the experimental complex logistics network [32], [36], [37].

B. GENERATION ALGORITHM OF COMPLEX LOGISTICS NETWORK

We define the complex logistics network as a logistics infrastructure network $G = (V, E)$. V represents the nodes that realize all of the functions in the logistics system, such as package sending and receiving, transit and circulation, processing, warehousing and information processing, etc., which include logistics parks, logistics centers, distribution centers and storage centers. E represent 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 have 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 logistics infrastructure network can be abstracted into an undirected weighted BA network model, whose generation algorithm is 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 connections 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, such that:

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

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

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

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 the $s_i > s_0$ case of the network are selected, and the partial nodes and all edges connected to the 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.

C. AMENDING THE NETWORK MODEL FOR LOGISTICS

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 1, the number of initialization network nodes is 1000, and the average degree is 4. The node degrees are shown in Figure 2. The degree distribution of the complex logistics network is shown in Figure 3. It can be seen from Figures 2 and 3 that the network conforms to the power law distribution characteristic of complex networks.

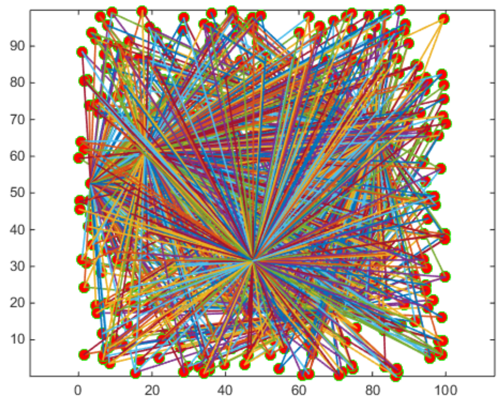

FIGURE 1. Extended BA network.

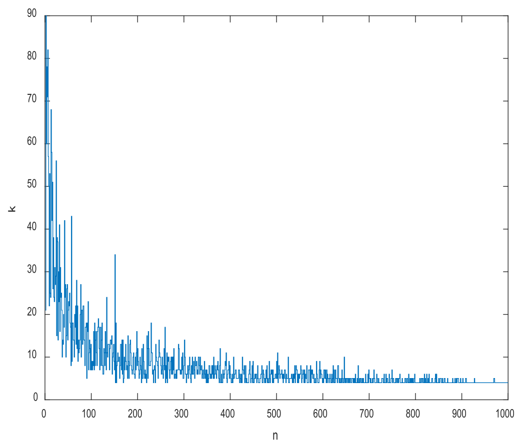

FIGURE 2. The degree of the nodes.

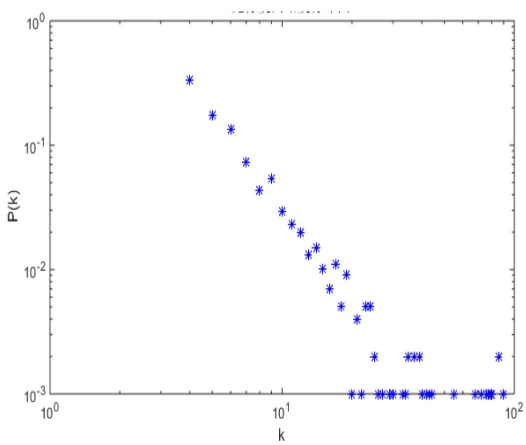

FIGURE 3. Distribution of network degrees.

III. MODELING OF CASCADING FAILURE

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 accident situation. 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 too could surpass their own load capacities. The above phenomenon is called the cascading failure of the complex logistics network.

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 [12], [27], [38]–[40]. 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

$$L_i^0 = (k_i \sum_{m\in\Gamma_i} k_m)^\alpha, \quad i = 1, 2, \cdots, N \tag{3}$$

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

In consideration of the load-capacity model and the load-redistribution strategy have different effects on the controllability robustness of the network, an empirical analysis of the load-capacity characteristics of the complex logistics network is carried out in this section. On the one hand, the nonlinear relationship between load and capacity in the real logistics network is demonstrated; on the other hand, the characteristics of the NLC model are revealed through an analysis of the relationship between γ and β. Furthermore, in order to select the best combination of load-capacity model and load-redistribution strategy, the results of applying the LLC and NLC models under different load-redistribution strategies are compared through model analysis, using formulas and simulations applied by means of the MATLAB software tools.

A. EMPIRICAL LOGISTICS AND LOAD–CAPACITY CHARACTERISTICS OF NETWORK

1) EXISTENCE OF NONLINEAR RELATIONSHIP BETWEEN LOAD AND CAPACITY OF REAL LOGISTICS NETWORK

The node capacity of the complex logistics network is the maximum logistics load ability, which is proportional to the controllability robustness against cascading failure. That is, the greater is the capacity, the stronger is the controllability robustness. However, in a real logistics network, the node capacity cannot be increased indefinitely due to the limitations of the logistics economic cost. Therefore, figuring out how to obtain the largest residual capacity within a limited cost range is a key issue when looking at the controllability robustness of a complex logistics network. The LLC model is adopted to define node capacity in complex logistics networks [1], [27], [28]:

$$C_i = (1 + \beta)L_i^0, \quad i = 1, 2, \cdots, N \tag{4}$$

where i is the node in the network, C_i is the capacity of node i, L_i^0 is the initial load of node i, and β is a tolerance parameter, $\beta > 0$.

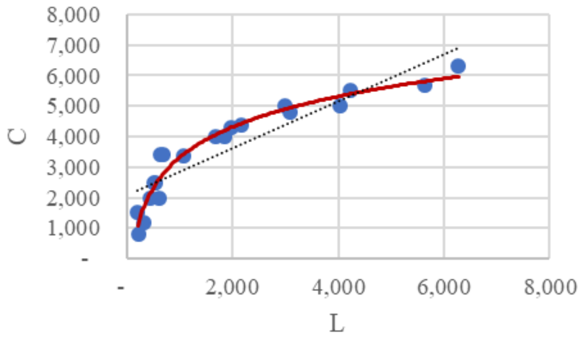

FIGURE 4. **The relationship between the load and capacity of a logistics distribution network of product 1.**

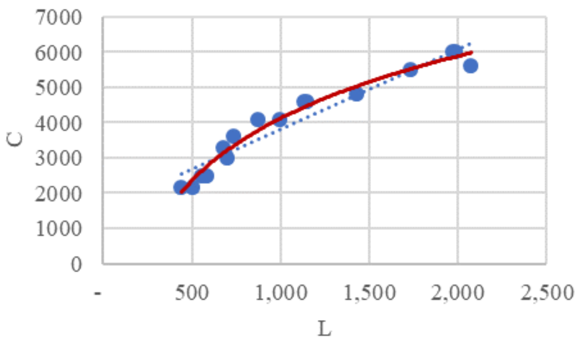

FIGURE 5. **The relationship between the load and capacity of a logistics distribution network of product 2.**

To analyze the load-capacity relationship characteristics of real logistics networks, the following two different real logistics infrastructure networks of a Fortune 500 company are taken as examples. Figure 4 and 5 shows the relationship between the logistics storage capacity and the real-time load of nodes of two different products of logistics distribution network across the country. The nodes include supply nodes, transshipment nodes and demand nodes. The abscissa and ordinate of figure 4 and figure 5 are the number of products under real-time load and the maximum number of storage capacity under load of product 1 and product 2, respectively. It can be seen from the two figures that the relationship between load and capacity in real logistics networks is very close to but not exactly linear. Obviously, from an accuracy perspective, the definition of load-capacity as linear describes real logistics networks closely, but the nonlinear model is more accurate.

2) NLC MODEL AND ITS CHARACTERISTICS

The capacity of a complex logistics network is defined based on the NLC model [29]–[31]:

$$C_i = L_i^0 + \beta L_i^{0\gamma} \tag{5}$$

where C_i is the capacity of node i, and β, γ are the tolerance parameters, with $\beta \geq 0$, $\gamma > 0$. Note that if $\gamma = 1$, the NLC model degenerates to the classical linear load-capacity model (4). By adjusting the tolerance parameters,

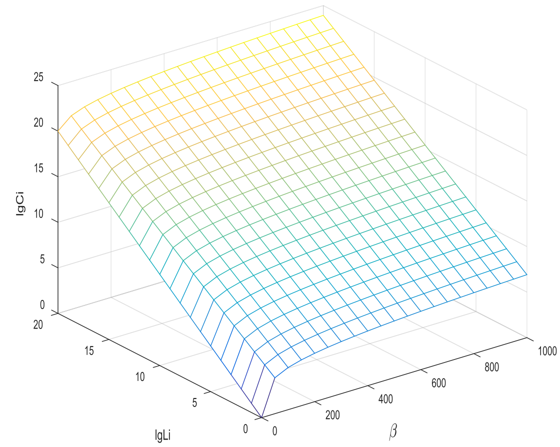

FIGURE 6. **Load-capacity relationship with β.**

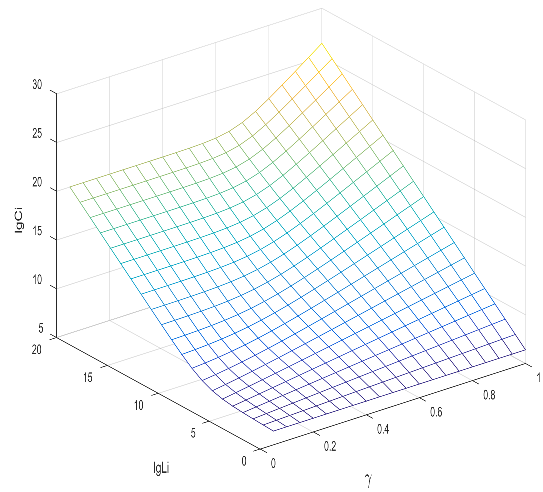

FIGURE 7. **Load-capacity relationship with γ.**

it is possible to simulate the nonlinear relationship between the capacity and load of the real complex logistics network. The following figures show the relationship between load, capacity and parameters β and γ respectively, on a log scale. Figure 6 shows the relationship between β and load-capacity, when $\gamma = 0.85$. Figure 7 shows the relationship between γ and load-capacity when $\beta = 600$. As can be seen from Figure 6, β determines the overall approximate ratio and the amount of the load. When the value of β is lower than 50, the influence on the relationship between load and capacity is large, and when the value of β is higher than 50, the influence on the relationship between load and capacity is small. As can be seen from Figure 7, the effect of γ on the relationship between load and capacity is significant, in that the residual of the node capacity is severely shrunk as γ increases when the load value is large. Moreover, it can be seen from the comparison between Figures 6 and 7 that the effect of γ on the relationship between load and capacity is more remarkable than the effect of β. Therefore, the NLC model can adjust the parameters β and γ more flexibly to control the relationship between the capacity and the initial load of the node, so as to obtain a more accurate node residual capacity.

B. COMPARATIVE ANALYSIS OF RESULTS OF APPLYING LLC AND NLC MODELS UNDER DIFFERENT LOAD-REDISTRIBUTION STRATEGIES

After cascading failure, the redistributed load of the adjacent nodes of the failed node will differ when different load-redistribution strategies are adopted under the same load-capacity model. Thus, a better combination of load-redistribution strategy and load-capacity model will produce stronger controllability robustness in the complex logistics network. In order to compare and analyze the results of applying the LLC and NLC models under the two different load-redistribution strategies IL and IRC, the following derivation proves whether the loads redistributed to the adjacent nodes of the failed node are the same.

1) IL AND IRC LOAD-REDISTRIBUTION STRATEGIES BASED ON LLC MODEL

Based on the LLC model of the complex logistics network under cascading failure, the redistribution results of the IL and IRC load-redistribution strategies are the same. The formulaic derivations are as follows:

Using Eq. (4), the extra load ΔL_{ji1} of the adjacent node j, moved from failed node i under the IL load-redistribution strategy, is defined as

$$\Delta L_{ji1} = L_i \times \frac{L_{\mathrm{j}}^0}{\sum_{n\in\Gamma_i} L_n^0} \tag{6}$$

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's 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 that the load of the first attacked node in the cascade 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. Equation (6) shows that the load L_i of the failed node i is allocated to the adjacent node according to the proportion of the initial load of the adjacent node to the total of the initial load of all the adjacent nodes.

Let C_j denote the capacity of the adjacent node j of node i. The extra load ΔL_{ji} of the adjacent node j, moved from the failed node i under the IRC load-redistribution strategy, is defined as

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

Substituting (4) into (7), the extra load L'_{ji1} of the adjacent node j, moved from the failed node i under the IRC load-redistribution strategy, is

$$\begin{aligned}\Delta L'_{ji1} &= L_i \times \frac{C_j - L_j^0}{\sum_{n\in\Gamma_i} (C_n - L_n^0)} \\ &= L_i \times \frac{(1+\beta)L_j^0 - L_j^0}{\sum_{n\in\Gamma_i} ((1+\beta)L_n^0 - L_n^0)} \\ &= L_i \times \frac{L_j^0}{\sum_{n\in\Gamma_i} L_n^0}\end{aligned} \tag{8}$$

According to (6) and (8), it can be seen that

$$\Delta L_{ji1} = \Delta L'_{ji1} \tag{9}$$

It can be seen from Eq. (9) that, based on the LLC model of the complex logistics network under cascading failure, the extra load of the adjacent node, moved from the failed node under the IL and IRC redistribution strategies, is the same. This indicates that the controllability robustness of the complex logistics network under the IL and IRC redistribution strategies, based on the LLC, is the same.

2) IL AND IRC LOAD-REDISTRIBUTION STRATEGIES BASED ON NLC MODEL

Based on the NLC model of the complex logistics network under cascading failure, the redistribution results of the IL and IRC load-redistribution strategies are different. Formulaic derivations are as follows:

Using Eq. (5), the extra load L_{ji2} of the adjacent node j, obtained from the failed node i under the IL load-redistribution strategy, is

$$\Delta L_{ji2} = L_i \times \frac{L_{\mathrm{j}}^0}{\sum_{n\in\Gamma_i} L_n^0} \tag{10}$$

Substituting (5) into (7), the extra load $\Delta L'_{ji2}$ of the adjacent node j, obtained from the failed node i under the

$$\begin{aligned}\Delta L'_{ji2} &= L_i \times \frac{C_j - L_j^0}{\sum_{n\in\Gamma_i} (C_n - L_n^0)} \\ &= L_i \times \frac{L_j^0 + \beta L_j^{0\gamma} - L_j^0}{\sum_{n\in\Gamma_i} (L_n^0 + \beta L_n^{0\gamma} - L_n^0)} \\ &= L_i \times \frac{L_j^{0\gamma}}{\sum_{n\in\Gamma_i} L_n^{0\gamma}}\end{aligned} \tag{11}$$

Comparing Eq. (10) with Eq. (11), it can be seen that

$$\Delta L_{ji2} \neq \Delta L'_{ji2} \tag{12}$$

The above derivation proves theoretically that the redistribution results of the IL and IRC load-redistribution strategies based on the NLC model are different, which means that the controllability robustness of the two strategies are different. Moreover, comparing Eq. (12) with Eq. (9), the controllability robustness of the two strategies based on the LLC model are the same, which means that the NLC model is more flexible than the LLC model and provides a greater possibility of optimization to improve the controllability robustness of the complex logistics network. Based on the NLC model, comparing Eq. (10) with Eq. (11), the extra load ΔL_{ji} can be adjusted flexibly by changing the parameter γ based on the IRC load-redistribution strategy, which is more flexible than the IL load-redistribution strategy in terms of altering the controllability robustness of the complex logistics network. In conclusion, the IRC redistribution strategy based on the NLC model is theoretically an optimal cascading model when cascading failures occur, for achieving a better robustness of network control.

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

A. CONTROLLABILITY ROBUSTNESS AND ECONOMIC EVALUATION INDICATORS

1) CONTROLLABILITY ROBUSTNESS (P_i)

The controllability robustness of a complex logistics network is the ability of the network to provide critical logistics services or functions when a node or edge is damaged due to an accident that causes cascading failure. In order to describe the ability of the entire network to resist cascading failures, one node is removed at a time, and then, the controllability robustness P_i is selected to measure the effect of cascading failure [20], [21], [32], [41].

$$P_i = \frac{F_i}{N-1} \tag{13}$$

where F_i is the number of failed nodes caused by the failed node i, N is the total number of nodes in the network and P_i is the proportion of cascading failure nodes caused by the failed node i which is selected as the indicator of controllability robustness of the complex logistics network. It can be seen from Eq. (13) that the smaller is P_i, the stronger is the controllability robustness of the network.

2) COST (e)

A real logistics network not only relies heavily on controllability robustness, but also depends on the economic cost. While ensuring the stability of the network, designing a more reasonable cascading failure model with a lower cost and higher controllability robustness is a practical and significant problem for a real logistics network. Suppose that $\sum_{i=1}^{N} C_i$ is the total capacity of the network and $\sum_{i=1}^{N} L_i(0)$ is the total initial load of the network. The cost of the network e is defined as in [39]:

$$e = \sum_{i=1}^{N} C_i \bigg/ \sum_{i=1}^{N} L_i(0) \tag{14}$$

B. CASCADING FAILURE MODEL SIMULATION - EXPERIMENT DESIGN

A simulation experiment is carried out to model a complex logistics network after cascading failure, using the cascading failure model with different combinations of load-capacity models and load-redistribution strategies, to analyze the effect of parameters γ and β on the controllability robustness of the complex logistics network. We test four cascading failure models:

(1) Model 1: LLC model and IL load-redistribution strategy.

(2) Model 2: LLC model and IRC load-redistribution strategy.

(3) Model 3: NLC model and IL load-redistribution strategy.

(4) Model 4: NLC model and IRC load-redistribution strategy.

As the probability of multiple nodes failing independently in a real logistics network is small, this paper assumes that only one node fails at a time, and the failed node cannot automatically renew to its normal state. Based on the complex logistics network constructed in Section II, the cascading failure simulation process under the above four cascading failure models is as follows:

Step 1. Select LLC or NLC model to define the relationship between the initial load and capacity of the network.

Step2. 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 nodes j in accordance with the IL or IRC load-redistribution strategy. 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, calculate the controllability robustness P_i and network cost e of the complex logistics network.

C. SIMULATION ANALYSIS WITHOUT CONSIDERING ECONOMY

The simulation results of the cascading failure of the complex logistics network based on the four cascading failure models are shown in the figures below.

Figure 8 shows the relationship between β and P_i in the complex logistics network under Model 1. It can be seen from the figure that P_i becomes lower with an increase in β under the same α. The critical threshold of β becomes smaller with an increase in α. It can be seen from the figure that every P_i has only two values, 1 and 0, except on the two lines where α is 0.4 and 1.0 respectively. When $\alpha = 1.0$, P_i is 0.6 when $\beta = 0.9$; when $\alpha = 0.4$, P_i is 0.4 when $\beta = 1.2$. This obviously shows that P_i never takes a value in the interval (0, 1) except when $\alpha = \{0.4, 1.0\}$. This indicates that the controllability robustness after cascading failure, based on Model 1, is nearly

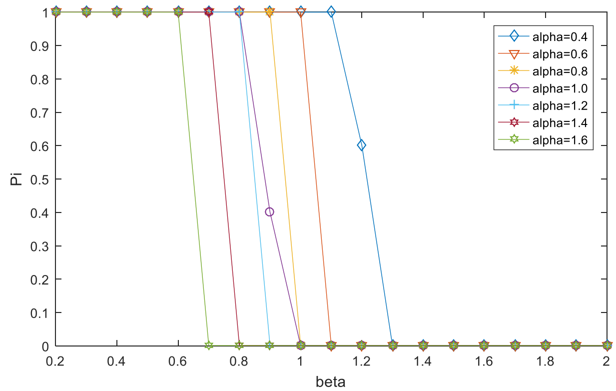

FIGURE 8. The relationship between β and P_i in the complex logistics network under Model 1.

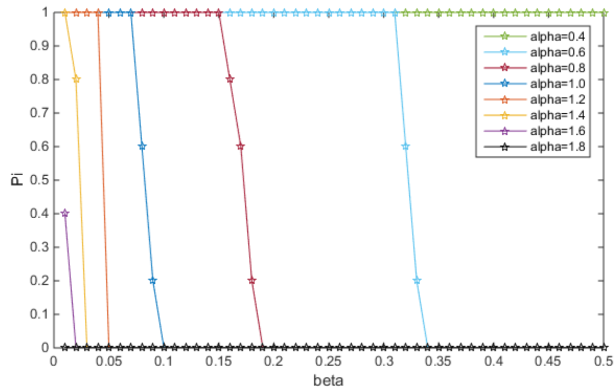

FIGURE 9. The relationship between β and P_i in the complex logistics network under Model 3.

uncontrollable. Since the extra loads of the IL and IRC load-redistribution strategies based on the LLC model are same, the simulation results from Model 2 are the same as those from Model 1, and are thus not described here.

Figure 9 shows the relationship between β and P_i in a complex logistics network under Model 3. It can be seen from the figure that P_i becomes lower as β increases, under the same α, which indicates that the controllability robustness becomes stronger as β increases, under the same α. Also, the critical threshold of β becomes smaller with an increase in α, which means that the controllability robustness of the network is becoming stronger. The critical threshold of β differs widely under different values of α. One can see that the critical threshold of β is 0.02 when $\alpha = 1.6$ and the critical threshold of β is 0.1 when $\alpha = 1.0$, which indicates that the critical threshold of β is not a fixed value, but changes as α changes; it can be seen from the figure that P_i does not only take the two values of 1 and 0, but several other values within the interval (0, 1), such as {0.2, 0.6, 0.8} when $\alpha = 0.8$ and {0.6, 0.8} when $\alpha = 1.0$. It can be seen that the controllability robustness after cascading failure based on Model 3 is controllable. Comparing Figure 8 with Figure 9, one can see that the controllability robustness after cascading failure based on Model 3 is more controllable than that based on Models 1 and 2. This explains the conclusion of

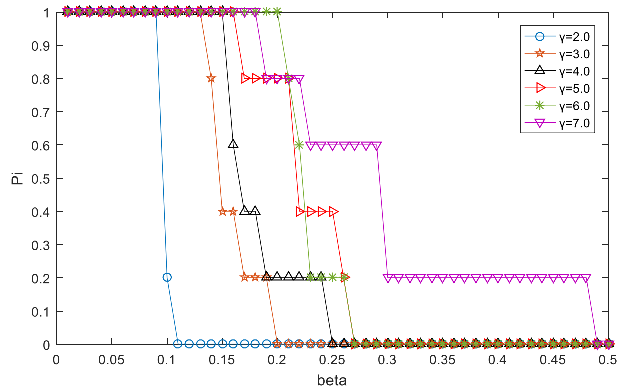

FIGURE 10. The relationship between β and P_i in the complex logistics network under Model 4 with $\alpha = 0.4$.

the derivation of the formula in Section III(B) and indicates that the NLC model is more flexible than the LLC model in that the controllability robustness can be adjusted to its optimum by changing α to correspond to different values of β. Moreover, when α is fixed, the critical threshold of β based on the NLC model is always better than the one based on the LLC model. This means that stronger controllability robustness of the complex logistics network is obtained based on the NLC model, with lower capacity and cost. So, next we simulate the cascading failure process based on Model 4 under a fixed value of α, and show the results in Figure 10.

Figure 10 shows the relationship between β and P_i in the complex logistics network under Model 4 with $\alpha = 0.4$. It can be seen that $P_i = 0.2$ when $\gamma = 4$ and $0.19 < \beta < 0.25$; $P_i = 0.4$ when $\gamma = 5$ and $0.23 < \beta < 0.26$; and $P_i = 0.2$ when $\gamma = 7$ and $0.29 < \beta < 0.49$. This indicates that Model 4 can control the robustness of the network by controlling the value of γ and the value interval of β. At the same time, under the guarantee of the same controllability robustness, we can be more selective over the value of β, which means that the capacity of the complex logistics network can be controlled with flexibility, and the cost can be controlled with precision. Comparing the values of P_i in Figures 8, 9 and 10 in the range (0, 1), the controllability robustness of the complex logistics network based on Model 4 is the most controllable.

In the next section, we present the 3D simulation analysis of the relationship among controllability robustness, the logistics network cost and γ based on Model 4.

D. SIMULATION ANALYSIS CONSIDERING ECONOMY

According to the above demonstration and the economy of the real logistics network, the relationship among the logistics network cost e, robustness P_i and γ of the complex logistics network is analyzed in three dimensions, under the cascading failure Model 4 which is based on the NLC model with IRC load-redistribution strategy. The reason why γ is chosen over β is that it is proved in Section 3 that the effect of γ on the relationship between load and capacity is more remarkable than the effect of β. The simulation results are shown in the following figures.

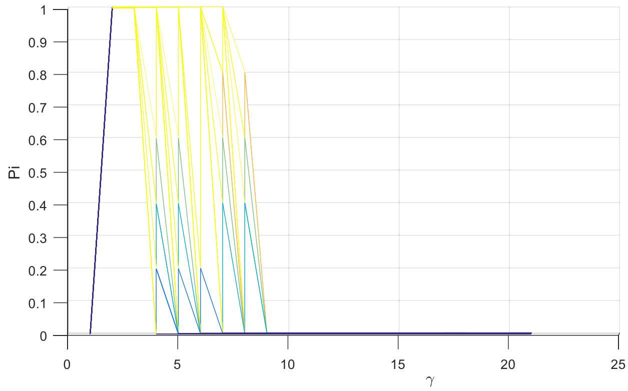

FIGURE 11. Relationship between P_i and γ under NLC model and IRC load-redistribution strategy.

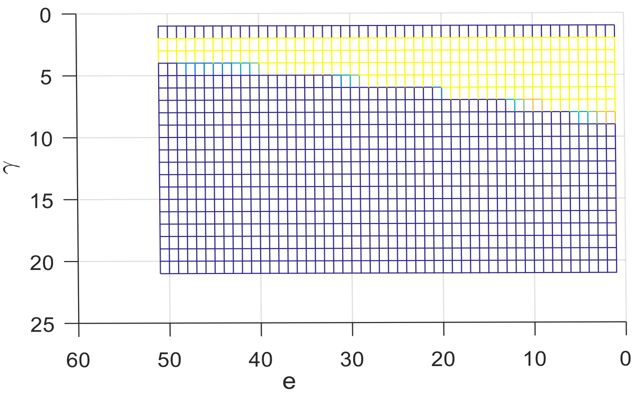

FIGURE 12. Relationship between e and γ under NLC model and IRC load-redistribution strategy.

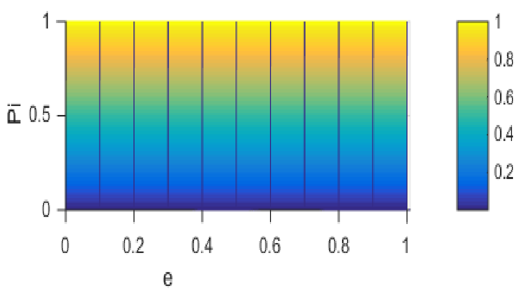

FIGURE 13. Relationship between P_i and e under NLC model and IRC load-redistribution strategy.

Based on the NLC model with IRC load-redistribution strategy in the complex logistics network, the relationship between P_i and γ is shown in Figure 11, the relationship between e and γ is shown in Figure 12, the relationship between P_i and e is shown in Figure 13, and the relationship among P_i, γ and e is shown in Figure 14. Figures 11, 12 and 13 respectively show the plane view and the side view in two directions of Figure 14. It can be seen from Figure 11 that the controllability robustness of the complex logistics network is not stable in the interval $0 < \gamma \leq 1$, is worst in the interval $1 < \gamma \leq 2$ and is controllable in the interval $2 < \gamma \leq 9$. The controllability robustness of

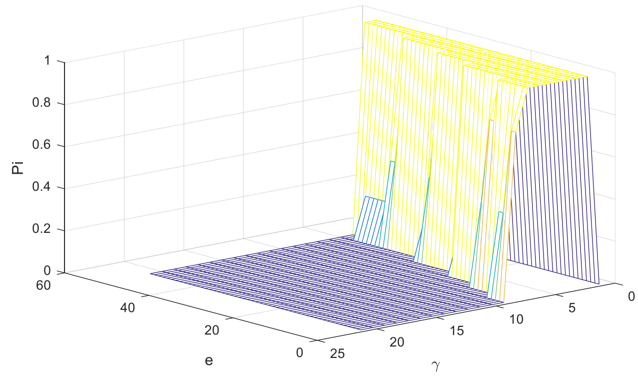

FIGURE 14. Relationship among P_i, γ and e under NLC model and IRC load-redistribution strategy.

the network can be optimized by controlling γ to fit the actual economic requirements of the logistics cost e according to Figure 12. Under the premise of a fixed cost for the complex logistics network, the controllability robustness is stronger as γ increases. It can be seen from Figure 14 that, under the premise of a fixed cost, the controllability robustness is greatly affected by γ, especially when $2 < \gamma \leq 9$. Thus, it is more flexible and can be more precisely controlled. This indicates that, when the cost is fixed, the controllability robustness becomes stronger with an increase in γ; when the cost is expected to be as low as possible, the critical threshold of γ should be as low as possible to control the robustness of the network; the lower is the network cost, the smaller is the critical threshold of γ needed to ensure the strongest controllability robustness.

V. CONCLUSION

In this paper, we construct a complex logistics network based on complex network theory and the agglomeration and sprawl evolution mechanism; the existence of the nonlinear load-capacity (NLC) characteristics of a real logistics network is proved and the NLC model of complex logistics networks is proposed, which is more suitable than LLC model for real logistics networks. Controllability robustness simulation analysis and influencing factors analysis of the complex logistics network are carried out, under different cascading failure models. The conclusions are as follows:

(1) The NLC model is more accurate for describing complex logistics networks than the LLC model based on the analysis of two real logistics networks. (2) The main influencing factors of the NLC model are β and γ, but the effect of γ on the load-capacity relationship is more significant than that of β under the NLC model. (3) Formula derivations and simulation analyses verify that the optimal cascading model is that based on the NLC model with IRC load-redistribution strategy when cascading failures occur, as this achieves better robustness of network control. (4) From an economic perspective, the relationship among network cost, controllability robustness and the tolerance parameter γ of the complex logistics network is as follows: the controllability robustness is stronger with an increase in γ, and the

robustness of the network is controllable in the interval $2 < \gamma \leq 9$. In short, we can control the residual capacity of the nodes of the complex logistics network by adjusting the parameter γ in the interval $2 < \gamma \leq 9$ according to the real logistics cost requirements, thus optimizing the controllability robustness of the complex logistics network.

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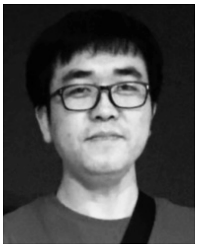

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