Optimizing Supply Chain Resilience in Dynamic Environments: A Network Equilibrium Approach for Collaboration between Large and Small Enterprises

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Abstract: Supply chain resilience is the ability of a supply chain to keep performance when facing global crises. Large enterprises (LEs) and small- and medium-enterprises (SMEs) cooperate with each other to achieve better performance and increase resilience. In the present study, we establish a dynamic equilibrium model by considering supply chain resilience. Numerical simulations demonstrate that the network connectivity, cooperation closeness, and production adjustment capability will positively affect the resilience and overall performance of the supply chain network. This positive effect will be more significant for the scale-free network structure. The present study implicates that large manufacturer have the advantage of scale effect and play an important role in the supply chain network in response to supply chain crises. Increasing the capability of production capacity exchange between large manufacturers and small- and medium-manufacturers will be an important strategy for the entire supply chain network to deal with the crises as a whole.

1. Introduction

The ongoing global tariff friction makes supply chain resilience (SCR) increasingly crucial for regional economies. The traditional supply chain management theory holds that the large enterprises (LEs) in the supply chain have the advantage of scale effect. LEs play a leading role in the whole supply chain and dominate the creation of supply chain value [1]. They aggregate large-scale market demand by taking the scale advantage to directly connect with large-sized manufacturing enterprises, so as to provide brand products with reliable quality and competitive price. In the supply chain collaboration literature, LEs and SMEs compete and integrate in both vertical and horizontal directions [2]. LEs act as the leader of the supply chain integration to make a shorter and straighter supply structure to control the entire supply chain and subsequently leverage the resilience [3]. With this vertical integration strategy, LEs can cooperate with some SMEs closely to reduce the negative impacts of uncertainty [4]. On the other hand, the supply chain partners, including both LEs and SMEs, establish the sharing strategies of optimal inventory, production capacity, and other resources to mitigate stockout risks and enable supply chain resilience [5]. In order to fight against the extremely fluctuant situation, the supply chain partners cooperate adaptively with each other by redistributing the demand to prevent the cascading failure of the entire supply system [6].

Supply chain equilibrium (SCE) is the state of the supply chain that decision makers move simultaneously and compete in a noncooperative manner to achieve a supply chain network equilibrium [7]. Most of the time, the equilibrium conditions are established using variational inequality in a non-cooperative game context [8]. In order to survive in the severe and recurrent disruptions, the supply chain partners need to cooperate closely than before [9]. They need to rethink and reconfigure the cooperative and competitive relationships between LEs and SMEs to reach a new equilibrium solution [10]. There is lack of equilibrium models considering the supply chain resilience and survivability of supply chain network in the literature. In addition, there is also lack of concerns about the situation and performance of SMEs, which is regarded as playing an important role in sustaining supply chain goals in the context of pandemic [11]. The present study attempts to fill these gaps by establishing a dynamic equilibrium model.

The rest of the paper is organized as follows. In Section II, we conduct a brief literature review on supply chain resilience. An equilibrium model considering resilience based on the supply chain complex network model is proposed in Section III. Simulations and the results are presented in Section IV. Finally, we draw conclusions in Section V.

2. Related Studies

Supply chain resilience has become an active field of supply chain risk management in recent years since the fluctuated global situation. Li, Chen, and Guo advised that policymakers should consider regulatory environments and ownership structures when promoting digital adoption to strengthen supply chain resilience [12]. Hussian et al. explored the underlying antecedents and consequences of supply chain resilience and established boundary condition effects of supply chain complexity on the proposed relationships.[13]. Zhou provided a novel perspective that the application of emerging IT technologies positively moderates the impact of supply chain ESG governance on supply chain network capability [14].

In the supply chain equilibrium literature, most scholars emphasized on the optimal cooperation among supply chain partners [7,8]. Dong, Zhang, and Nagurney optimized the various decision-makers and derived the equilibrium conditions to establish the finite-dimensional variational inequality formulation of a supply chain network model consisting of manufacturers and retailers associated with random demands [15]. Hsueh and Chang evaluated the profit of coordination between manufacturers on corporate social responsibility (CSR) under network equilibrium, which is the system-optimal solution of a supply chain network problems since each member tries to maximize its own profit [16]. Edirisinghe, Bichescu, and Shi investigated the channel power on supply chain stability in a setting where multiple suppliers sell substitutable products through a common retailer, and obtained the Stackelberg non-cooperative games with all suppliers sharing balanced decision-making power [17]. Zhang et al. revealed that the equilibrium decision (service level, price) or profit may exhibit the opposite changing trend with respect to cross-channel price coefficients between traditional physical channel and direct e-commerce channel [18].

3. The Dynamic Equilibrium Model

3.1. The Supply Chain Complex Network Model

In the present study, we focus on the network equilibrium problem composed of N manufacturers, in which manufacturers produce homogeneous products and sell them through retailers. We suppose there can be cooperative relations between manufacturers. The manufacturers network can be modeled by a bidirectional and weighted graph, $G = (V, E, W)$. Herein, $V = (v_1, v_2, \ldots, v_N)$ denotes the set of manufacturer nodes. According to the scale and business volume of enterprises, the manufacturer nodes can be divided into hub manufacturers (i.e., LEs) and no-hub manufacturers (i.e., SMEs), because we suppose that LEs have more business connections than that of SMEs. $E = (e_1, e_2, \ldots, e_M)$ denotes the set of edges (i.e., cooperation between manufacturers), in which, we employ $e_{ij} = 1$ to represent the directed edge of cooperation between manufacturer v_i and manufacturer v_j. W denotes the set of weights on edges (i.e., the intensities of cooperation). The closer the cooperation between two manufacturers, the greater the weight. On the contrary, the less cooperation, the less weight. N and M represent the number of manufacturer nodes and edges.

We adapt the definition of Ref. [19] to represent the manufacturer node v_i's initial load (L_i^0), which can be set by Formula 1.

$$L_i^0 = \left[d_i \sum_{j\in A_i} d_j\right]^\lambda, i, j = 1,2, \ldots, N, \tag{1}$$

where d_i denotes the degree of node v_i; A_i denotes the set of nodes adjacent to node v_i; d_j represents the degree of node v_i's adjacent node v_j; and $\lambda(0 \le \lambda \le 1)$ is an adjustment parameter for the initial load intensity. The capacity of a manufacturer to process orders is usually limited by factors such as production scale and production cost. When the order quantity exceeds the maximum production capacity of the manufacturer, the normal delivery of orders will be delayed and the manufacturer's revenue will be reduced. When the order quantity is less than the minimum production capacity of the manufacturer, the normal operation will be affected at a loss. In the present study, we suppose that the manufacturer v_i's upper bound of production capacity (CU_i) is proportional to its initial load L_i^0 (Formula 2):

$$CU_i = \alpha L_i^0, i = 1,2, \dots, N, \tag{2}$$

where $\alpha \ge 1$ is an adjustment parameter of maximum production capacity. The bigger the value of α, the stronger the production capacity of manufacturer v_i. We also suppose that the manufacturer v_i's low bound of production capacity (CU_i) is proportional to its initial load L_i^0 (Formula 3):

$$CL_i = \beta L_i^0, i = 1,2, \dots, N, \tag{3}$$

where, $\beta(0 \le \beta \le 1)$ is an adjustment parameter for minimum production capacity. The smaller the value of β, the stronger the adaptability of the manufacturer vi. When each manufacturer in the network operates normally, the capacity meets $CL_i \le L_i = rCU_i \le CU_i$, where $r(0 \le r)$ is an adjustment parameter of actual order quantity.

We suppose that the edge weight can be represented as the intensities of business relationship between manufacturer v_i and manufacturer v_j (Formula 4) [20]:

$$w_{ij} = \left(d_i d_j\right)^{\gamma}, \tag{4}$$

where $\gamma(0 \le \gamma \le 1)$ is an adjustable parameter.

Considering that the larger the manufacturer's capacity, the lower the production cost. We suppose the manufacturer's production cost [21] is inversely proportional to the shortest path between the two nodes (Formula 5):

$$cw_{ij} = 1/l_{ij} \tag{5}$$

where l_{ij} is defined as the shortest path between node v_i and node v_j. If there is no path between node v_i and node v_j, then $l_{ij} = +\infty$ and $cw_{ij} = 0$. If there is only one path between node v_i and node v_j, then $l_{ij} = w_{ij}$, and $cw_{ij} = 1/w_{ij} = 1/(d_i d_j)^{\gamma}$.

We also suppose that the manufacturer node v_i's production cost can be represented as the edge cost average between manufacturer node v_i and its' adjacent nodes (Formula 6):

$$cw_{ij} = \frac{\sum_{j \in A_i} \frac{1}{w_{ij}}}{k}, \tag{6}$$

where k is defined as the number of the node v_i's adjacent nodes.

3.2. The Equilibrium Model of Supply Chain Network

The variables and parameters involved in this study are shown in Table 1.

Table 1. Relevant Parameters

Parameter	Description
d_i	Manufacturer v_i's degree.
L_i^0	Manufacturer v_i's initial load.
CU_i	Manufacturer v_i's upper bound of production capacity.
CL_i	Manufacturer v_i's lower bound of production capacity.
w_{ij}	The edge weight between manufacturer vi and manufacturer v_j.
L_i	Manufacturer v_i's order quantity.
l_{ij}	The shortest path between manufacturer vi and manufacturer v_j.

λ	The adjustment parameter of initial load intensity.
γ	The adjustment parameter of edge weight.
α	The adjustment parameter of maximum production capacity.
β	The adjustment parameter of minimum production capacity.
cw_i	The manufacturer v_i's production cost.
q_{ii}	The output produced by the manufacturer v_i.
q_{ij}	The output processed by the manufacturer v_j.
q_i	The business volume between manufacturer v_i and retailers.
ρ_i	The product transaction price between manufacturer v_i and retailers.
$f_i(q_{ii})$	Self-produced cost function of the manufacturer v_i.
$f_i(q_{ij})$	Processing cost function of the manufacturer v_j.
$f_i(q_i)$	Manufacturer v_i's cost function, $f_i(q_i) = f_i(q_{ii}, q_{ij})$.
$c_i(q_i)$	Transaction cost function between manufacturer v_i and retailers.
C_i	Transaction cost between manufacturer v_i and retailers, $C_i = c_i(q_i)$.

We suppose that all manufacturers' production can be recorded as N-dimensional column vector ($q \in R_+^N$). The self-produced cost function of the manufacturer v_i can be represented as $f_i(q_{ii})$, which is not only related to the manufacturer v_i's output (q_{ii}), but also related to the other manufacturers' output $q_{-1} = (q_1, q_2, \ldots, q_{i-1}, q_{i+1}, \ldots, q_N)$. The processing cost function of the manufacturer v_j for the manufacturer v_i can be represented as $f_i(q_{ii})$, which is related to the manufacturer v_j's output (q_{jj}). The manufacturer v_i's cost function can be represented as $f_i(q_i) = f_i(q_{ii}, q_{ij})$. The transaction cost function between manufacturer v_i and retailers can be represented as $c_i(q_i)$.

If the manufacturer v_i produces according to the order (i.e., $CL_i \le q_i \le CU_i$), the quantity of products produced and the transaction volume between manufacturer v_i and retailers satisfy the flow conservation equation (i.e., $q_{ii} + \sum_{j=1}^{m} q_{ij} = q_i$). If $q_i < CL_i$, the manufacturer v_i will consider stopping production because it does not generate profits, which is equivalent to the failure of manufacturer in the network. In this paper, we suppose the manufacturer v_i's failure can be represented as $F(i) = 1$.

In the model, the manufacturer v_i's total cost is equal to the sum of the production cost and the transaction cost between the manufacturer v_i and the retailers (i.e. $\sum_{j=1}^{N} f_i(q_{ii}, q_{ij}) + c_i(q_i)$, whose profit is sales revenue, and then the manufacturer v_i's profit can be represented as $\rho_i q_i - \sum_{j=1}^{N} f_i(q_{ii}, q_{ij}) - c_i(q_i)$. So, the profit maximization model of supply chain network can be represented as follows (7):

$$max(M_G) = max \sum_{i=1}^{N} \left[\rho_i q_i - \sum_{j=1}^{N} f_i(q_{ii}, q_{ij}) - c_i q_i \right]$$

$$s.t.\ \rho_i \ge 0, q_i \ge 0, q_{ii} \ge 0, q_{ij} \ge 0, \tag{7}$$

$$\forall i, j \in N, q_{ii} + \textstyle\sum_{j=1}^{N} q_{ij} > CU_i, CL_j \le q_{jj} + \sum_{i=1}^{N} q_{ij} \le CU_j,$$

$$min(F_G) = \textstyle\sum_{i=1}^{N} F(i).$$

We suppose that the manufacturer v_i's cost function meets the following condition as $f_i(q_i) = f_i(q_{ii}, q_{ij})$, and $c_i(q_i)$ is a continuous convex function, then for $q_i^* \in \Omega$, all manufacturers satisfying the optimality condition can be expressed as the following variational inequality (8) [22]:

$$\sum_{i=1}^{N} \left[\sum_{j=1}^{N} \frac{\partial f_i(q_{ii}^*, q_{ij}^*)}{\partial q_i} + \frac{\partial c_j(q_i^*)}{\partial q_j} - \rho_i \right]^* \cdot [q_i - q_i^*] \ge 0, \tag{8}$$

where $\Omega = \{ q_i^* \in R_+^N | CL_i \le q_{ii}^* \le CU_i, q_{ij}^* \le CU_j, i, j = 1,2, \ldots, N \}$.

The economic significance of the above inequality is that if the commodity price is less than the manufacturer v_i's marginal cost (i.e., the sum of marginal production cost and marginal transaction cost), the manufacturer v_i is unprofitable, the transaction volume is 0 (i.e., $q_i^* = 0$). And if the product price is equal to the manufacturer v_i's marginal cost (i.e., ρ_i = the transaction volume is greater than 0 (i.e., $q_i^* > 0$). What's more, in Formula 4, the parameter ρ_i is an endogenous variable.

We substitute Formula 1 and 6 into Formula 7 to calculate the network profit as (Formula 9):

$$profit = \sum_{i=1}^{N} L_i(\rho_i - cw_i - C_i). \tag{9}$$

Meanwhile, manufacturers are also restricted by production scale, economic strength, etc. When the orders exceed the upper bound of production capacity, the manufacturer cannot delivery products by itself normally, while a manufacturer will operate at a loss when the orders is less than the lower bound of production capacity. We suppose that if $q_i > CU_i$, the manufacturer v_i will find other cooperative manufacturers with lower production costs for processing; and if $q_i < CL_i$, the manufacturer v_i does not generate profits, it will consider stopping production, that is, the capacity is 0.

4. Numerical Simulations

Most supply chain networks are dynamic and complex, extant studies demonstrated that supply chain networks have scale-free and self-adaption characteristics [23]. For supply chain management, an important basis for designing elastic supply chain network is to consider the networks' complexity and adaptability [24,25]. In the study, we designed to compare the profit balance of the supply network system on Erdös-Rényi (ER) model [26] and Barabási-Albert (BA) model [27]. The experiments were simulated with python3.6, and each simulation is conducted 20 times and the results are averaged. In the experiments, the artificial networks are generated with 1000 nodes, in which we select the top 20% nodes with the highest degree as hub nodes, and the remaining 80% nodes as no-hub nodes according to the "80-20 rule," and we suppose no-hub manufacturers' orders increased by 50% (i.e., r = 1.5) and adjust the hub manufacturers' orders. The other parameters settings are: the average degree $<k>=10$, ρ= 50, and Ci = 30. Each simulation is conducted 100 times and the results are averaged. Fig. 1 demonstrates the flow chart of the simulation algorithm.

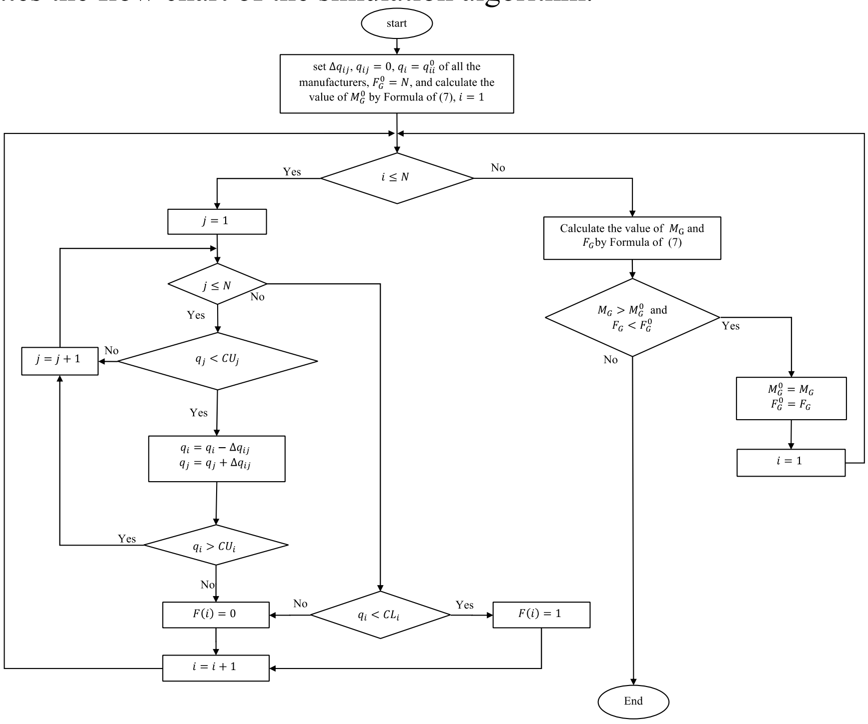
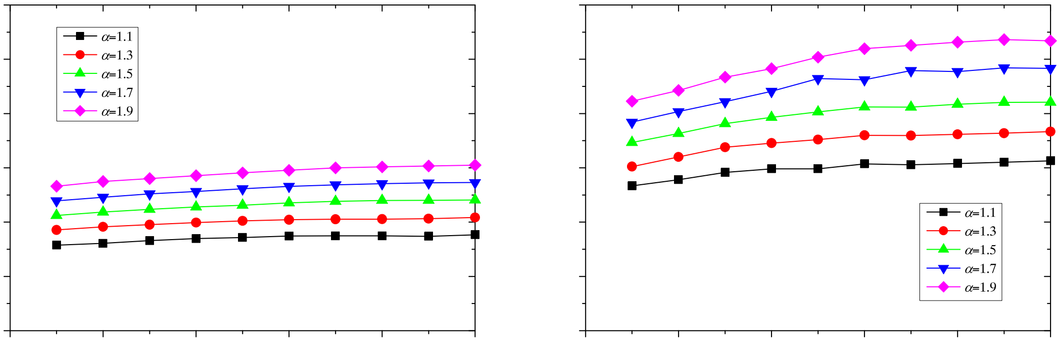


Figure 1. The flow chart of the simulation algorithm.

4.1. Adjustment Parameter of Maximum Production Capacity

First, we simulate the adjusting effects of maximum production capability. The results of the network profit of ER and BA structured supply networks that varies with the adjustment of maximum production capacity are presented in Fig. 2. Generally, with different α, the network profit rises with the rising of the parameter of the hub manufacturers' orders (r). Under the same α, the profit of BA network is higher than that of ER network. For the same r, increasing the maximum production capacity will impact positively the network profit. For instance, for ER networks, when $\alpha = 1.1$ and $r = 0.2$, the profit is about 6.5×10^5 (Fig. 2(a)). When α is adjusted to 1.9, the profit improves closely to 1.1×10^6 (Fig. 2(a)). The similar situations exist in BA networks (Fig. 2(b)). Therefore, we find that increasing α will facilitate the supply chain profit.

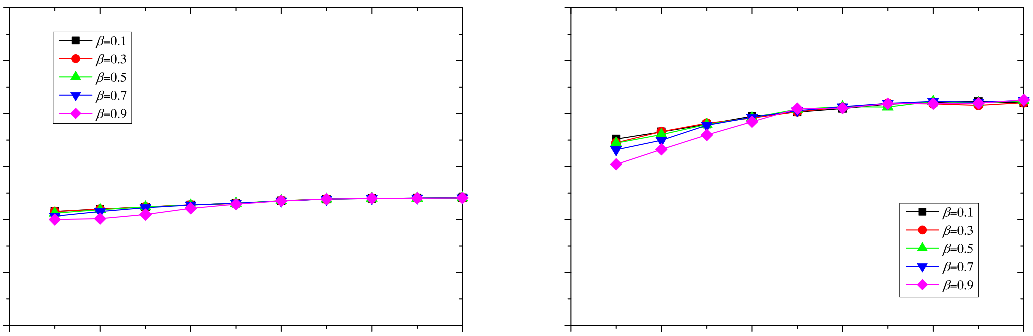


(a) ER network (b) BA network

Figure 2. Network profit with respect to adjustment parameter of maximum production capacity (α). Additionally, $\beta = 0.5$, $\gamma = 0.5$, and $\lambda = 0.5$.

4.2. Adjustment Parameter of Minimum Production Capacity

Second, we simulate the adjusting effects of minimum production capability. The results of the network profit of ER and BA structured supply networks that varies with the adjustment of minimum production capacity are presented in Fig. 3. Generally, with different β, the network profit and viability rise with the rising of the parameter of the hub manufacturers' orders (r). Under the same β, the profit of BA network is higher than that of ER network. For the same r, increasing the minimum production capacity will impact negatively the network profit and. For instance, for ER networks, when $\beta = 0.5$ and $r = 0.3$, the profit is about 9×10^5 (Fig. 3(a)). When β is adjusted to 0.9, the profit is closely to 8×10^5 (Fig. 3(a)). The similar situations exist in BA networks (Fig. 3(b)). Therefore, we find that lowering β will facilitate the supply chain profit.



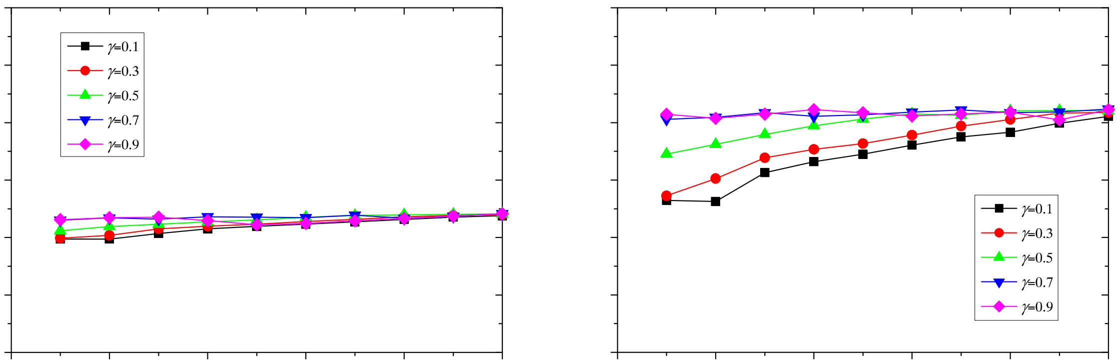
(a) ER network (b) BA network

Figure 3. Network profit with respect to adjustment parameter of minimum production capacity (β). Additionally, $\alpha = 1.5$, $\gamma = 0.5$, and $\lambda = 0.5$.

4.3. Adjustment Parameter of Edge Weight

Thirdly, we simulate the adjusting effects of edge weight. The results of the network profit of ER and BA structured supply networks that varies with the adjustment of edge weight are presented in Fig. 4. Generally, the networks profit rise with the rising of the edge weight (γ). For BA networks, the profit rises obviously, while the profit variation range in ER network is relatively small. This phenomenon is related to the network structure, and under the same edge weight, the profit of BA network is higher than that of ER network.

On the other side, increasing the edge weight adjustment parameter γ will impact network profit. For instance, for BA networks, when $\gamma = 0.1$ and $r = 0.2$, the profit is about $1.0\text{x}10^6$ (Fig. 4(b)), which means that all the hub manufacturers stop production; and when γ is adjusted to 0.9, the profit increases to $1.6\text{x}10^6$ (Fig. 4(b)). The similar situations exist in ER networks (Fig. 4(a)). Therefore, we find that the larger the edge weight is, the lower the cost for hub manufacturers to process for no-hub manufacturers. On the one hand, it can increase no-hub manufacturers achieve economic benefits as well as the production capacity of hub manufacturers, thus improving the profits and viability of the whole supply chain network.

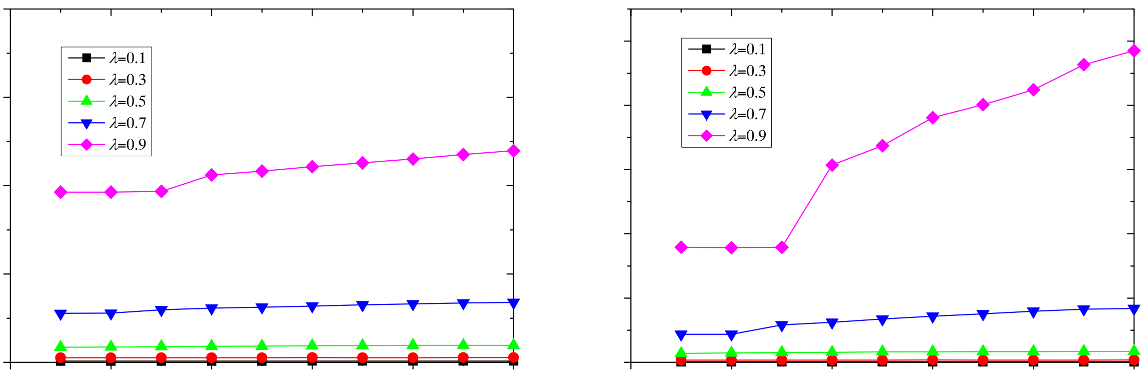


(a) ER network (b) BA network

Figure 4. Network profit with respect to adjustment parameter of edge weight (γ). Additionally, $\alpha = 1.5$, $\beta = 0.5$, and $\lambda = 0.5$.

4.4. Adjustment Parameter of Initial Intensity

Additionally, we simulate the adjusting effects of initial intensity. The results of the network profit of ER and BA structured supply networks that varies with the adjustment of initial intensity are presented in Fig. 5. Generally, the network profits rise with the increasing of the initial intensity (λ). And under the same initial intensity, the profit of BA network is higher than that of ER network. For instance, for ER networks, when $\lambda = 0.3$ (Fig. 5(a)), and for BA networks, when $\lambda = 0.5$ (Fig. 5(b)), the profit is close to 0. While for ER networks, when $\lambda = 0.9$ and $r = 1.0$, the profit is close to $1.2\text{x}10^7$ (Fig. 5(a)) and for BA networks, when $\lambda = 0.9$ and $r = 1.0$ (Fig. 5(b)), the profit is close to $4.8\text{x}10^7$, which means that all the hub manufacturers stop production. Therefore, we find that the initial intensity factor has a certain threshold value. If the initial intensity is not within the threshold range, and the overall network orders are relatively small, the no-hub manufacturers do not have enough orders to transfer to the hub manufacturers for processing, which also affect the profits of the whole network.

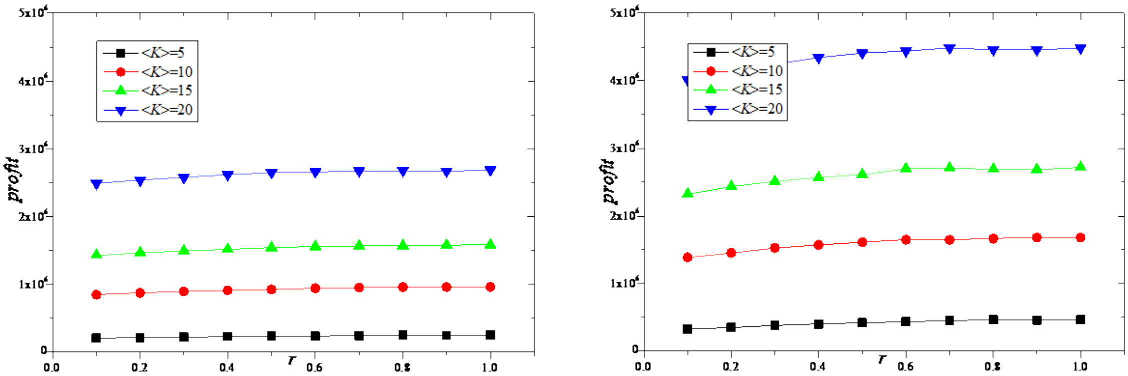


(a) ER network (b) BA network

Figure 5. Network profit with respect to adjustment parameter of initial intensity (λ). Additionally, $\alpha = 1.5$, $\beta = 0.5$, $\gamma = 0.5$.

4.5. Effects of Network Average Degree

Finally, we simulate the adjusting effects of network average degree. The results of the network profit of ER and BA structured supply networks that varies with the adjustment of network average degree are presented in Fig. 6. Generally, the network profits rise with the increasing of the network average degree (<*k*>). And under the same initial intensity, the profit of BA network is higher than that of ER network. On the other side, increasing the network average degree (<*k*>) will impact positively hubs' resilience. For instance, for BA networks, when <*k*>= 5 and r = 0.2, the profit is close to = $0.9 \text{x} 10^6$ (Fig. 6(b)), which means that approximately ten percent of the hub manufacturers stop production. When <*k*> is adjusted to 15, the profit increases to $2.5 \text{x} 10^6$. The similar situations exist in ER networks (Fig. 6(a)). Therefore, we find that increasing the <*k*> value means that the number of no-hub manufacturers connected with the hub manufacturers in the network increases. When the orders of the hub manufacturers in the network decrease, more connected no-hub manufacturers can subcontract the excess orders to them for processing, which avoids the shutdown of hub manufacturers, and improves the network profits.



(a) ER network (b) BA network

Figure 6. Network profit with respect to adjustment parameter of network average degree (<*k*>). Additionally, α = 1.5, β = 0.5, γ = 0.5, and λ = 0.5.

5. Conclusion and Discussion

The supply chain resilience problem is not only about the robustness and elasticity of a company or a supply chain, but also about how the entire supply chain system can keep performance when facing global crises. In the present study, by constructing the complex network model and the network equilibrium model of supply chain network, and through the numerical simulation method, we study the characteristics of the supply chain network structure, the network adjustment capability, and the impact of the capacity adjustment capability on the resilience and overall performance of the supply chain. The results show that the connection density (i.e., network average degree) will impact positively the overall performance of the supply chain network. That is to say, whether it is a balanced ER network structure or an unbalanced BA network structure, the more capacity exchange channels between manufacturers' networks, the better to avoid the failure of hub manufacturers and better improve the overall resilience and performance of the supply chain network. And this positive impact is more obvious for the unbalanced BA supply chain network. This conclusion suggests that the scale effect advantage of hub manufacturers plays a very important role in the overall resilience and performance of the supply chain network.

Secondly, the higher the degree of cooperation between manufacturers (i.e., the edge weight factor), the smaller the resistance of manufacturers to reallocate capacity, and the easier it is for the supply chain network to be reorganized after suffering from supply chain damage, so as to improve the overall resilience and performance of the entire network. Moreover, the positive impact is more obvious for the unbalanced BA supply chain network, which is related to the scale effect advantage of the hub manufacturers in the unbalanced supply chain network, that is, in the BA supply chain network, the order demand obtained by other manufacturers can be more widely re-aggregated to the hub manufacturers, so as to make full use of their scale advantage.

Finally, the capacity elasticity of manufacturers (i.e., the initial intensity factor) is also an important factor. Under the condition of maintaining the minimum capacity limit, improving the capacity elasticity of enterprises is one of the strategies to deal with the demand fluctuations. The benefits of this strategy also have better results in the unbalanced BA supply chain network.

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