The resilience of logistics network against node failures

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Abstract: This paper studies the resilience of logistics network against node failures in the context of express industry owing to disruption in the network. By considering the flow capacity between the nodes and the impact of each node's failure, we propose a load redistribution mechanism in the presence of cascading failures which is akin to a criticality-based resilience assessment or stress testing the supply chain. To further investigate the impact of the node/nodes failure, we simulate and propose algorithms for two cascading failure scenarios, illustrating the different adjustment schemes for resilience improving strategies. A sensitivity analysis with managerial insights is also performed to investigate the effect of the adjustment schemes on the criticality of the nodes and the resilience of the express logistics network.

Keywords: Network resilience, logistics network, load redistribution, cascading failure, node failure, simulation

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1 Introduction

A complex logistics network is considered resilient when it can maintain a near-peak performance while facing disruptions. The network complexity stems from the size of the logistics arm and the intensity in which it coordinates with its partners while disruptions caused by the demand side is dependent on the performance of the e-commerce player. For example, Cainiao, Alibaba's logistics arm and its partners have set up 40,000 pickup facilities, while JD.com, China's second-biggest e-commerce player, has built a logistics network comprising seven major logistics centers and 335 warehouses in 2,691 cities (Li, 2017).

Coping with demand surge is an example of disruption due to mega online shopping events such as Cyber Monday in the US and Europe, and Singles' Day in China. In 2020, the Singles' Day event saw 3.96 billion parcels passing through the distribution network within 12 days (Xue, 2020). The maximum single-day throughput for this event reached 675 million parcels (Lou, 2020), which places immense pressure on the logistics and distribution network.

To avoid network congestion, one can identify and allocate popular items to lead warehouses before the event (Xiong, 2020). This form of inventory prepositioning strategy is a good starting point but would require a flexible load reconfiguration and rebalancing mechanism before it can be considered a resilient network. That is any tactical and operational decisions such as the number of delivery vehicles to add, the number of extra workers to hire, and which pickup and delivery nodes to improve as pressure mounts on the network should be rapidly adjusted when facing network disruption.

The main aim is of this paper is to suggest recommendations for load redistribution and in turn improve network efficiency when facing the risk of service disruption. In the real world, a logistics network for the express delivery is responsible for transferring and distributing packages between a set of origin and destination nodes through several intermediate facilities, which essentially rely on public transportation networks, such as land and air. The express delivery company must ensure that its network is robust, agile, and can effectively absorb demand fluctuations (Fleuren et al., 2013), which improves customer experience (Cui et al., 2020).

Existing literature (e.g. Kleindorfer and Saad, 2009; Peng et al., 2011; Klibi and Martel, 2012; Lu et al., 2015; Bimpikis et al., 2019) mainly study disruption and resilience of networks from the perspective of what happens to the nodes when disruption occurs, thus resulting in the attempt of designing-out these problems at the source. In short, these studies (with the exception of Peng et al., 2011) focus on the optimal design of the logistics network but do not emphasise on the "how-to-cope" mechanism when intermediaries snowballed into massive network disruption. This is important because, in the express industry, volume in any intermediary nodes can often be overloaded due to over-capacity problems causing traffic congestion which require immediate redistribution to other nodes. Given that the logistics network of the express industry is a complex network of pickup facilities, distribution centres and warehouses, and distribution stations, the failure of one or a few nodes could congest a network or inefficiently redistribute package flows, leading to a chain reaction and ultimate collapse of the whole network, i.e. the cascading failure (Świerczek, 2014). Nonetheless, few studies to date have investigated how the different nodes/nodes failure scenario and the cascading failure affect the resilience of the express logistics network. This paper designed an improved cascading failure simulation process in the event of single-node or simultaneous double-node failures and proposes measures of adjustment based on the tolerance ability of the selected nodes. We raise the following questions in our paper:

1. How can we characterise resilience of the logistics network in the event of cascading failure?
2. What is more efficient strategy to improve resilience of the logistics network by adjusting the tolerance ability of the nodes?

In addition to developing a cascading failure model for express logistics network, our contributions is two-fold:

1. We characterize the load redistribution mechanism when facing network disruption and how to cope with package assignments between the failed logistics facility and neighbouring logistics facilities.

2. We establish efficient algorithms to simulate the cascading failure with guarantee of convergence and speed under conditions of an actual express logistics network structure. Our model is based on a simulation express logistics networks using land logistics service data provided by ZTO express, which is a leading express delivery company in China and one of the largest express delivery companies globally. We demonstrate that by improving the tolerance ability of the nodes, in topology, the criticality of each node and each node-pair can be suppresed and the resilience of the logistics network can be improved.

We conclude by introducing three promising starting points for solving real-world issues that our results reveal: using complex network to find topology characteristics, using load redistribution mechanism to control cascading failure, and designing strategies to improve systemic resilience.

The rest of the paper is organized as follows. Section 2 provides a brief review. Section 3 illustrates the context of cascading failure and load redistribution of the logistics network, and Section 4 outlines the simulation process and algorithm. Section 5 provides a comprehensive sensitivity analysis and elaborates on the managerial insights. Section 6 concludes the study with some directions for future research.

2 Literature review

The disruption of logistics network is usually caused by the failures or disturbances of the components, i.e. nodes (facilities) and arcs (links), which result in network irreversible structural changes. For example, disabled key suppliers of Toyota after Tohoku earthquake (Ang et al., 2016; Bimpikis et al., 2019), Fiat Chrysler halted production for being in short supply of parts from China for COVID-19 (Ivanova and Dolgui, 2020), and congestion of the transportation network caused by the accidents, earthquake, traffic signal failure and road maintenance (Sharma et al., 2009). Because the disruption of logistics network usually leads to service rate reduction and causes economic loss, how to reduce the impact and enhance the resilience becomes a hot topic for the past decades. Nair et al. (2010) proposed a quantitative measure for resilience and employed to determine the best set of actions to improve security at nodal facilities in an intermodal freight network. Chen and Miller-Hooks (2012) defined an indicator of network resilience that quantifies the ability of an intermodal freight transport network to recover from disruptions due to natural or human-caused disaster, and proposed a stochastic mixed-integer program for quantifying network resilience and identifying an optimal postevent course of action to take. Yücel et al. (2018) presented a two-stage stochastic programming model to optimize link strengthening decisions for improving post-disaster road network accessibility. And in addition to the research focused on the transportation network, there are a large number literature related to the supply network of resource/power (Yao et al., 2008; Rocchetta et al., 2017; Moret et al., 2020), supply chain network (Babich et al., 2007; Kleindorfer and Saad, 2009; Baghalian et al., 2013; Gao et al., 2019), and humanitarian logistics network (Ben-Tal et al., 2011; Diabat et al., 2019; Nikolopoulos et al., 2020).

Literature on the disruption/risk, capacity and resilience/robustness/vulnerability of transportation network have been comprehensively and systematicly discussed by Gu et al. (2020). And those related to logistics/supply and supply chain network can be found in Klibi et al. (2010), Kim et al. (2015), Kamalahmadi and Parast (2016), Brusset and Teller (2017), Govindan et al. (2017), and Besiou and Van Wassenhove(2020).

When a hub node is completely disrupted, the spokes originally allocated to it must be reallocated to other operational hub nodes. In the power grid and supply chain network, when the reallocation/redistribution occurses, a cascading failure may be explored due to the capacity of the related nodes and links (Sreedevi and Saranga, 2017), i.e. as one part of the network fails with compensating by nearby nodes and links, the nodes and links will fail as well if they are overloaded, and prompting additional nodes to fail one after another. In blackouts caused by cascading failures in the power grid, a relatively small local disturbance triggers a sequence of grid component failures, causing potentially large portions of the network to become inactive, with costly outcomes (Yang et al. 2017). Then how to design the load redistribution mechanism and assess the resilience of the network turn to be the key elements of the research on network with cascading failure, a brief introduction of related literature can be found **Table 1**. It is found that for different network topology, different load redistribution mechanism and different resilience assessment methodologies are proposed, given the characters of the flow, node and link. For example, Qian et al. (2015) assessed the resilience by the network cascading failure node point and the collapse of the time lag for the redundant capacity for a traffic network.

Table 1 Existing research on cascading failure: the load redistribution mechanism and the resilience assessment

Reference	Example network and failure type	Load redistribution mechanism	Resilience assessment
Motter and Lai, (2002)	● Scale-free networks ● Power grid network Internet ● Node failure	● The new load of other vertices/nodes are recomputed according to the degree of distribution (Barabási and Albert, 1999; Motter et al., 2002).	● The damage caused by a cascade, which is quantified in terms of the relative size of the largest connected component
Wang (2012)	● Scale-free network ● Power grid network Internet ● Link failure	● The load is redistributed to the neighbouring edges connecting to the nodes of broken edge according to the proportion of its initial load and the total load of all the edges connected to the nodes of broken edge.	● The average avalanche size by removing each edge, and the avalanche size refers to the number of broken edges induced by removing an edge
Qian et al. (2015)	● Weighted undirected network ● Traffic network ● Link failure	●The load of the fault node is redistributed to its neighbouring nodes according to the proportion of its capacity and the quantity of the nodes connected.	● The network cascading failure node point and the collapse of the time lag for the redundant capacity
Wang et al. (2016)	● Weighted undirected network ● Power grid network Internet Cluster supply network ● Node failure	● The load is redistributed to the neighbouring node connecting to the failed node according to the proportion of the degree/weight of the node and the total degree/weight of all the nodes of the failed node.	● The degree of fragmentation of the whole network with the number of nodes in the largest connected component, the number of failed edges, and the avalanche size of failed nodes
Liu et al. (2017)	● Weighted undirected network ● Power grid network Transportation network Internet ● Node failure	● The load is redistributed to the neighbouring nodes connecting to the failed node according to the proportion synthesized by the remaining life cycle of a node and the load of a node.	● The normalized indices of the number of failed nodes in the network after the cascading failure.
Ghanbari et al. (2018)	● Unweighted undirected networks ● Watts–Strogatz networks IEEE 30-bus network Power grid network ● Node failure	● The load is redistributed to the neighbouring node connecting to the failed node with the betweenness centrality lower than their capacity.	● A positive (or direct) correlation between the cascade depth and centrality measures means that the higher the centrality of a node, the more sever effect its failure has on the network. ● A negative (or inverse) correlation indicates that failure in nodes with higher centrality has less effect (i.e., lower cascade depth) than failure in those with lower centrality values.
Shen et al. (2019)	● Bi-directional networks ●Traffic network Metro network ● Node failure	● The edge with high edge betweenness will have more of the redistributed flow. ● A η-based flow redistribution model was proposed to improve the robustness of metro networks without changing their topologies.	●When the failure stops spreading, a balanced failure proportion, i.e. the ratio of the number of station failures to the original network size N, the perturbation that leads to global network failure is used to measure the robustness of the network.
Fu and Yang (2021)	● Weighted undirected network ●peer-to-peer network Internet of Things ● Node failure Link failure	● Once the relay nodes is attacked, all load in the network is redistributed to base stations and links that reach the base station	● The relative size of the giant component after removing a certain number of nodes or links is used to measure the network survivability against cascading failures.

3 Cascading model for express logistics network

3.1 The description of express logistics network with cascading failure

Express logistics networks possess complex structure due to the size of stakeholders, infrastructures and the intermediary processes. A number of stakeholders and their transporting/warehousing departments are involved with the support of the transportation infrastructures and freight terminal, such as the railway, highway, warehouse and distribution centre. All the transiting facilities and terminal can be treated as nodes in the express logistics network, and the material flow between the nodes can be treated as edges, as shown as **Figure 1**, which translates into a weighted undirected graph (Sun and Wandelt, 2014; Archetti et al., 2017). In this paper, we consider the disruption resulting from node failures as a motivating element for investigating the uncertainty and the resilience of the express logistics network system. Once disruption occurs, i.e., node failure, the related downstream nodes may not operate normally and the related upstream nodes may end its operation, due to the supply failures and causing demand to decline respectively.

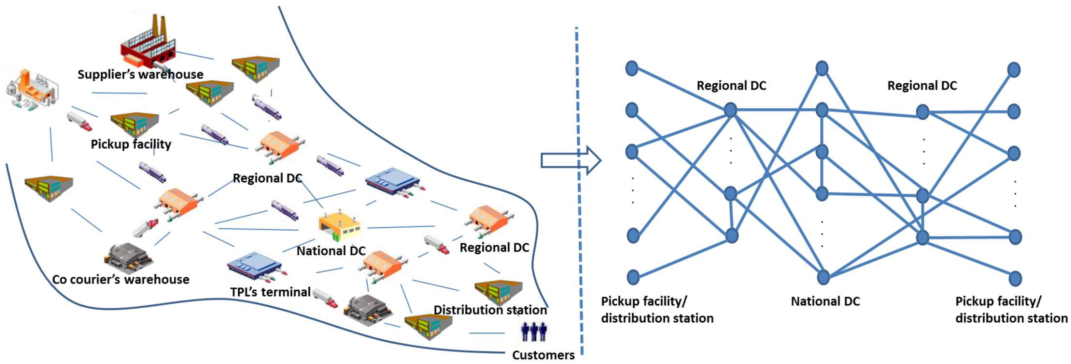


Figure 1 A typical express logistics network

We model the express logistics network as a graph, $G=\{V,E\}$, where $V=\{v_1,v_2,\cdots,v_n\}$ is a set of nodes, $E=\{(v_i,v_j)|e_{ij}=1\,\text{or}\,0\}$ is a set of connected edges/links and $i=1,2,\cdots,n$. In addition, e_{ij} represents the connection performance of the link between node v_i and node v_j and the supply-demand relationship between node i and j:

$$e_{ij}=e_{ji}=\begin{cases}1, & d_{ij}\neq 0 \text{ and } l_{ij}\neq 0\\ 0, & \text{otherwise}\end{cases} \tag{1}$$

where $d_{ij}=d_{ji}$ is the distance between node v_i and node v_j, $l_{ij}=l_{ji}$ is the load (or material flow) of the link and $i,j=1,2,\cdots,n$.

The load intensity on per unit distance is a measure representing the strength of business relations between the nodes in an express logistics network. The load intensity of the link e_{ij} can be represented as

$$a_{ij}={l_{ij}}/{d_{ij}} \tag{2}$$

Then there exists an adjacency matrix $\mathbf{A}_{n\times n}=\{a_{ij}\}_{n\times n}$.

For the proposed express logistics network, each node is supposed to have an initial load I_i and a load capacity C_i, which refer to the initial quantity of the material and the handling capacity of node v_i respectively. Here, we introduce the classic "*C-L*" model for cascading failures proposed by Motter and Lai (2002), in which, each node carries the maximum load that it can handle, and in man-made networks, node capacity is limited by economic costs (Tang et al., 2016). Then the capacity C_i and its initial load I_i have the following proportional relation:

$$C_i = (1+\beta)I_i \tag{3}$$

where, $\beta \geq 0$ is the tolerance parameter of the express logistics network system, and $i = 1,2,\cdots,n$.

3.2 Load redistribution mechanism for cascading failure

Based on the characteristics of the express logistics network, here only the node failure is considered, there is no capacity limitation in the links and the total load stays constant during the cascading process. Similar to the cascading failure analysed by Seo et al. (2015), once a node fails, its load is usually apportioned to its neighbouring nodes. In **Figure 2**, when node v_1 fails, its load is reallocated to the neighbouring nodes $v_j \in V_1$, where $V_1 = \{v_2, \ v_3, \ v_4\}$ is the set of neighbouring nodes of node v_1. For these neighbouring nodes, once the updated load at a node becomes larger than its capacity, the node overloads and fails. For example, node v_2 becomes overloaded in a cascading failure of node v_1 for $\Delta F_{1\to 2} + F_2 > C_2$, where $\Delta F_{1\to 2}$ is the load of node v_1 redistributed to node v_2, F_2 is the real load before the load redistribution, and $\Delta F_{1\to 2} + F_2$ is the updated load. Then node v_2 will reallocate its overload $F_2' - C_2$ to its neighbours $v_j \in V_2$, where $V_2 = \{v_5, \ v_6, \ v_7\}$ and the real load after the load redistribution is $F_2' = \Delta F_{1\to 2} + F_2$. The cascading failure process stops when no further node fails due to overload.

Definition 1. During the load redistribution process for cascading failure caused by the failure of node v_i, the neighbouring node v_j will fail from overloading when $\Delta F_{i\to j} + F_j > C_j$.

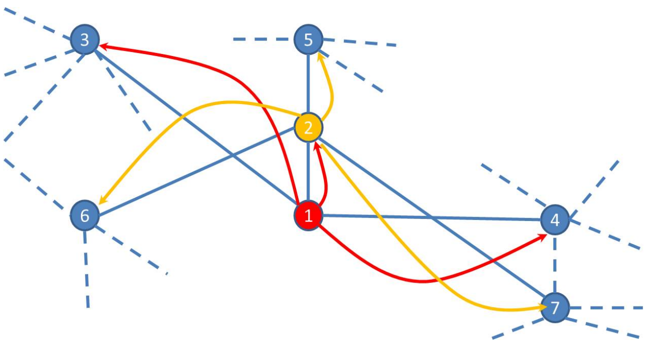


Figure 2 A simple example of cascading failure and load redistribution mechanism

In practice, when a logistics node fails, in order to limit the impact on the neighbouring nodes and to enhance the robustness of the logistics system, the packages handled will be allocated to those linked nodes according to the strength in business relations. Then the business-oriented load redistribution strategy can be noted as follows, which is different from previous works that allocate based on equal load-share policy (Scala and Lucentini, 2016) or by the preferential probability of the degree of the node (Wang et al., 2016).

$$\Delta F_{i\to j} = \begin{cases} F_i \dfrac{a_{ij}}{a_i}, & \text{where } v_i \in V \text{ is a failed node, and } v_j \in V_{\mathrm{i}} \\ (F_i - C_i)\dfrac{a_{ij}}{a_i}, & \text{where } v_i \in V \text{ is a overloaded node, and } v_j \in V_{\mathrm{i}} \end{cases} \tag{4}$$

where, $a_i = \sum_{j\in V_i} a_{ij}$ represents the total load intensity of the node v_i with its neighbouring nodes, $\Delta F_{i\to j}$ is the additional load of node v_j reallocated from node v_i.

3.3 Criticality of the node and the resilience of the express logistics network

According to Craighead et al. (2008), node criticality is the importance of a node within a supply chain. As such, a critical node is expected to have more serious consequences than a noncritical node under the same disruptive event. After the load redistribution and the cascading, the consequence of the cascading failure can be quantified simply and conveniently by the number of the failed nodes and the overloaded nodes due to the failure of node v_i. The failed node with more affected nodes usually is the more critical one. Here, based on Motter and Lai (2002), and similar to Zhao et al. (2004) and Craighead et al. (2008), we noted the criticality of node v_i as S_i, in which the cascaded nodes and failed node v_i itself are included, as Eq(5) shows, and apparently $0 \le S_i \le 1$.

$$S_i = \frac{1}{n}\sum_{v_j \in V}\delta_j \tag{5}$$

where, $\delta_j = 1$ when node $v_j \in CN_i$, i.e. node v_j is the failed nodes or the overloaded nodes due to the failure of node v_i, and $CN_i \subseteq V$ is the set of the failed nodes; otherwise, $\delta_j = 0$.

For the double-node failure scenario, there is C_n^2 combination of failed nodes, where $C_n^2 = \frac{1}{2}n(n-1)$. Then the criticality of double-node b can similarly be presented as $S_b = \frac{1}{n}\sum_{v_j \in V}\delta_j$, where $b = 1,2,\cdots,C_n^2$, $\delta_j = 1$ when node $v_j \in CN_i$, i.e. node v_j is the failed node or the overloaded node due to the failure of double-node b, and $CN_i \subseteq V$ is the set of failed nodes; otherwise, $\delta_j = 0$.

According to the definition of Holling (1973), resilience is a measure of the persistence of systems and of their ability to absorb change and disturbance while still maintaining the same relationships between populations or state variables. A large number of literature covers the modeling and evaluation of systems in the field of logistics, such as the resilience of transportation network (Chen and Miller-Hooks, 2012; D'Lima and Medda 2015) and supply network (Klibi et al., 2010). Within a logistics/supply network context, resilience can be viewed as a system or firm's capability to return to its initial condition or even to a more desirable state after disruption (Tang, 2006; Govindan et al., 2017).

Hence, we require criticality assessment of the nodes, where the a lower criticality value indicates a higher network resilience under cascading failures. The resilience of the express logistics network is expressed as follows.

$$R = 1 - \frac{\sum_K (S_i - S_{\min})}{K} \tag{6}$$

where, $S_{\min} = \min\{S_i\}$ is the minimum criticality of the nodes or pair-nodes, K is the total number of nodes or double-node in the express logistics network, where $K = n$ for the single-node failure scenario and $K = C_n^2$ for the double-node failure scenario.

4 Simulation process and algorithm

4.1 Simulation process of the cascading failure

When a single node fails, the process of the load redistribution and cascading failure occurs as follows:

Step 1. When node v_i fails, node v_i is included in the set of CN_i.

Step 2. The load of the failed node v_i first propagates through links with neighbouring nodes $v_j \in \overline{CN_i}$ (where, $CN_i \cup \overline{CN_i} = V$) depending on the preferential redistribution strategy in Eq (4), and update the loads of the remaining nodes that belong to set $\overline{CN_i}$ and their connected links.

Step 3. According to **Definition 1**, evaluate the unaffected nodes. When $\Delta F_{i \to j} + F_j > C_j$ is satisfied, then include node v_j into the set of CN_i, delete the links connected to node v_j, and turn to **Step 4**; otherwise turn to **Step 6**.

Step 4. The load of the overloaded node v_j propagates through connectivity links onto the neighbouring nodes $v_{j'} \in V_j$ according to the preferential redistribution strategy in Eq (4), and update the load of the remaining nodes, which exclude the set CN_i. Also, update the loads of connected links.

Step 5. According to **Definition 1**, evaluate the unaffected nodes. When $\Delta F_{j' \to j} + F_{j'} > C_{j'}$ is satisfied, then include node $v_{j'}$ into the set of CN_i, delete the links connected to node $v_{j'}$, and turn to **Step 4**; otherwise turn to **Step 6**.

For the double-node failure scenario, **Step 1** and **Step 2** above needs to be adjusted as follows to avoid the cross-redistribution of the load of the double-node.

Step 1. When the node-pair v_i and v_k fails, node v_i and v_k are included as a set in CN_i. Repeat the following steps respectively for each node-pair of the double-node failure.

Step 2. The load of the failed node v_i first propagates through connectivity links to the neighbouring nodes $v_j \in \overline{CN_i}$ (where, $CN_i \cup \overline{CN_i} = V$) according to the preferential redistribution strategy in Eq (4), and update the load of the remaining nodes that exclude the set of CN_i. Also, update the load of the connected links.

4.2 Cascading failure and load redistribution algorithm

We code the information of the nodes and links as $node(i, F_i, C_i, \beta, I_i, a_i)$ and $link(i, j, d_{ij}, l_{ij}, a_{ij})$ with the initial information as $F_i = 0$, $C_i = 0$ and $a_i = 0$ for the nodes, and $a_{ij} = 0$. Based on the above steps, all of the information on the nodes and links need to be updated as described in **Step 2** and **Step 4** at every iteration of load redistribution (see Algorithm 1)

Algorithm 1 Information update of the nodes and links before/after load redistributing

Input: $G = \{V,E\}$, the initial value of I_i, β, d_{ij} and l_{ij}
Output: updated $G = \{V,E\}$ with $node(i, F_i, C_i, \beta, I_i, a_i)$ and $link(i, j, d_{ij}, l_{ij}, a_{ij})$
for $i = 1$ to n **do**
  $F_i = I_i$ and $C_i = (1+\beta)I_i$
 for $v_j \in \overline{CN_i}$ **do**
  if $e_{ij} = 1$ **then**
  $a_{ij} \leftarrow l_{ij} / d_{ij}$
  $a_i \leftarrow a_i + a_{ij}$
  end if
 end for
end for

Intuitively, we can design an algorithm for the load redistribution caused by the failed node and overloaded node respectively, as described in **Algorithm 2** and **Algorithm 3**. Here, to simplify the process, we consider two aspects: first, the initial load redistribution initiated due to a failed node but unable to reallocate, and second, the load redistribution caused by an overloaded node.

Algorithm 2 load redistribution caused by failed node

Input: the numbering of the node failed i and its adjusted tolerance parameter α
Output: a set CN_i of S_i cascading failed
 Update $G = \{V,E\}$ with $node(i, F_i, C_i, \beta, I_i, a_i)$ and $link(i, j, d_{ij}, l_{ij}, a_{ij})$
 Initialize $CN_i = \{v_i\}$, $S_i = 1$
 for $v_j \in \overline{CN_i}$ **do**

```
    if  e_ij = 1  then
    F_j ← F_j + F_i a_ij/a_i
    l_ij ← l_ij + F_i a_ij/a_i  or  l_ji ← l_ji − F_i a_ij/a_i
      if  F_j > C_j  then
      CN_i ← CN_i ∪ {v_i}
      S_i ← S_i + 1
      end if
    end if
  end for
```

Algorithm 3 load redistribution caused by overloaded node

Input: the numbering of the node failed i and its adjusted tolerance parameter α

Output: a set CN_i of S_i cascading failed

```
  Update  G = {V,E}  with  node(i, F_i, C_i, β, I_i, a_i)  and  link(i, j, d_ij, l_ij, a_ij), and  CN_i,  S_i
 for  v_j ∈ overline(CN_i)  do
   if  F_j > C_j  then
     for  v_k ∈ overline(CN_i)  do
       if  e_jk = 1  then
         F_k ← F_k + (F_j − C_j) a_jk/a_j
         l_jk ← l_jk + (F_j − C_j) a_jk/a_j  or  l_kj ← l_kj − (F_j − C_j) a_jk/a_j
         if  F_k > C_k  then
          CN_i ← CN_i ∪ {v_k}
          S_i ← S_i + 1
         end if
       end if
     end for
   end if
 end for
```

5. Simulation and results

5.1 Simulation case design and base outcomes

In this section, a numerical case is used to illustrate the procedures and the effects of the proposed method in analysing the resilience of the express logistics network. This simulation express logistics network in **Figure 3** is simplified by using land logistics service data provided by ZTO express in Yangtze River Delta. ZTO's express logistics network spans over 28,900 pickup/delivery outlets and 79 sorting hubs that covers more than 97.69% of the cities and counties and 81.5% of the towns in China. In **Figure 3**, the initial information of the express logistics network is also illustrated. Take node v_1 and link e_{16} for example, at node 1, the initial load $I_1 = 20$, and the distance between node v_1 and node v_6 is $d_{16} = 27$, the initial load of the link is $l_{16} = 30$. Here, we set a same initial load for all the links, and the initial tolerance parameter of the express logistics network system is $\beta = 0.05 \sim 2.00$.

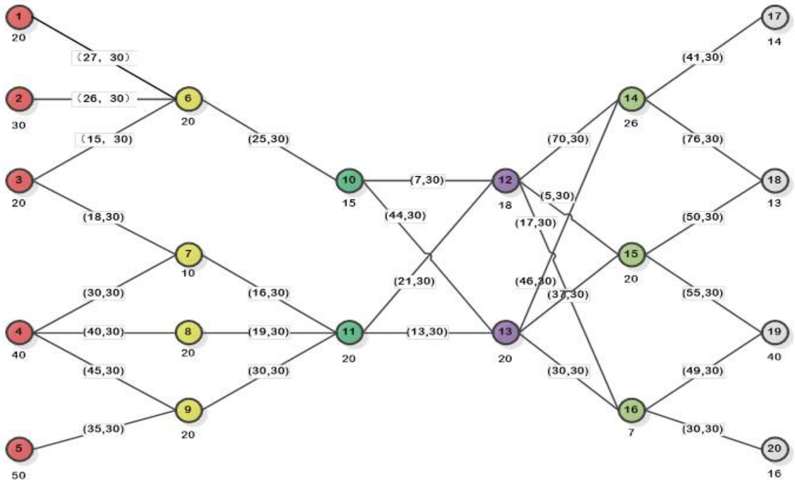


Figure 3 The topology of express logistics network

Two scenarios are analysed for the single-node failure scenario and the double-node failed scenario, respectively. In the single-node failure scenario, the simulation process of the cascading failure is carried out by removing one node initially at one time, and in the double-node failure scenario, the process of the cascading failure is carried out by removing two nodes at a time. The results of the two scenarios with tolerance parameter $\beta = 0.2$ are listed in **Table 2** and **Table 3,** respectively. In addition, the results of the failed nodes in both scenarios are listed in **Table 4**, in which node v_5 and node v_{14} independently failed in the single-node failure scenario and dependently failed in the double-node failure scenario.

Table 2 The criticality of single-node failure and the resilience of the express logistics network when $\beta = 0.2$

Node	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Number of nodes failed	5	7	4	8	10	5	2	3	2	3	3	4	3	5	4	1	3	2	11	4
Node criticality , S_i	0.25	0.35	0.2	0.4	0.5	0.25	0.1	0.15	0.1	0.15	0.15	0.2	0.15	0.25	0.2	0.05	0.15	0.1	0.55	0.2
Resilience, R										0.9071										

Table 3 The criticality of double-node failure and the resilience of the express logistics network when $\beta = 0.2$

Node	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1		0.60	0.45	0.60	0.65	0.40	0.30	0.40	0.35	0.45	0.40	0.50	0.50	0.55	0.45	0.30	0.40	0.35	0.75	0.45
2			0.45	0.70	0.70	0.50	0.40	0.55	0.55	0.50	0.50	0.55	0.60	0.60	0.55	0.45	0.55	0.55	0.85	0.55
3				0.65	0.60	0.40	0.20	0.45	0.25	0.40	0.40	0.45	0.45	0.50	0.40	0.25	0.40	0.30	0.70	0.45
4					0.95	0.75	0.60	0.75	0.65	0.75	0.50	0.75	0.75	0.75	0.50	0.55	0.70	0.70	0.90	0.65
5						0.70	0.50	0.75	0.65	0.65	0.35	0.65	0.70	0.80	0.65	0.60	0.75	0.70	0.95	0.70
6							0.30	0.40	0.35	0.45	0.40	0.50	0.50	0.55	0.45	0.30	0.40	0.35	0.75	0.45
7								0.30	0.15	0.25	0.25	0.35	0.25	0.45	0.35	0.15	0.25	0.20	0.60	0.30
8									0.40	0.35	0.45	0.40	0.40	0.50	0.50	0.30	0.35	0.35	0.70	0.40
9										0.25	0.35	0.40	0.35	0.45	0.35	0.15	0.30	0.20	0.60	0.30
10											0.35	0.40	0.45	0.45	0.40	0.20	0.35	0.35	0.55	0.35
11												0.40	0.50	0.50	0.50	0.25	0.40	0.35	0.65	0.35
12													0.45	0.50	0.50	0.30	0.45	0.45	0.65	0.40
13														0.45	0.45	0.30	0.45	0.45	0.55	0.35
14															0.55	0.35	0.30	0.50	0.65	0.50
15																0.30	0.30	0.30	0.35	0.35
16																	0.20	0.25	0.50	0.10
17																		0.35	0.70	0.35
18																			0.60	0.40
19																				0.65
20																				
R										0.6300										

Table 4 The results of nodes failed in different scenarios with $\beta = 0.2$

The single-node failure scenario								The double-node failure scenario			
Node v_5 failed				Node v_{14} failed				Node v_5 and v_{14} failed			
Node type	Number	Load	Load capacity	Node type	Number	Load	Load capacity	Node type	Number	Load	Load capacity
Nodes failed	5	50.0		Nodes failed	14	26.0	31.2	Nodes failed	5	50.0	60.0
	9	70.0			13	40.6	24.0		14	26.0	31.2
	4	58.4	48.0		11	26.7	24.0		9	70.0	24.0
	11	47.6	24.0		15	25.1	24.0		13	40.6	24.0
	7	22.0	12.0		16	9.9	8.4		4	58.4	48.0
	8	29.6	24.0	Nodes unfailed	1	20.0	24.0		11	54.3	24.0
	12	22.7	21.6		2	30.0	36.0		15	25.1	24.0
	13	27.5	24.0		3	29.0	24.0		16	9.9	8.4
	3	30.1	24.0		4	40.0	48.0		7	27.5	12.0
	6	26.1	24.0		5	50.0	60.0		8	34.2	24.0
Nodes unfailed	1	20.0	24.0		6	20.0	24.0		12	29.2	21.6
	2	30.0	36.0		7	10.8	12.0		3	25.5	24.0
	10	16.7	18.0		8	20.7	24.0		10	24.6	18.0
	14	28.3	31.2		9	20.4	24.0		6	38.2	24.0
	15	20.8	24.0		10	16.9	18.0		1	26.9	24.0
	16	7.5	8.4		12	21.0	21.6		2	37.2	36.0
	17	14.0	16.8		17	16.5	16.8	Nodes unfailed	17	16.5	16.8
	18	13.0	15.6		18	14.7	15.6		18	14.7	15.6
	19	40.0	48.0		19	40.7	48.0		19	40.7	48.0
	20	16.0	19.2		20	16.6	19.2		20	16.6	19.2

The results show that the resilience of the express logistics network with single-node failure is much higher than that of the double-node failed scenario, i.e. the resilience in single-node failed scenario is 0.9071 and that in double-node failed scenario is 0.63. This implies that when more than one node fails, the express logistics network faces a slower recovery process. By setting the tolerance parameter, we too show that the double-node failure scenario will lead to a more severe damage than by the single-node failure scenario, i.e. the quantity of failed nodes in the double-node scenario is much higher than that the single-node failed scenario.

5.2 Managerial insights of capacity improving strategies

5.2.1 Equally improving strategy

In our first set of simulations, we examine the single-node failure and double-node failure scenarios with the same parameter perturbation for all nodes, i.e. an equally improving strategy. As discussed in the previous section, we can evaluate the criticality of the nodes to account for the resilience of the express logistics network. In the following simulations, we further investigate how the node capacity impact the critical node and the resilience of the express logistics network.

5.2.1.1 Equally improving strategy in single-node failed scenario

For simplicity, we firstly investigate the effects of tolerance parameter β on the criticality of the node and the resilience of the express logistics network in the single-node failure scenario with an equally improving strategy. We find that there exists a diminishing marginal utility for the nodes' criticality by improving nodes' capacity equally, so as the network's resilience. **Figure 4** shows that all the nodes' criticality decline with increasing β, which declines sharply at first and then smoothens out. **Figure 5** shows that the express logistics network resilience increases with increasing β, which increases sharply at first and then tapering off.

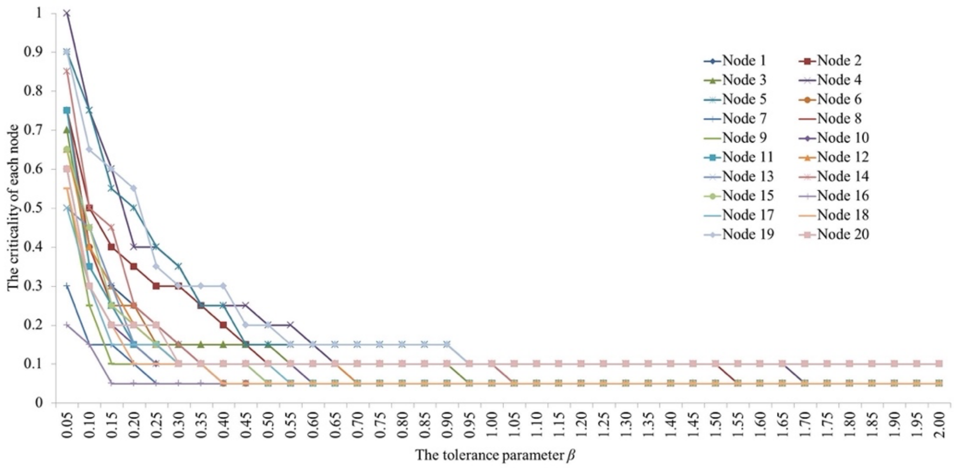


Figure 4 Criticality of each node with increasing tolerance parameter in the single-node failure scenario

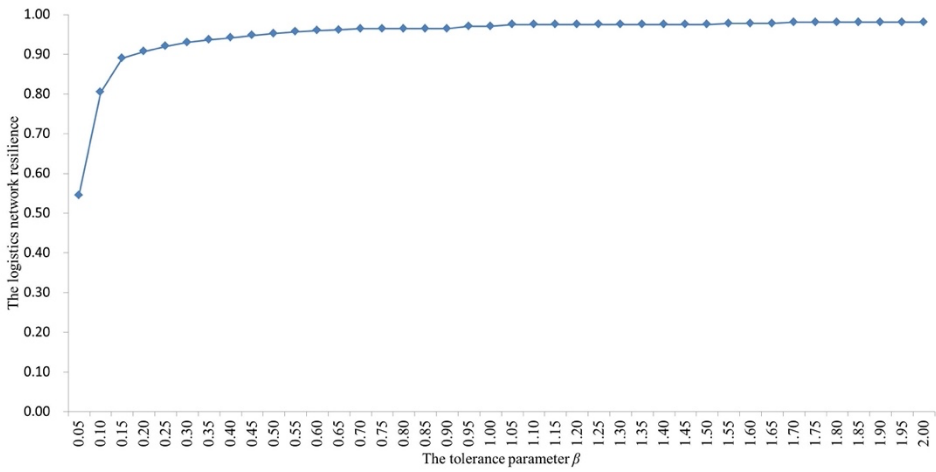


Figure 5 The resilience when increasing tolerance parameter β for the single-node failure scenario

Further, in the single-node failure scenario with an equally improving strategy, we find that the ranking of the nodes' criticality exhibits the same pattern. In **Figure 6**, it can be found that node 4, 5 and 19 remain the top-three places with the tolerance parameter $\beta = 0.05, 0.20, 0.40$ and 2.00, i.e. the failed node on more affected nodes translates into a higher criticality ran. Here, we name these nodes as key nodes of the express logistics network.

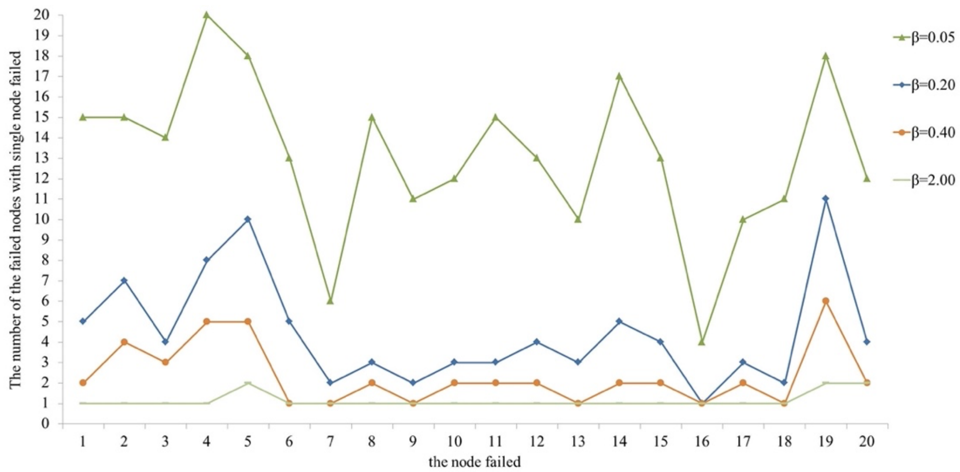


Figure 6 The quantity of affected nodes with different tolerance parameter in the single-node failure scenario

In summary, decision-makers can improve the tolerance ability of the nodes by monitoring the decrease of the nodes' criticality. However, it is not a good strategy to blindly chase after the lowest criticality by improving all nodes' tolerance ability equally because the total investment is huge and will steeply increase with increasing β. For example, as shown in **Figure 5**, to make a slight improvement in capability of all nodes from 1.00 to 1.05 simultaneously is more cost-efficient than attempting to improve one node from 1.00 to 2.00, with the latter translating into a very small resilient improvement.

5.2.1.2 Equally improving strategy in the double-node failure scenario

Similarly, we investigate the effects of tolerance parameter β on the criticality of the node and the resilience of the express logistics network in the double-node failure scenario with an equally improving strategy. We also find that there exists a diminishing marginal utility for the double-node's criticality when improving thenodes' capacity equally, so as the network's resilience. **Figure 7** shows that each combination of double-node's criticality declines with increasing β, and the decreasing margin shrinks under increasing β. The line with triangle markers in **Figure 8** shows that the express logistics network's resilience increases with increasing β for the double-node failure scenario, which increases sharply at first and then gently. We also find that the network's resilience in the double-node failure scenario is lower than that of the single-node failure scenario within the range of tolerance parameter $\beta \in (0,\ 1.2)$, which is consistent with the previous analysis results gained in Section 5.1.

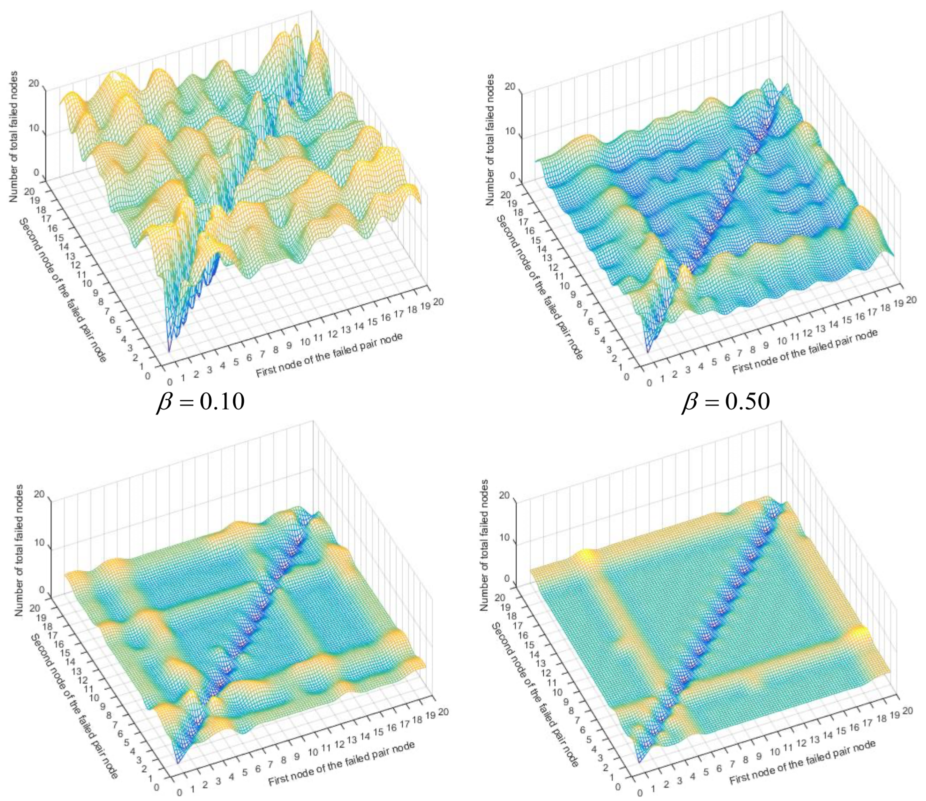


Figure 7 Each combination of the double-node's criticality when increasing tolerance parameter β

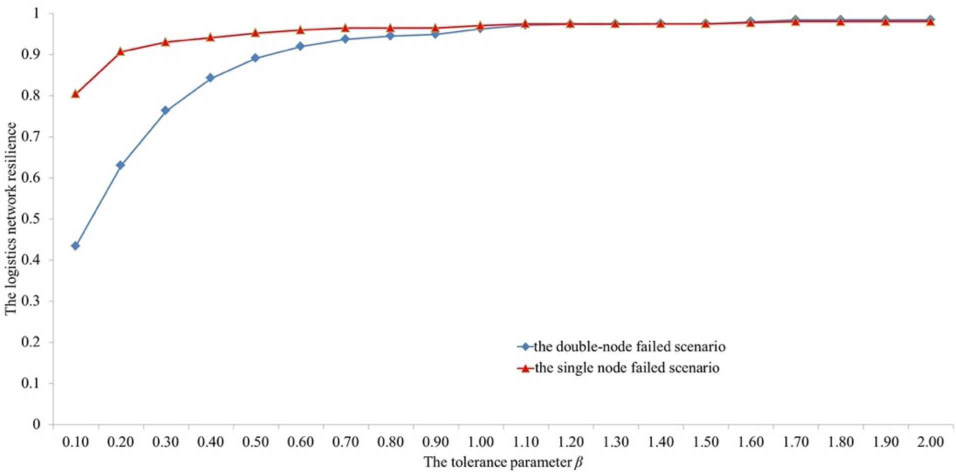


Figure 8 The express logistics network resilience with different tolerance parameter β for the double-node failure scenario

Then, we investigate the ranking of the double-node's criticality under an equally improving strategy. From **Table 5** and **Table 6**, it can be found that nodes 4, 5 and 19 are the key nodes of the express logistics network, whose frequency places them in the top-three. Also, we name these double-nodes as key double-nodes of the express logistics network.

Table 5 The top-fifty combination of double-nodes failure under schemes of $\beta = 0.1, 0.5, 1.00, 2.00$

Ranking	$\beta=0.10$			$\beta=0.50$			$\beta=1.00$			$\beta=2.00$		
	First node	Second node	Number of failed nodes	First node	Second node	Number of failed nodes	First node	Second node	Number of failed nodes	First node	Second node	Number of failed nodes
1	5	6	20	4	5	10	4	5	5	5	19	4
2	5	17	20	5	4	10	5	4	5	5	20	4
3	5	19	20	4	19	8	1	4	4	19	5	4
4	5	20	20	5	19	8	1	5	4	20	5	4
5	6	5	20	14	19	8	1	14	4	1	2	3
6	17	5	20	19	4	8	1	19	4	1	5	3
7	19	5	20	19	5	8	1	20	4	1	19	3
8	20	5	20	19	14	8	2	4	4	1	20	3
9	1	5	19	1	4	7	2	5	4	2	1	3
10	1	19	19	2	4	7	2	14	4	2	3	3
11	2	4	19	3	4	7	2	19	4	2	5	3
12	2	5	19	3	19	7	2	20	4	2	19	3
13	2	17	19	4	1	7	4	1	4	2	20	3
14	2	19	19	4	2	7	4	2	4	3	2	3
15	4	2	19	4	3	7	4	8	4	3	4	3
16	4	6	19	4	8	7	4	9	4	3	5	3
17	5	1	19	4	12	7	4	14	4	3	19	3
18	5	2	19	4	14	7	4	19	4	3	20	3
19	5	8	19	5	8	7	4	20	4	4	3	3
20	5	18	19	5	9	7	5	1	4	4	5	3
21	6	4	19	5	11	7	5	2	4	4	11	3
22	6	19	19	8	4	7	5	7	4	4	19	3
23	8	5	19	8	5	7	5	8	4	4	20	3
24	8	19	19	9	5	7	5	12	4	5	1	3
25	17	2	19	10	19	7	5	13	4	5	2	3
26	18	5	19	11	5	7	5	14	4	5	3	3
27	19	1	19	12	4	7	5	19	4	5	4	3
28	19	2	19	12	19	7	5	20	4	5	6	3
29	19	6	19	14	4	7	7	5	4	5	7	3
30	19	8	19	19	3	7	8	4	4	5	8	3
31	1	4	18	19	10	7	8	5	4	5	9	3
32	2	18	18	19	12	7	9	4	4	5	10	3
33	2	20	18	1	2	6	12	5	4	5	11	3
34	3	4	18	1	19	6	12	19	4	5	12	3
35	3	5	18	2	1	6	13	5	4	5	13	3
36	4	1	18	2	3	6	13	19	4	5	14	3
37	4	3	18	2	6	6	14	1	4	5	15	3
38	4	5	18	2	19	6	14	2	4	5	16	3
39	5	3	18	3	2	6	14	4	4	5	17	3
40	5	4	18	3	5	6	14	5	4	5	18	3

41	5	9	18	4	6	6	14	19	4	6	5	3
42	5	13	18	4	7	6	14	20	4	6	19	3
43	5	14	18	4	10	6	15	19	4	6	20	3
44	5	15	18	4	11	6	18	19	4	7	5	3
45	6	14	18	4	13	6	19	1	4	7	19	3
46	9	5	18	4	17	6	19	2	4	7	20	3
47	13	5	18	4	20	6	19	4	4	8	5	3
48	14	5	18	5	3	6	19	5	4	8	19	3
49	14	6	18	5	12	6	19	12	4	8	20	3
50	15	5	18	5	14	6	19	13	4	9	5	3

Table 6 The ranking of node's frequency of the top-ten combination of double-node failures in schemes of $\beta = 0.1, 0.5, 1.00, 2.00$

Ranking	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Node	5	4	19	2	1	3	14	20	8	6	12	9	13	7	17	11	18	10	15	16
Frequency	90	55	48	35	26	20	20	18	16	14	10	8	8	7	6	5	5	4	4	1

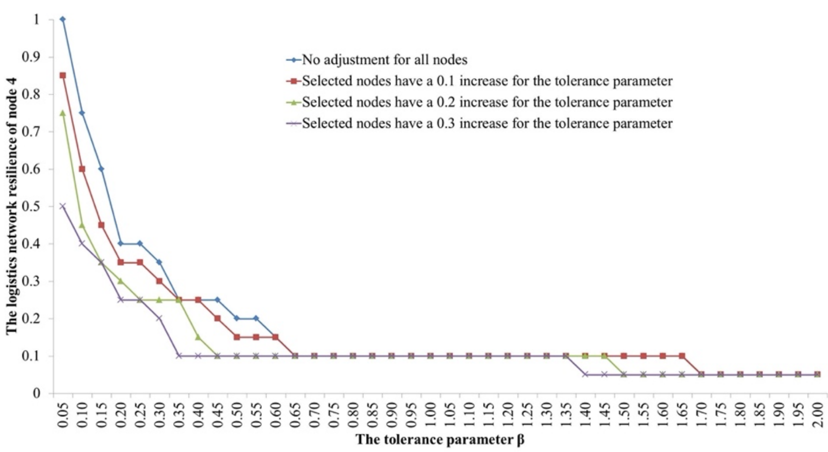
In summary, for the decision-maker of the logistics system, improving the tolerance ability of the nodes will lead to a decrease of the double-nodes' criticality. Similar to the results of the equally improving strategy of the single-node failure scenario, it is also not a good strategy to blindly chase after the lowest criticality of the double-node by improving all nodes' tolerance ability equally.

5.2.2 Targeted improving strategy

In our second set of simulations, we examine the single-node failure and double-node failure scenarios with parameter perturbation for the targeted nodes. As discussed in the previous section, we can gain the key nodes and key double-nodes of the express logistics network in each failure scenario respectively. Given the cascading failure and load redistribution mechanism in our study, i.e. once a node fails, its load is shifted to its neighbouring nodes, we can then set the neighbouring nodes of the key node and key double-node as targeted nodes for capacity improvement. Next, we further investigate how the targeted nodes capacity improving strategies impact the critical node and the resilience of the express logistics network.

5.2.2.1 Targeted improving strategy in single-node failed scenario

Here, we design three adjusting scheme of the targeted nodes' capacity to examine the criticality of the key nodes and the resilience of the express logistics network in the single-node failure scenario, i.e. a targeted improving strategy. **Figure 9** shows that the criticality of nodes 4, 5 and 19 changes with different adjusting schemes, which increase the tolerance ability of nodes 7,8,9,15 and 16 by 0.1, 0.2 and 0.3 more than other nodes of the network whose tolerance parameter belong to $[0.05, 2.00]$. It is found that the criticality of nodes 4, 5 and 19 in the three adjustment schemes is respectively lower than that without adjustment, i.e. adjusting the tolerance ability of the selected nodes can also lower the criticality of the key nodes. In the sub-graph of node 19 in **Figure 9**, when $\beta = 0.20$, it is found that the scheme with 0.1 improvements of the selected nodes' tolerance ability has the smallest criticality.



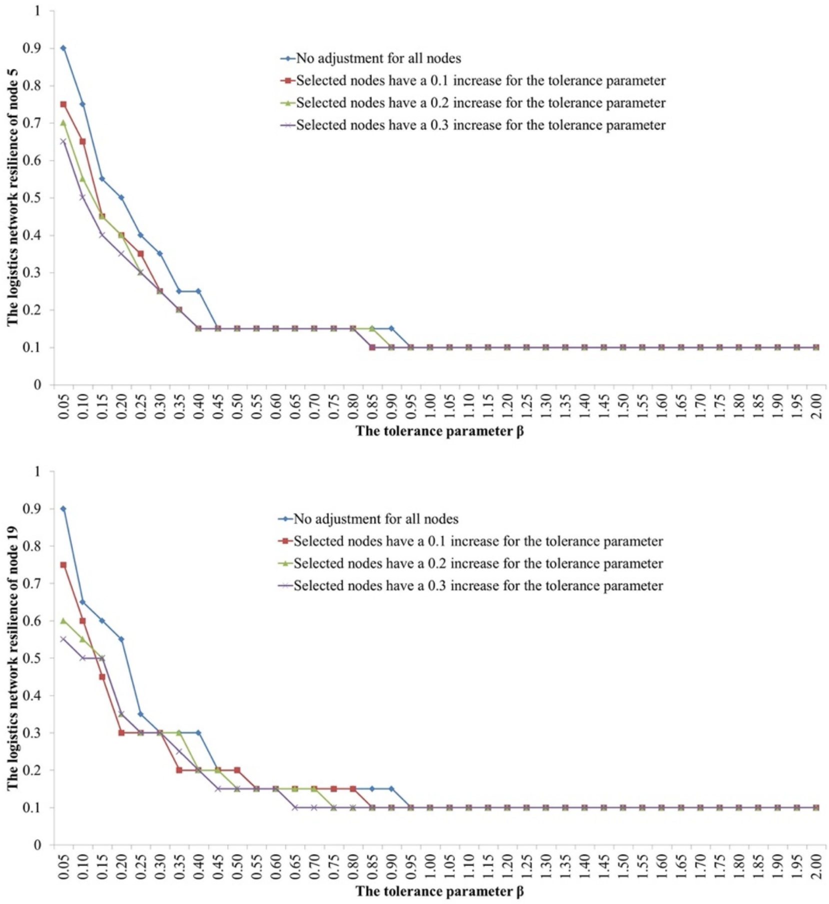


Figure 9 The criticality of key nodes change with adjusting schemes for the single-node failure scenario

With the adjustment schemes designed, the resilience is higher than that without adjustment**,** and the higher the capacity improvement, the higher the resilience as illustrated in **Figure 10**. In **Figure 10**, the line with diamond markers is the resilience without adjustment, which is the same as the line with diamond markers in **Figure 5**. In other words, improving the tolerance ability of the nodes linked to key nodes is a cost-efficient way to improve the resilience of the logistics network.

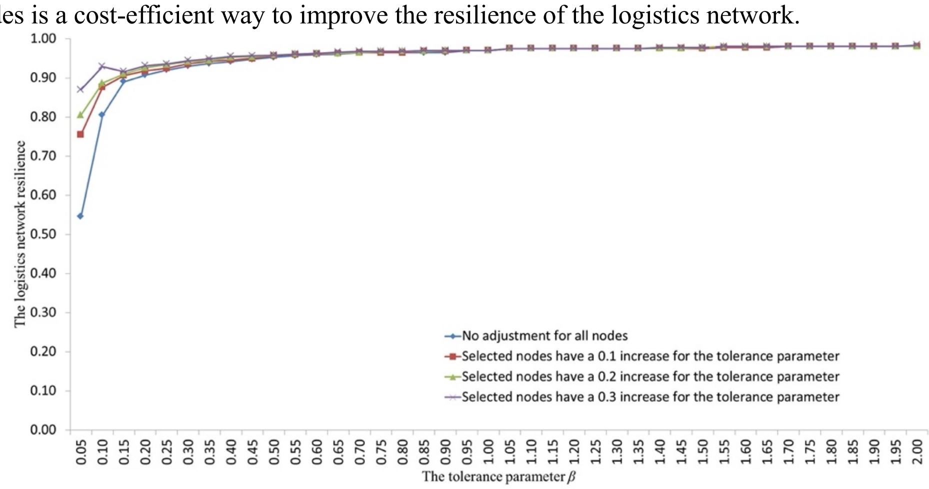


Figure 10 The resilience with different adjusting scheme for the single-node failed scenario

In summary, the best strategy for the decision-maker to address a higher resilience when single-node fails is to find out the key nodes of the network and adjust the tolerance ability of the nodes linked to the key nodes. We also find that the tolerance ability of the node excluded from the key nodes will impact the performance of the scheme.

5.2.2.2 Targeted improving strategy in double-node failed scenario

Finally, we investigate the effects of improving the targeted nodes' capacity on the criticality of the node and the resilience of the express logistics network in the double-node failure scenario via a targeted improving strategy. **Figure 11** shows that the criticality of each combination of double-node changes with different adjustment schemes, which increase the tolerance ability of nodes 7,8,9,15 and 16 by 0.1, 0.2 and 0.3 than that of other nodes of the network whose tolerance parameter belongs to $\beta = 0.1, 0.5, 1.00, 2.00$.

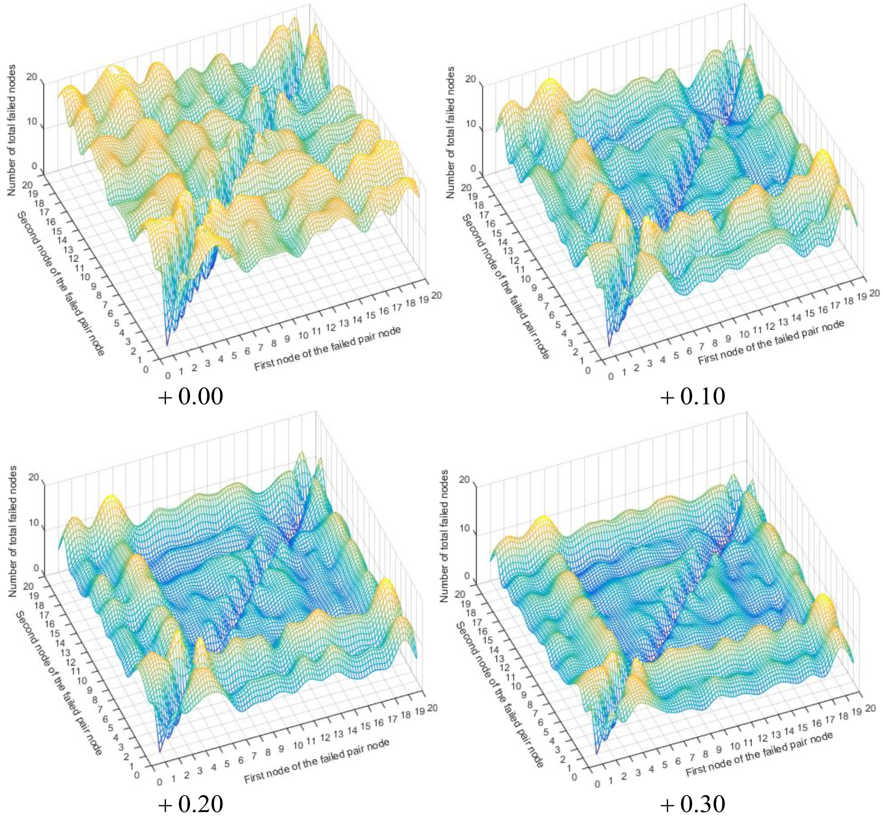


Figure 11 Each combination of double-node's criticality change with adjusting schemes for the double-node failed scenario

From **Figure 11**, we find tha the criticality of the nodes is lower than that without adjustment, i.e. adjusting the tolerance ability of the selected nodes can also lower the criticality of the key node, which is similar to the single-node failure scenario.

By adjusting the schemes, the resilience is higher than that without adjustment as illustrated in **Figure 12**. In **Figure 12**, the line with diamond markers is the resilience without adjustment which is the same as the line with diamond markers in **Figure 8**. Similarly, we find that by improving the tolerance ability of the nodes linked to key nodes is a cost-efficient way to improve the resilience of the express logistics network.

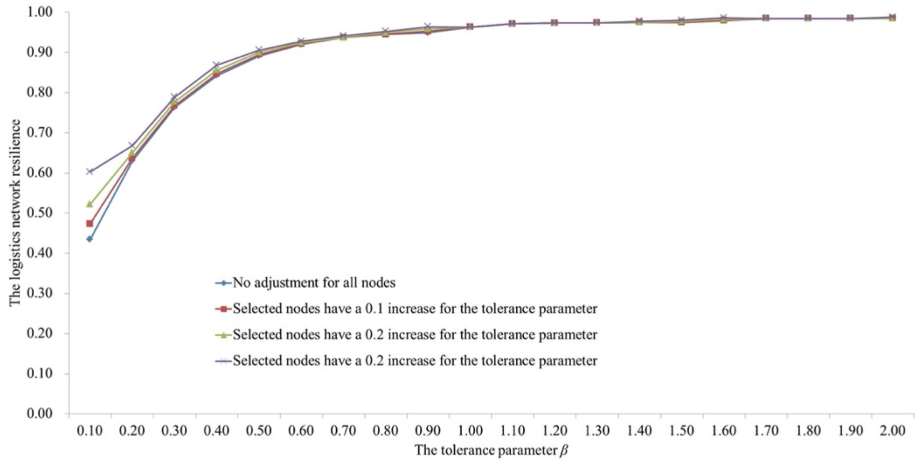


Figure 12 The express logistics network resilience with varying adjustment schemes for the double-node failures

In summary, for the decision-maker of the logistics system, improving the tolerance ability of the nodes will lead to a decrease of the each combination of double-node's criticality. Similar to the single-node failure scenario, we find that by adjusting the tolerance ability of the nodes linked to the key nodes is a more cost-efficient than by improving all nodes' tolerance ability simultaneously.

6. Concluding Remarks and Suggestions for Future Research

The main objective of this work is to understand the characteristics and strategies a decision-maker can consider when cascading failure disrupts an express logistics network. Hence, simulation processes and algorithms for cascading failure were designed for single-node and double-node failure scenarios.

By improving the tolerance ability of the nodes, the criticality of each node and each node pair can be suppressed and the resilience of the express logistics network can be improved. Comparing single-node and double-node failure scenarios, the resilience of the express logistics network with single-node failures is much higher than that of double-node failures. A more cost-efficient way to improve the resilience of the express logistics network is by increasing the tolerance ability of the nodes linked to key nodes. This means that key nodes have to be identified according to their criticality ranking for both failure scenarios. Hence, to design a resilient logistics network, the improvement schemes can be used as a strategy to prevent escalation owing to disruption in the express logistics network.

For future work, it is necessary to incorporate the edge/links (e.g., Wang, 2012; Qian et al., 2015; Scala and Lucentini, 2016). This is important for the express logistics industry because channel disruption is common and load redistribution mechanisms incorporating supply chain metrics can help monitor the ongoing impact of changes on productivity. Finally, future studies should cover different network sizes and complexity for a broader recommendation scheme to aid decision-makers under various disruptions.

Acknowledgments

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References

[1] Ang, E., D. A. Iancu, R. Swinney. 2016. Disruption Risk and Optimal Sourcing in Multi-tier

Supply Networks. *Manage. Sci.* 63(8): 2397-2419.

[2] Archetti, C., L. Bertazzi, D. Laganà, F. Vocaturo. 2017. The Undirected Capacitated General Routing Problem with Profits. *Eur. J. Oper. Res.* 257(3): 822-833.

[3] Babich, V., A. N. Burnetas, P. H. Ritchken. 2007. Competition and Diversification Effects in Supply Chains with Supplier Default Risk. *Manuf. Serv. Oper. Manag.* 9(2): 123-146.

[4] Baghalian, A., S. Rezapour, R. Z. Farahani. 2013. Robust Supply Chain Network Design with Service Level qgainst Disruptions and Demand Uncertainties: A Real-life Case. *Eur. J. Oper. Res.* 227(1): 199-215.

[5] Barabási, A. -L., R. Albert. 1999. Emergence of Scaling in Random Networks. *Science*, 286(5439): 509-512.

[6] Ben-Tal, A., B. D. Chung, S. R. Mandala, T. Yao. 2011. Robust Optimization for Emergency Logistics Planning: Risk Mitigation in Humanitarian Relief Supply Chains. *Transport. Res. B-Meth.* 45(8): 1177-1189.

[7] Besiou, M., L. N. Van Wassenhove. 2020, Humanitarian Operations: A World of Opportunity for Relevant and Impactful Research. *Manuf. Serv. Oper. Manag.* 22(1): 135-145.

[8] Bimpikis, K., O. Candogan, S. Ehsani. 2019. Supply Disruptions and Optimal Network Structures. *Manage. Sci.* 65(12): 5449-5956.

[9] Brusset, X., C. Teller. 2017. Supply Chain Capabilities, Risks, and Resilience. *Int. J. Prod. Econ.* 184: 59-68.

[10] Chen, L., E. Miller-Hooks. 2012. Resilience: An Indicator of Recovery Capability in Intermodal Freight Transport. *Transport. Sci.* 46(1), 109-123.

[11] Craighead, C. W., J. Blackhurst, M. J. Rungtusanatham, R. B. Handfield. 2007. The Severity of Supply Chain Disruptions: Design Characteristics and Mitigation Capabilities. *Deci. Sci.* 38(1), 131-156.

[12] D'Lima, M., F. Medda. 2015. A New Measure of Resilience: An Application to the London Underground. *Transport. Res. A-Pol*. 81: 35-46.

[13] Cui, T., Y. Ouyang, Z. J. M. Shen. 2010. Reliable Facility Location Design Under the Risk of Disruptions. *Oper. Res.* 58(4-part-1): 998-1011.

[14] Cui, R., M. Li, Q. Li. 2020. Value of High-Quality Logistics: Evidence from a Clash Between SF Express and Alibaba. *Manage. Sci.* 66(9): 3799-4358.

[15] Diabat, A., A. Jabbarzadeh, A. Khosrojerdi. 2019. A Perishable Product Supply Chain Network Design Problem with Reliability and Disruption Considerations. *Int. J. Prod. Econ.* 212: 125-138.

[16] Fleuren, H.A., C. Goossens, M. Hendriks, W. J. M. Meuffels, J. Poppelaars. 2013. Supply Chain–Wide Optimization at TNT Express. *Interfaces* 43(1): 5-20.

[17] Feng, Y., Sun, B., & Zeng, A. (2017). Cascade of Links in Complex Networks. *Phys. Lett. A* 381(4): 263-269.

[18] Fu, X., Y. Yang. 2021. Modeling and Analyzing Cascading Failures for Internet of Things. *Inform. Sci.* 545: 753-770.

[19] Gao, S. Y., D. Simchi-Levi, C. P. Teo, Z. Yan. 2019. Disruption Risk Mitigation in Supply Chains: The Risk Exposure Index Revisited. *Oper. Res.* 67(3), 599-904.

[20] Ghanbari, R., M. Jalili, X. Yu. 2018. Correlation of Cascade Failures and Centrality Measures in Complex Networks. *Future Gener. Comp. Sy.* 83: 390-400.

[21] Govindan, K., M. Fattahi, E. Keyvanshokooh. 2017. Supply Chain Network Design under Uncertainty: A Comprehensive Review and Future Research Directions. *Eur. J. Oper. Res* 263(1): 108-141.

[22] Gu, Y., X. Fu, Z. Liu, X. Xu, A. Chen. 2020. Performance of Transportation Network under Perturbations: Reliability, Vulnerability, and Resilience. *Transport. Res. E-Log.* 133, January 2020, 101809.

[23] Holling, C. S. 1973. Resilience and Stability of Ecological Systems. *Annu. Rev. Ecol. S.* 4(1): 1-23.

[24] Ivanova, D., A. Dolgui. 2020. OR-methods for Coping with the Ripple Effect in Supply Chains during COVID-19 Pandemic: Managerial Insights and Research Implications. *Int. J. Prod. Econ.* Available online 15 September 2020, 107921.

[25] Kamalahmadi, M., M. M. Parast. 2016. A Review of the Literature on the Principles of Enterprise and Supply Chain Resilience: Major Findings and Directions for Future Research. *Int. J. Prod. Econ.* 171: 116-133.

[26] Kim, Y., Y. S. Chen, K. Linderman. 2015. Supply Network Disruption and Resilience: A Network Structural Perspective. *J. Oper. Manage.* 33: 43-59.

[27] Kleindorfer, P. R., G. H. Saad. 2009. Managing Disruption Risks in Supply Chains. *Prod. Oper. Manage.* 14(1): 53-68.

[28] Klibi, W., A. Martel, A. Guitouni. 2010. The Design of Robust Value-Creating Supply Chain Networks: A Critical Review. *Eur. J. Oper. Res.* 203(2): 283-293.

[29] Klibi, W., A. Martel. 2012. Modeling Approaches for the Design of Resilient Supply Networks under Disruptions. *Int. J. Prod. Econ.* 135(2): 882-898.

[30] Liu, H. R., Y. L. Hu, R. R. Yin, Y. J. Deng. 2017. Cascading Failure Model of Scale-free Topology for Avoiding Node Failure. *Neurocomputing*, 260: 443-448.

[31] Lou, Wangshu. Tech Employed to Facilitate Singles Day Shopping Spree. Available at: http://www. chinadaily.com.cn/a/202011/13/WS5fadde2fa31024ad0ba93d55.html (accessed date December 20, 2020).

[32] Lu, M., L. Ran, Z. J. M. Shen. 2015. Reliable Facility Location Design Under Uncertain Correlated Disruptions. *Manuf. Serv. Oper. Manag.* 17(4): 427-619.

[33] Motter, A. E., Y. C. Lai. 2002. Cascade-based Attacks on Complex Networks. *Phys. Rev. E.* 66(6): 065102.

[34] Motter, A. E., T. Nishikawa, Y. C. Lai. 2002. Range-based Attack on Links in Scale-free Networks: Are Long-range Links Responsible for the Small-world Phenomenon? *Phys. Rev. E.* 66(6 Pt 2): 065103.

[35] Moret, S., F. Babonneau, M. Bierlaire, F. Marechal. 2020. Decision Support for Strategic Energy Planning: A Robust Optimization Framework. *Eur. J. Oper. Res.* 280(2): 539-554.

[36] Nair, R., H. Avetisyan, E. Miller-Hooks. 2010. Resilience Framework for Ports and Other Intermodal Components. *Transport. Res. Rec*. (2166): 54-65.

[37] Ni, N., B. J. Howell, T. C. Sharkey. 2018. Modeling the Impact of Unmet Demand in Supply Chain Resiliency Planning. *Omega* 81:1-16.

[38] Nikolopoulos, K., S. Punia, A. Schäfers, C. Tsinopoulos, C. Vasilakis. 2020. Forecasting and Planning During a Pandemic: COVID-19 Growth Rates, Supply Chain Disruptions, and Governmental Decisions. *Eur. J. Oper. Res.* 290(1): 99-115.

[39] Peng, P., L. V. Snyder, A. Lim, Z. Liu. 2011. Reliable Logistics Networks Design with Facility Disruptions. *Transport. Res. B- Meth.* 45(8): 1190-1211.

[40] Qian, Y., B. Wang, Y. Xue, J. Zeng, N. Wang. 2015. A Simulation of the Cascading Failure of a Complex Network Model by Considering the Characteristics of Road Traffic Conditions. *Nonlinear Dynam*. 80(1-2): 413-420.

[41] Rocchetta, R., E. Zio, E. Patelli. 2017. A Power-flow Emulator Approach for Resilience Assessment of Repairable Power Grids Subject to Weather-induced Failures and Data Deficiency. *Appl. Energ.* 210: 339-350

[42] Scala, A., P. G. D. S. Lucentini. 2016. The Equal Load-sharing Model of Cascade Failures in Power Grids. *Physica A* 462, 737-742.

[43] Seo, J., S. Mishra, X. Li, M. T. Thai. 2015. Catastrophic Cascading Failures in Power Networks.

Theor. Comput. Sci. 607, 306-319.

[44] Sharma, S., S. Ukkusuri, T. Mathew. 2009. Pareto Optimal Multiobjective Optimization for Robust Transportation Network Design Problem. *Transport. Res. Rec.* (2090): 95-104.

[45] Shen, Y., G. Ren, B. Ran. 2019. Cascading Failure Analysis and Robustness Optimization of Metro Networks Based on Coupled Map Lattices: A Case Study of Nanjing, China. *Transportion* Available online 08 November 2019.

[46] Sreedevi, R., H. Saranga. 2017. Uncertainty and Supply Chain Risk: The Moderating Role of Supply Chain Flexibility in Risk Mitigation. *Int. J. Prod. Econ.* 193: 332-342.

[47] Sun, X., S. Wandelt. 2014. Network Similarity Analysis of Air Navigation Route Systems. *Transport. Res. E-Log* 70: 416-434.

[48] Świerczek, A. 2014. The Impact of Supply Chain Integration on the "Snowball Effect" in the Transmission of Disruptions: An Empirical Evaluation of the Model. *Int. J. Prod. Econ.* 157: 89-104.

[49] Tang, C. S. 2006. Perspectives in Supply Chain Risk Management. *Int. J. Prod. Econ.* 103(2): 451-488.

[50] Tang, X., J. Liu, X. Hao. 2016. Mitigate Cascading Failures on Networks using a Memetic Algorithm. *Sci. Rep.* 6:38713.

[51] Wang, J. 2012. Mitigation of Cascading Failures on Complex Networks. *Nonlinear Dynam.* 70(3): 1959-1967.

[52] Wang, J., E. Sun, B. Xu, P. Li,C. Ni. 2016. Abnormal Cascading Failure Spreading on Complex Networks. *Chaos Soliton. Fract.* 91: 695-701.

[53] Xue, Yujie. Singles' Day: Record-breaking Sales Focus New Attention on Packaging Waste as Almost 4 Billion Parcels are Shipped. Available at: https://ph.news.yahoo.com/singles-day-record-breaking-sales-040018366.html (accessed date December 20, 2020).

[54] Xiong, Edison. How Alibaba's Logistics Platform Delivers Parcels Faster than a Takeaway. Available at: https://daoinsights.com/opinions/how-alibabas-logistics-platform-delivers-parcels-faster-than-a-takeaway/ (accessed date December 20, 2020).

[55] Yao, J., I. Adler, S. S. Oren. 2008. Modeling and Computing Two-Settlement Oligopolistic Equilibrium in a Congested Electricity Network. *Oper. Res.* 56(1): 34-47.

[56] Yang, Y., T. Nishikawa, A. E. Motter. Small Vulnerable Sets Determine Large Network Cascades In Power Grids. *Science* 358, eaan3184: 1-7.

[57] Yücel, E., F.S. Salman, I. Arsik. 2018. Improving Post-disaster Road Network Accessibility by Strengthening Links Against Failures. *Eur. J. Oper. Res.* 269(2): 406-422.

[58] Zhao, L., K. Park, Y. C. Lai. 2004. Attack Vulnerability of Scale-free Networks Due to Cascading Breakdown. *Phys. Rev. E.* 70(3): 035101.