Sustainable supplier selection and order allocation for multinational enterprises considering supply disruption in COVID-19 era

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Abstract: The unprecedented outbreak of COVID-19 has left many multinational enterprises facing extremely severe supply disruptions. Besides considering triple-bottom-line requirements, managers now also have to consider supply disruption due to the pandemic more seriously. However, existing research does not take these two key objectives into account simultaneously. To bridge this research gap, based on the characteristics of COVID-19 and similar global emergency events, this paper proposes a model that aims to solve the problem of sustainable supplier selection and order allocation considering supply disruption in the COVID-19 era. It does so by using a multi-stage multi-objective optimization model applied to the different stages of development and spread of the pandemic. Then, a novel nRa-NSGA-II algorithm is proposed to solve the high-dimensional multi-objective optimization model. The applicability and effectiveness of the proposed model is illustrated in a well-known multinational producer of shortwave therapeutic instruments.

Keywords: sustainable supplier selection; order allocation; supply disruption; multi-stage multi-objective optimization; nRa-NSGA-II; COVID-19

1. Introduction

In recent years, due to increased attention being given to social and environmental issues, sustainable supply chain management (SSCM) has become an important practice globally (Christ and Burritt, 2019; Wu et al., 2021), enabling companies to improve their brand image, and have better economic stability, environment friendly and social benefits (Banerjee, 2002; Zhu and Sarkis, 2004; Zhu and Lai, 2019). However, global supply chains are more likely to be faced with a variety of destructive events, such as natural disasters, man-made attacks and technical failures (Hosseini et al., 2019), leading to supply chain disruptions, which in turn give rise to failure to meet of supply chain sustainability goals (Amindoust, 2018). Particularly, in the recent COVID-19 pandemic, global supply chains have been facing unprecedented challenges, due to a big imbalance between supply and demand (Ivanov and Dolgui, 2020). 94% of the Fortune 1000 companies have seen their supply chain disrupted due to COVID-19 (Sherman, 2020). For example, Hyundai closed its assembly plant in South Korea due to a lack of parts made in China, Renault suspended production in Busan, South Korea (Isidore, 2020), the world's leading ventilator manufacturer Hamilton, was unable to obtain humidifiers, the core accessory of ventilator, due to export restrictions of medical products in Romania, resulting in a suspension of production (Aspan and Elegant, 2020). These cases all show that it is essential to consider supply disruption in SSCM.

Sustainable supplier selection (SSS) is already a key issue in SSCM, and so appropriate decision-making is the first precondition for supplier selection and order allocation (Wu and Barnes, 2012; Wu et al., 2020a, b). The resilience and geographical locations of suppliers are crucial to reduce the vulnerability of the focal company and the supply chain as a whole (Valipour Parkouhi et al., 2019). An efficient supply chain constructed from suppliers with high levels of both resilience and sustainability will be able to recover rapidly from supply disruption in time, and supply chain sustainability will be unaffected, or less affected, in the case of disruption (Amindoust, 2018). To this end, segregating suppliers geographically is an important strategy to reduce the risk of supply disruption (Hosseini et al., 2019) due to lockdowns caused by the outbreak of COVID-19 and similar global emergency events. In such case, cooperation with local suppliers becomes more important and needs more attention (Sharma et al., 2020). Consequently, for multinational manufacturing enterprises, it is crucial to build localized procurement networks (Sharma et al., 2020) and decentralize the location of suppliers (Hosseini et al., 2019) to enhance the resilience of the whole supply chain to deal with such global risk events.

Breaking down complex problems into a series of separate phases or stages can improve the efficiency of problem solving significantly (Wu and Barnes, 2012). On the one hand, the performance of suppliers may change during different phases resulting in different decision-making and order allocation schemes (Harridan and Cheaitou, 2017). For instance, Azadnia et al. (2015) and Moheb-Alizadeh and Handfield (2019) both found that the modification of supplier parameters during different decision-making periods will change the final decision-making and industrial manufacturing order allocation. On the other hand, demand and supply usually change over time in different periods (Cano-Belman and Meyr, 2019). Therefore, the dynamics of emergency events must be taken into account when adjusting supplier selection and order allocation (Kaur and Prakash Singh, 2021), especially for pandemics like COVID-19. The impact on SSCs is difficult to predict (Karmaker et al., 2021) because the performance of suppliers and the decision-making environments are changing rapidly. As the pandemic develops, the lockdown policies adopted and market demand at different stages are different, which will have a great impact on decision-making. Therefore, it is highly necessary to have a temporal model that reflects the different development phases of the pandemic, from the perspective of supply disruption in SSCM.

The resilience and sustainability of the supply chain are both important in SSCM (Golan et al., 2020; Karmaker et al. 2021). On the one hand, supply disruption will seriously affect the sustainability of the whole supply chains. On the other hand, only considering sustainability will cause the supply chains to be unable to adjust and respond in time when a disruption suddenly occurs. However, current SSS and order allocation models in SSCM pay more attention to sustainability, and rarely consider how to respond to a pandemic such as COVID-19, which leads to regional and global lockdowns and disruption, and develops in a predictable pattern. This paper proposes a model capable of solving the first-tier supplier selection and order allocation problem of multinational enterprises when faced with the risk of supply disruption due to the COVID-19 pandemic and similar global emergency events. It will do this by:

1) Proposing a five-stage temporal model of the pandemic.
2) Grouping potential suppliers into one of four categories based on their geographical locations.
3) Constructing an evaluation criteria system using intuitionistic fuzzy set to describe the evaluation value of decision-makers and calculating the sustainability and resilience scores for each supplier using TOPSIS and entropy weight method.
4) Building a multi-stage multi-objective optimization model for SSS and order allocation considering geographical separation procurement and localized procurement to resist global supply disruption in different pandemic periods. The solutions of the model can reflect the optimal results of SSS and order allocation at the same time.
5) Improving and extending the multi-objective optimization algorithm NSGA-II to make it converge with the decision-makers' preferred direction in high-dimensional multi-objective optimization problems and eliminating the influence of different data types of each objective.

The rest of the paper is organized as follows. Section 2 provides the literature review on supply disruption and resilience, and SSS and order allocation. Section 3 introduces the proposed multi-stage multi-objective optimization model and solution procedure. In section 4, the feasibility of the proposed model is demonstrated through an illustrative application in a well-known multinational producer of shortwave therapeutic instruments. Sensitivity analysis and comparative analysis are provided to demonstrate the advantages of the improved algorithm in Section 5. Section 6 discusses the results and considers the managerial implications. Finally, Section 7 presents some conclusions and considers the scope of future research work.

2. Literature review

2.1 Supply disruption and resilience

Supply disruption is usually caused by natural disasters such as earthquake, flood and volcanic explosion, or human factor such as political turmoil, terrorist attacks, which has a great negative impact on supply chains (Esmaeili-Najafabadi et al., 2019). Companies have realized that supply disruption can seriously affect their ability to successfully manage the supply chain and lead to the decline of supply chain sustainability (Li et al., 2010; Amindoust, 2018). Hence, more and more researchers have paid attention to this issue and how to as address it.

Juttner and Maklan (2011) proposed the concept of supply chain resilience, and considered its relationship with supply chain vulnerability and supply chain risk management. Rajesh and Ravi (2015) define resilience in suppliers as the ability to provide high quality products at an economic price and with enough flexibility to adapt to changes in demand with a short lead time at low risk without compromising safety and environmental practices. Rezapour et al. (2017) design a resilient supply chain network, which includes emergency inventory, additional reserve capacity at suppliers and multiple sources. It shown that even if these measures do increase costs, they can still ensure that enterprises can maintain market share in the face of disruption. Scheibe and Blackhurst (2018) identify three dimensions to help explain the spread of a supply chain disruption, including the nature of the disruption, structure and dependence, and managerial decision-making. Li et al. (2020) studied the compensation, contingent purchase and inventory consumption strategies in a make-to-order supply chain during the two periods of disruption duration and disruption recovery, in order to reduce disruption loss. The above research provides a theoretical basis for dealing with supply chain disruption risk, defines the relationship between resilience and supply chain risk, analyzes the causes of disruption propagation and puts forward countermeasures.

Specifically, in view of the disruption risk caused by COVID-19, Ivanov (2020) proposed a simulation prediction model to observe and predict the short-term and long-term impacts of the pandemic outbreak on the supply chain, and help so decision-makers make supply chain plans during the pandemic. Govindan et al. (2020) proposes a decision-making tool to classify community members and manage the demand of medical supply chains. Li et al. (2021) studied the different effects of forward and backward disruption propagation on the supply chain in the pandemic, finding that forward disruption propagation has a greater impact on the supply/assembly network, and backward disruption propagation has a greater impact on the distribution company. Mahmoudi et al. (2021) proposed a supplier selection model from the green and resilience point of view to deal with the disruption of the pandemic, yet, social benefits are not considered.

In short, on the one hand, individual qualified suppliers need to have sufficient resilience to resist different impact factors and ensure consistent supply (Rajesh and Ravi, 2015; Valipour Parkouhi et al., 2019; Kaur and Prakash Singh, 2021). On the other hand, it is also necessary to ensure that the entire sustainable supply chain has the lowest disruption probability.

2.2 Sustainable supplier selection and order allocation

Establishing partnerships with suppliers which have environmental, social and economic strength can improve the overall performance of supply chains (Buyukozkan and Cifci, 2011). How to choose the appropriate number of suppliers has always been an important issue (Burke et al., 2007). Reducing the number of suppliers can bring cost advantages through economy of scale but it increases the risk of disruption (Meena and Sarmah, 2015; Torabi et al., 2015). Therefore, many optimization methodologies have been proposed to determine the right number of suppliers and the order size allocation to each. In order to review current research on supplier selection and order allocation, and analyze the different advantages and disadvantages of model construction and solution methods, eleven representative studies about supplier selection and order allocation in relation to "sustainable", "resilience", or "disruption" in high ranked journals were selected. Table 1 presents a comparison of them.

[Take in Table 1 about here.]

From Table 1 we can see that most existing studies are based solely on sustainability (e.g. Govindan et al., 2015; Cheraghalipour and Farsad, 2018; Harridan and Cheaitou, 2017) or resilience (e.g. Torabi et al., 2015; Mari et al., 2019). Only Vahidi et al. (2018) took both sustainable and resilience into account by mixing them proportionally. As enterprises pay more attention to the risk of supply chain disruption, many studies consider disruption probability (risk) (e.g. Meena and Sarmah, 2015; Cheraghalipour and Farsad, 2018; PrasannaVenkatesan and Goh, 2016; Vahidi et al., 2018; Hosseini et al., 2019; Kaur and Prakash Singh, 2021). However, most of them combine disruption probability with other objectives, such as cost, rather than taking disruption probability as an individual objective. This makes their consideration of disruption probability insufficient, especially in this pandemic era.

As to the construction and solution of the multi-objective optimization models, only a minority of studies are based on a single objective function (Meena and Sarmah, 2015; Kaur and Prakash Singh, 2021). When considering multi-objective functions, some studies transformed the multi-objective optimization problem into a single objective optimization problem (e.g. Vahidi et al., 2018; Torabi et al., 2015; Hosseini et al., 2019), whilst others apply multi-objective optimization algorithms (e.g. Cheraghalipour and Farsad, 2018; PrasannaVenkatesan and Goh, 2016; Mari et al., 2019; Kannan et al., 2013; Govindan et al., 2015; Harridan and Cheaitou, 2017). However, both of these approaches have their own drawbacks. Whilst it is easy to opt for a local optimal solution, this risk losing important information when the multi-objective model is transformed into the single objective model. However, existing models of multi-objective supplier selection and order allocation usually only consider two to three low dimensional optimization problems (Wu and Barnes, 2016a). Thus, current optimization algorithms are more suitable for the single objective optimization problems, like ε-constraint- differential evolution algorithm (Torabi et al., 2015; Vahidi et al., 2018), mixed integer programming (Hosseini et al., 2019; Kaur and Prakash Singh, 2021) or low dimensional multi-objective optimization problems, include multi-objective linear programming (Kannan et al., 2013), MOHEV algorithm (Govindan et al., 2015), multi-choice goal programming (Cheraghalipour and Farsad, 2018), and multi-objective PSO algorithm (PrasannaVenkatesan and Goh, 2016; Wu and Barnes, 2016b). Only Hosseini et al. (2019) have so far considered geographical separation when allocating orders, providing a quantitative mathematical expression for the geographic separation of suppliers. However, they did not consider the importance of local procurement nor the characteristics of suppliers in different geographical locations.

2.3 Research gaps

Through the above comprehensive literature review, four main research gaps can be summarized as follows:

1) Supply chain disruption can have a great negative impact on supply chain performance (Esmaeili-Najafabadi et al., 2019). At present, SSC are facing serious disruptions due to the global medical crisis. Additionally, travel restrictions and lockdowns implemented by many countries have further affected the balance of supply and demand (Nikolopoulos et al., 2021). Even though existing research in the context of the pandemic has made contributions to impact prediction (Ivanov, 2020), demand management (Govindan et al., 2020), disruption propagation impact (Li et al., 2021), and green supplier selection (Mahmoudi et al., 2021), none of the above research has taken into account the impact of the pandemic on SSCM at different development stages. Without a temporal model of the pandemic, SSS decision-making will result in low efficiency and effectiveness.

2) Whilst all the studies have taken cost into account, sustainability, resilience and disruption probability (risk) are rarely considered simultaneously. In other words, most current research only considers the traditional and basic triple-bottom-line sustainability or resilience perspectives separately. In order to cope with the challenges of the pandemic, focal companies should not only consider the basic triple-bottom-line of sustainability individually, but also consider resilience and suppliers' geographic separation, simultaneously.

3) Existing research transforms multiple objectives into a single objective (Vahidi et al., 2018; Hosseini et al., 2019) which are not suitable for multi-objective optimization, or only considers a small number of objective functions (Govindan et al., 2015; Prasanna Venkatesan and Goh, 2016). However, current optimization algorithms are not good in high-dimensional situations, where the Pareto solutions will occupy the whole frontier. Then, the effectiveness of the decision-making will be affected.

4) Since COVID-19, lockdown policies have been implemented both regionally and globally (Nikolopoulos et al., 2021). Many companies stopped production because they are unable to obtain semi-finished products or raw materials from centralized suppliers (Aspan and Elegant, 2020). Although some studies have proposed the geographical separation of suppliers (Hosseini et al., 2019), they have not studied the appropriate division of suppliers according to their geographical locations in order to improve the ability of the whole supply chain to resist the risk of disruption, nor have they considered the establishment of localized procurement network to deal with the risk of global supply disruption caused by health emergencies.

This research plans to bridge the above research gaps by proposing a multi-stage multi-objective optimization model for SSS and order allocation considering supply disruption in COVID-19 era, and a corresponding algorithm to solve it effectively.

3. The sustainable supplier selection and order allocation model

This section proposes a multi-stage multi-objective optimization model for SSS and order allocation considering supply disruption in COVID-19 era, and an improved heuristic algorithm to solve it. The proposed framework is shown in Figure 1.

[Take in Figure 1 about here.]

As Figure 1 shows, potential suppliers are firstly divided into one of four categories according to their geographical location to reflect the different impact of the pandemic on suppliers in different geographical locations. Secondly, intuitionistic fuzzy numbers (IFNs) (Atanassov, 1986) are used to describe the performance of potential suppliers in terms of sustainability and resilience. The key reason for using IFNs is that decision-makers are more likely to undertake imprecise fuzzy evaluation through descriptive language when the evaluation criteria are difficult to quantify. IFNs can capture the fuzziness and uncertainty of evaluation language more comprehensively by using its membership degree, non-membership degree and hesitation degree (Li et al., 2014). At the same time, in order to obtain the weightings of different criteria objectively, and to reflect the relationship between alternatives and positive/negative ideal reference points comprehensively (Wang et al., 2016), both the entropy weight method (Zou et al., 2006) and TOPSIS method (Opricovic and Tzeng, 2004) are used to obtain the sustainability and resilience score of each potential supplier. Thirdly, the pandemic is divided into five stages, each with different characteristics. Fourthly, a multi-stage multi-objective order allocation optimization model is constructed, which considers sustainability, resilience, geographical separation, disruption probability and total costs. The characteristics of different stages of the pandemic are reflected by specific parameter settings. In order to make up for the problem that the classical NSGA-II cannot effectively stratify in high dimension and reflect the decision-makers' preference for each objective, this paper improves the dominance relation Ra-dominance (Zou et al., 2020) and proposes a novel nRA-NSGA-II algorithm, which can reflect the preference of decision-makers and eliminate the influence of different data types of each objective. Finally, according to the principle of maximum expected order completion rate, the optimal solution of each stage is selected from the non-dominated solution set.

3.1 Multi-period division

The dynamics of emergencies must be considered in supplier selection and order allocation (Kaur and Prakash Singh, 2021). Different phases of the pandemic have their own characteristics, which have great impact on the decision-making for SSS and order allocation. This research postulates a temporal model that divides the development and spread of COVID-19 into five periods, which refer to the daily confirmed cases in the United States (from January 23, 2020 to July 8, 2021 as shown in Figure 2), and to the impact on supply disruption in each period (Figure 3), including: workplace closures during the COVID-19 pandemic (column #1), restrictions on internal movement during the COVID-19 pandemic (column #2), and international travel controls during the COVID-19 pandemic (column #3).

[Take in Figure 2 and 3 about here.]

Firstly, the time before January 2020 is the normal stage. At this stage, the pandemic has not appeared, there is no lockdown policy, and the probability of supplier disruption is very low. Secondly, from January to March is the early stage. At this stage, the pandemic has just begun to appear, and the number of confirmed cases per day is very small. International and global lockdown policies have been adopted, but they are relatively minor, mainly affecting international and global suppliers. Thirdly, from March to November is the outbreak stage. At this stage, the number of daily confirmed cases increased day by day, and began to close workplaces and restrict internal movement in the country, resulting in slight local and regional lockdown, further serious border lockdown policy. All suppliers were affected to varying degrees according to the lockdown policy, local and regional suppliers are less affected, while international and global suppliers are more affected. Fourthly, from November to

January is the peak stage, in which the number of confirmed cases is very large and stable every day. Various types of lockdown policies are more serious than in the previous stage. Local, regional, international and global suppliers are seriously affected by the lockdown policy. Finally, from January to July is the recovery stage, in which the number of daily confirmed cases decreased day by day, and various types of lockdown policies became slight. Thus, combined with the basis of stage division, each period is characterized by differences in total demand, probability of disruption and priority of SSCM (shown as Table 2).

[Take in Table 2 about here.]

From Table 2 we can see that the first period is the Normal stage before the pandemic occurs. SSCs pay more attention to cost reduction and high efficiency. Then, in the second stage, the Early stage of the pandemic, customer demand rises slightly. SSCs are less concerned about costs, and more concerned about sustainability and the probability of disruption. In the third stage, the Outbreak stage, customer demand rises sharply. And the probability of supply disruption is high due to serious blockages in international and global transportation. In the fourth stage, the Peak stage, customer demand remains high, and the probability of supply disruption is very high as international, global, regional and local transportation are seriously blocked as well. SSCs have to pay more attention to sustainability and the probability of disruption during the third and fourth stage. In the last stage, the Recovery stage, customer demand returns to normal levels. The probability of supply disruption is lower due to the easing of various lockdown policies. SSCs will re-focus on cost reduction, while paying attention to sustainability and resilience. In short, according to above specific characteristics of the different stages, decision-makers can make more accurate and appropriate decisions.

3.2 Multi-objective optimization model

3.2.1 Notations

The notations used to formulate the decision-making problem are shown in Table 3.

[Take in Table 3 about here.]

3.2.2 Programming objectives

(1) Decentralized procurement

Decentralized procurement, separating suppliers geographically, is an important proactive strategy, which helps to reduce the risk of supply disruption geographically (Hosseini et al., 2019). Objective function (1) maximizes the sum of the distances between selected suppliers, so as to isolate the suppliers and carry out decentralized procurement.

$$\text{Max } \sum_{ni,nj \in L,R,I,J (ni \neq nj)} d_{ninj} x_{ni} x_{nj} \tag{1}$$

(2) Disruption probability

In order to avoid the failure of supply chain caused by the interruption of selected suppliers, objective function (2) minimizes the probability of all selected suppliers being interrupted.

$$\text{Min } \prod_{ni \in L,R,I,J} \theta_{nit} x_{ni} \tag{2}$$

(3) Sustainability score

The purpose of objective function (3) is to maximize the total sustainability score of the selected suppliers and ensure that more orders are allocated to those suppliers with a high sustainability score.

$$\text{Max } \frac{\sum_{ni \in L,R,I,J} \zeta_{ni} Q_{nit}}{\sum_{ni \in L,R,I,J} Q_{nit}} \tag{3}$$

(4) Resilience score

Objective function (4) maximizes the total resilience score of the selected suppliers and ensures that more orders are allocated to the suppliers with high resilience score.

$$\text{Max } \frac{\sum_{ni\in L,R,I,J} \eta_{ni} Q_{nit}}{\sum_{ni\in L,R,I,J} Q_{nit}} \tag{4}$$

(5) Total cost

Objective function (5) minimizes the total procurement cost, including fixed purchase costs, order costs, transportation costs, storage costs and penalty costs. $(1-\theta_{nit})Q_{nit}$ indicates the expected purchase quantity. The first part $\sum_{ni\in L,R,I,J} f_{ni}x_{ni}$ represents the total fixed purchase cost. The second part $\sum_{ni\in L,R,I,J} M_{nt}(1-\theta_{nit})Q_{nit}u_{ni}x_{ni}$ represents the total order cost, considering the procurement coefficient of each geographical region in each stage. The third part $\sum_{ni\in L,R,I,J} M_{nt}(1-\theta_{nit})Q_{nit}\alpha_{ni}d_{ni}x_{ni}$ represents the total transportation cost. The fourth part $\sum_{ni\in L,R,I,J} h\frac{(1-\theta_{nit})Q_{nit}}{2}$ represents the total storage cost. Assuming the manufacturer produces evenly over time, the average storage is half of the expected purchase quantity. The fifth part $\sum_{ni\in L,R,I,J} \beta(D_t - \sum(1-\theta_{nit})Q_{nit})$ represents the penalty cost of being out of stock.

$$\text{Min} \sum_{ni\in L,R,I,J} f_{ni}x_{ni} + \sum_{ni\in L,R,I,J} M_{nt}(1-\theta_{nit})Q_{nit}u_{ni}x_{ni} + \sum_{ni\in L,R,I,J} M_{nt}(1-\theta_{nit})Q_{nit}\alpha_{ni}d_{ni}x_{ni} + \sum_{ni\in L,R,I,J} h\frac{(1-\theta_{nit})Q_{nit}}{2} + \sum_{ni\in L,R,I,J} \beta(D_t - \sum(1-\theta_{nit})Q_{nit}) \tag{5}$$

3.2.3 Constraints

$$\sum_{Li\in L} x_{Li} \geq \varepsilon \tag{6}$$

$$Q_{nit} \leq C_{nit} \tag{7}$$

$$\sum_{ni\in L,R,I,J}(1-\theta_{nit})Q_{nit} \geq \sigma D_t \tag{8}$$

$$\tau C_{nit} \leq Q_{nit} \tag{9}$$

$$\sum_{ni\in L,R,I,J} x_{ni} \leq \varphi \tag{10}$$

$$Q_{nit} \in N \tag{11}$$

$$x_{ni} \in \{0,1\} \tag{12}$$

Constraint (6) guarantees that there is at least ε local supplier in the procurement plan.

Constraint (7) guarantees that the ordered quantity to each supplier does not exceed the supplier's production capacity. Constraint (8) indicates minimum expected order completion rate. Then, constraint (9) represents the minimum proportion of the purchase quantity from a single supplier and the production capacity of that supplier. Constraint (10) limits the number of suppliers. Constraint (11) ensures that the purchase quantity Q_{nit} is a positive integer. Constraint (12) ensures that the decision variable x_{ni} is binary.

3.3 Solution procedure

3.3.1 Determine sustainable & resilience score

The validity and reliability of the results obtained by the evaluation method are highly influenced by the criteria system (Rashidi et al., 2020). Hence, it is necessary to follow the triple bottom line (TBL) principle of sustainability and supplier resilience performance that needs to be considered carefully in a pandemic environment, and to build an appropriate evaluation criteria system according to the requirements of SSCM to determine the supplier's resilience and sustainable score firstly.

As noted above, entropy-TOPSIS under intuition fuzzy environment is used to calculate the sustainable score and resilience score of potential suppliers.

Definition 1 (Atanassov, 1986) Let *X* be a finite nonempty set. An intuition fuzzy set (IFS) *A* can be described as Equation (13):

$$A = \{< x, \mu_A(x), \nu_A(x) > \mid x \in X\} \tag{13}$$

where $\mu_A(x)$ and $\nu_A(x)$ denote the membership degree and non-membership degree of element *x* to the IFS *A*, $\mu_A(x), \nu_A(x) \in [0,1]$, and $0 \leq \mu_A(x) + \nu_A(x) \leq 1$.

Degree of hesitation $\pi_A(x)$ of the element *x* to *A* is defined as $\pi_A(x) = 1 - (\mu_A(x) + \nu_A(x))$. $\pi_A(x) \in [0,1]$, if $\pi_A(x) = 0$, the IFS *A* is similar to a fuzzy set.

Definition 2 (Zhao et al., 2010) Let $A_1 = (\mu_{A_1}, \nu_{A_1})$ and $A_2 = (\mu_{A_2}, \nu_{A_2})$ be two IFNs, then the follow rules are obtained as Equation (14) and Equation (15).

$$\mathrm{A_1 \oplus A_2} = (\mu_{A_1} + \mu_{A_2} - \mu_{A_1}\mu_{A_2}, \nu_{A_1}\nu_{A_2}) \tag{14}$$

$$\lambda A_1 = (1 - (1 - \mu_{A_1})^{\lambda}, {\nu_{A_1}}^{\lambda}) \tag{15}$$

Definition 3 (Szmidt and Kacprzyk, 2000) Let $A_1 = (\mu_{A_1}, \nu_{A_1}, \pi_{A_1})$ and $A_2 = (\mu_{A_2}, \nu_{A_2}, \pi_{A_2})$ be two IFNs, then, the distance between them is calculated by Equation (16):

$$d(A, B) = \sqrt{\frac{1}{2}[(\mu_{A_1} - \mu_{A_2})^2 + (\nu_{A_1} - \nu_{A_2})^2 + (\pi_{A_1} - \pi_{A_2})^2]} \tag{16}$$

Definition 4 (Wei, 2008) Let $A = (\mu_A, \nu_A, \pi_A)$ is an IFN, then the score function $S(A)$ and the accuracy function $H(A)$ are defined as Equation (17) and Equation (18):

$$S(A) = \mu_A - \nu_A \tag{17}$$

$$H(A) = \mu_A + \nu_A \tag{18}$$

Definition 5 (Wei, 2008) Let$A_1 = (\mu_{A_1}, \nu_{A_1}, \pi_{A_1})$, $A_2 = (\mu_{A_2}, \nu_{A_2}, \pi_{A_2})$ are two IFNs, then the comparison method between them is defined as:

(1) If $S(A_1) > S(A_2)$, then $A_1 > A_2$;

(2) If $S(A_1) < S(A_2)$, then $A_1 < A_2$;

(3) If $S(A_1) = S(A_2)$

① If $H(A_1) > H(A_2)$, then $A_1 > A_2$

② If $H(A_1) < H(A_2)$, then $A_1 > A_2$

③ If $H(A_1) = H(A_2)$, then $A_1 = A_2$.

Suppose that there are *m* suppliers $A = \{A_1, A_2, \cdots, A_m\}$, *n* evaluation criteria $C = \{C_1, C_2, \cdots, C_n\}$. Each supplier is evaluated by decision-makers with respect to *n* criteria to form a decision matrix denoted by $X = (x_{ij})_{m \times n}$. Let $W = (w_1, w_2, \cdots, w_n)$ be the relative weight vector of evaluation criteria, satisfying $\sum_{j=1}^{n} w_j = 1$.

Then the main steps of the sustainable & resilience score calculation model approach can be described as follows:

Step 1: Identify and define linguistic terms, obtain the corresponding fuzzy number of supplier A_i with IFNs $(\mu_{ij}, \nu_{ij}, \pi_{ij})$ on criterion C_j as Table 4, and then construct the decision matrix $X = (\mu_{ij}, \nu_{ij}, \pi_{ij})_{m\times n}$.

[Take in Table 4 about here.]

Step 2: Calculate the weight of each criterion by entropy weight method. For IFS, fuzzy entropy e_j is calculated as Equation (19) (Vlachos and Sergiadis, 2007):

$$e_j = -\frac{1}{m\ln 2}\sum_{i=1}^{m} (\mu_{ij} ln\, \mu_{ij} + \nu_{ij} ln\, \nu_{ij} - (1-\pi_{ij}) ln\, (1-\pi_{ij}) - \pi_{ij} ln 2) \quad (19)$$

Then, calculate the dispersion degree d_j of each criterion, obtain the weight w_j of each criterion as Equation (20) and Equation (21).

$$d_j = 1 - e_j, j = 1,2, \dots, n \quad (20)$$

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}, j = 1,2, \dots, n \quad (21)$$

Step 3: Calculate the distance between suppliers and positive and negative ideal solutions Δ_{ij}^{+}、Δ_{ij}^{-} under each criterion. Firstly, the score function and accurate function of each IFN are calculated by Definition 4, and the evaluation values under each criterion are sorted according to Definition 5, the positive and negative ideal solutions are obtained as Equation (22) and Equation (23). Then, Δ_{ij}^{+}、Δ_{ij}^{-} are calculated as Definition 3.

$$CS^{t+} = (\mu_{ij}^{+}, \nu_{ij}^{+}, \pi_{ij}^{+}) \quad (22)$$

$$CS^{t-} = (\mu_{ij}^{-}, \nu_{ij}^{-}, \pi_{ij}^{-}) \quad (23)$$

$$\text{Where } \pi_{ij}^{+} = 1 - \mu_{ij}^{+} - \nu_{ij}^{+},\ \pi_{ij}^{-} = 1 - \mu_{ij}^{-} - \nu_{ij}^{-}.$$

Step 4: Calculate the weighted distance d_i^+ 、 d_i^- between each supplier and positive and negative ideal solutions by Equation (24) and Equation (25).

$$d_i^+ = \sum_{j=1}^{n} w_j \Delta_{ij}^+ \tag{24}$$

$$d_i^- = \sum_{j=1}^{n} w_j \Delta_{ij}^- \tag{25}$$

Step 5: Calculate sustainable/resilience score CC_i of each supplier by Equation (26).

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{26}$$

3.3.2 Improved NSGA-II algorithm

NSGA (non-dominated sorting genetic algorithm) is a classical multi-objective optimization algorithm based on traditional genetic algorithm proposed by Srinivas (1994), which embodies the idea of classification based on non-dominated relationship. But it also has the problems of complicated calculation, lack of elite strategy and difficulty in selecting shared parameters. In order to cover the defects of basic NSGA algorithm, Deb et al. (2002) proposed NSGA-II, which reduces the complexity of the algorithm through a fast non-dominated sorting algorithm, introduces elite strategy to expand the sampling space, effectively prevents the loss of understanding, and uses a crowding operator instead of shared parameters to ensure the diversity of the population.

One of the major problems of multi-objective evolutionary algorithm based on Pareto sorting is that when the dimension of objective function is high, the convergence degree will decrease significantly. At the same time, it is necessary to proposed an algorithm considering decision-makers' preference to provide diversified demand for customers (Bi et al., 2020). Ra-dominance is a new dominance relation, which can guide the solution set to a more responsive range according to a reference point and decision-makers' preference (Zou et al., 2020). The steps of deciding individual relationship based on Ra-dominance are as follows:

Step 1: Determining reference direction vector v. The reference direction is defined as the vector from reference point g to solution x_{near}. Where x_{near} represents the nearest solution to g. The weighted distance of solution x to g is defined as Equation (27):

$$dis_x = \sqrt{\sum_{i=1}^{m} \omega_i (g_i - f(x)_i)^2} \tag{27}$$

where ω_i is the weight of ith objective given by decision-makers, and $\sum_{i=1}^{m} \omega_i = 1$.

However, there are often inconsistent dimensions of each objective in solving practical problems. This paper uses the idea of standardization, and defined the distance calculation equation as Equation (28):

$$dis_x = \sqrt{\sum_{i=1}^{m} \omega_i (\frac{g_i - f(x)_i}{\max f_i - \min f_i})^2} \tag{28}$$

Step 2: Determining preference radius r. The preference radius r is defined as Equation (29), which can represent the preference range of decision-makers:

$$r = dist(g, x_{near}) \cdot \tan \alpha \tag{29}$$

where α is determined by the intuitive parameter δ given by decision-makers as Equation (30):

$$\alpha = \begin{cases} \delta \cdot \frac{\pi}{2}, & if\ 0 < \delta < 1 \\ (1 - 10^{-4}) \frac{\pi}{2}, & if\ \delta = 1 \end{cases} \tag{30}$$

Step 3: Deciding individual dominance relationship. The Ra-dominance relationship is defined as follows: A solution x is said to Ra-dominate a solution y if:

(a) x dominates y in the Pareto sense, or

(b) x and y are Pareto-equivalent and $d(y, v) - d(x, v) > r$.

where v is reference direction vector, r is reference radius, $d(y, v)$ is the perpendicular distance from y to v.

In order to distinguish from the standard Ra-domination, this research defines the improved Ra-dominance as nRa-dominance. Combining with NSGA-II algorithm, the nRa-NSGA-II algorithm is proposed as follow.

Step* 1*: Initialize the population parameters, set the population size, evolution generations, crossover probability, mutation probability, obtain the reference point g and intuitive parameter δ of the decision-makers.

Step* 2*: Build the multi-stage multi-objective order allocation model, code decision variable x_{nit} by 0, 1 coding to indicate whether to select the supplier, and code decision variable Q_{nit} by integer coding to indicate the quantity purchased from the supplier, the schematic diagram is as Figure 4. Where shaded numbers represent decision variables x_{ni} and the number after them stands for Q_{nit}. Generate the initial parent population (order allocation scheme) P_t with the population size of N, where t is the population generation.

[Take in Figure 4 about here.]

Step 3: Perform fast non-dominated sorting and crowding degree calculation for all individuals based on nRa-dominance.

Step 4: Generation of offspring population. For tournament selection, the individual for each comparison is set as 50% of the population size, and the individual with the smallest non-dominant order and the largest crowding degree is selected each time. Then, the offspring population Q_t with population size N is obtained by crossover and mutation.

Crossover operation: Generate a random number between 0 and 1, if it is less than the crossover probability, perform the crossover operation. Due to the characteristics of coding method, genes appear in pairs, hence, two integers are randomly selected from

0 to chromosome length in step size of 2, and the partial exchange of two chromosomes between the two integers, the schematic diagram is shown in Figure 5. If the infeasible order allocation scheme is generated, the crossover is performed again until the feasible solution is generated.

[Take in Figure 5 about here.]

Mutation operation: A random number from 0 to 1 is generated for each point of the decision variable x_{ni}. If the random number is less than the mutation probability, the point of the decision variable x_{ni} is mutated. If x_{ni} is 1, it will be 0 after mutation; if x_{ni} is 0, it will be 1 after mutation. Also, due to the way of coding, the corresponding decision variable Q_{nit} becomes 0, or random numbers are generated. The schematic diagram is shown in Figure 6. If the infeasible order allocation scheme is generated, the mutation is performed again until the feasible solution is generated.

[Take in Figure 6 about here.]

Step* 5*: Merge the parent population and the offspring population. When the parent population and the offspring population are merged, because of the certain probability of crossover and mutation, some parent individuals do not carry out crossover and mutation. At the same time, due to the characteristics of integer coding, the same individuals may be generated in the crossover and mutation. In many experiments, it is found that there are more duplicate individuals in the merged population, which will seriously affect the diversity of the population. Therefore, it is necessary to eliminate duplicate individuals after population merging.

Step* 6*: Based on the nRa-dominance, the fast non-dominated sorting and crowding degree calculation were carried out to select the next generation of parent population P_{t+1} with population size N.

Step* 7*: Determine whether the maximum value of evolutionary generation is reached. If it is reached, the operation ends and the set of non-dominated order allocation scheme set is output. Otherwise, let $t = t + 1$ and return to Step 3 to continue iteration until the maximum value of evolutionary generation is reached.

3.3.3 Determining the optimal solution from the solution set

The optimal order allocation solution is obtained according to the maximum expected order completion rate of the solution set, which calculated according to Equation (31).

$$\text{Expected completion rate} = \frac{\sum_{ni \in L,R,I,J} (1 - \theta_{nit}) Q_{nit}}{D_t} \tag{31}$$

Thus, the optimal order allocation scheme in each stage is obtained.

4. Illustrative application

In this section, the feasibility of the proposed multi-stage multi-objective optimization model and the proposed algorithm is illustrated using the case of shortwave therapy equipment supply chain of Company B (a pseudonym, to ensure anonymity). Company B is a multinational enterprise established in the UK, now with offices in 55 countries, covering five continents, and having three medical product categories: cardiology, physiotherapy, and aesthetics. Shortwave therapeutic instruments have become subject to urgent and high demand during the COVID-19 era. However, the procurement of company's core components CPU mainboard, has been seriously affected, and has faced a high risk of supply disruption. The company has recognized the need to restructure their supply chains. Therefore, this paper uses the case of Company B to verify the feasibility and practicality of the proposed model.

4.1 Decision-making environment and assumptions

The basic decision-making problem and parameters required by the proposed model are based on a survey and interviews with the managers of the procurement and production departments of Company B. Considering the sensitive of business information, related costs, supplier capacity and market demand are converted according to a certain proportion of company survey data. The disruption probability and impact parameters of disruption in each period are also assumed based on the interviews. The manufacturing center for Company B has twelve potential suppliers for its core component CPU mainboard. The location of alternative suppliers is assumed as follows. There are four local suppliers, three regional suppliers, three international suppliers and two global suppliers. The geographical location of each supplier and the parameters of each period are shown in Appendices A to C. In addition, the unit holding cost and unit penalty cost are €0.7 and €1.4, respectively. According to the characteristics of the industry and the specific requirements of the Company B, the customized criteria system is constructed and shown in Table 5 and Table 6.

[Take in Tables 5 to 6 about here.]

4.2 Implementation and experimental results

Firstly, the sustainability and resilience evaluation values of each potential supplier are obtained (shown in Appendices D and E). Then, the sustainability score and resilience score of each supplier can be calculated according to section 3.3.1 (the results are shown in Table 7). Secondly, the decision-makers gives the reference point g of each period according to section 3.3.2 (shown in Table 8), the weight ω_i of each period (shown in Table 9) and the intuitive parameter δ (δ = 0.3). Based on interviews, we assume that if Company B wants to ensure a stable cooperation relationship with suppliers, then suppliers can give priority to supply when the supply risk occurs. The order quantity needs to reach about 65% of the supplier's capacity, the maximum number of suppliers is eight, the acceptable minimum order completion rate is 75%, ensure that there is at least one local supplier. Thus, $\sigma = 0.75, \tau = 0.65, \varphi = 8, \varepsilon = 1$.

[Take in Tables 7 to 9 about here.]

Then, the multi-stage multi-objective optimization model is solved in the MATLAB 2017b environment. In this case, the population size is 100, the evolutionary generation is 100, the crossover probability is 0.95, the mutation probability is 0.05. In the non-dominated solution set obtained at each period, the order allocation scheme with the highest expected order completion rate is selected as the optimal solution. The result of order allocation is shown in Table 10. Meanwhile, Table 11 shows the objective function value and out of stock units of each period. The evolution of objective function value in each period is shown in Figure 7. The proportion of procurement volume of suppliers in different geographical locations in each period is shown in Figure 8.

[Take in Tables 10 to 11 about here.]
[Take in Figures 7 and 8 about here.]

The following findings can be seen from the above results: Firstly, through the evolution of each generation of the objective function, it can be seen that the proposed algorithm has good convergence (shown in Figure 7). Secondly, as the pandemic situation becomes more and more serious, due to the impact of the pandemic, the transportation cost is greatly increased, and the interruption probability of suppliers is also increased, resulting in an increasing shortage (shown in Table 11). At the same time, the number of suppliers selected is also increasing, which reduces the overall disruption probability of the supply chain to a certain extent (shown in Table 10). Thirdly, from the proportion of suppliers' purchase volume in different geographical locations, it can be seen that with the development of the pandemic, the proportion of local and regional suppliers' purchase volume is increasing (orange portions vs. blue portions in Figure 8). This is due to the transportation obstruction caused by the pandemic, which makes manufacturers seek local and regional cooperation as much as possible.

5. Sensitivity and comparative analysis

5.1 Sensitivity analysis

Decision-makers can control the region of interest size by intuitive parameter δ to express the expected range near the reference direction vector, ranging from 0.1 to 1.

The weight reflects the decision-makers' preference for each objective. Thus, in order to study the influence of intuitive parameter δ and the weights of different objectives on the optimization results, this sub-section takes t_1 as an example, and makes sensitivity analysis by adjusting intuitive parameter δ and the weights of different objectives, respectively. The five scenarios of weight adjustment are shown in the Table 12. Due to the characteristics of heuristic method, programming results are slightly different each time, the experimental results in this section are run independently ten times, and the average value is taken. The average value of the objective functions and the size of the solution set in different scenarios are summarized in Table 13.

[Take in Tables 12 and 13, and Figure 9 about here.]

In order to analyse the differences between different parameter δ more intuitively, the average value of objective function in different period is standardized by Equation (32), and the results are shown in Figure 9.

$$\begin{cases} \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} & \text{if } j \text{ is benefit criteria} \\ \frac{1/x_{ij}}{\sum_{i=1}^{m} 1/x_{ij}} & \text{if } j \text{ is cost criteria} \end{cases} \tag{32}$$

From Figure 9 and Table 13 we can see that: Firstly, with the increase of the δ, the corresponding preference radius will increase, which makes the region intercepted on the front become larger, so the size of the solution set increases greatly (shown in Table 13). This will result that almost the whole population is the non-dominated solution set, and the hierarchical ability of the algorithm is significantly reduced. Therefore, the selection of δ should not be larger than 0.4. Secondly, from the performance of the objective function value (shown in Figure 9), when the δ ranges from 0.2 to 0.4, the average objective function value is better compared with other scenarios. It shows that too large or too small a solution set will have an adverse effect on the overall performance of the solution set. Therefore, the decision-maker should consider the performance of the objective function value and the size of the solution together when determining the intuitive parameter δ.

In addition, the average value of the objective function in the different scenarios obtained by adjusting weights are shown in Table 14 and the intuitive diagram is shown in Figure 10. From Figure 10 and Table 14 we can see that, when the specific objective weight is larger, the performance of the corresponding objective function is better. Therefore, the decision-maker can adjust the weights to make the solution set converge to the preferred objective(s). This phenomenon reflects that the proposed model and the algorithm can fully reflect the decision-makers' preference in different decision-making situations and make the solution set converge to the decision-makers' preference. For example, the decision-maker can determine the weight of each objective according to the needs of Company B in different stages of the pandemic, and identify a solution set which is more appropriate for the specific decision-making requirements.

[Take in Figure 10 and Table 14 about here.]

5.2 Comparative analysis

In order to verify the advantages of the proposed nRa-NSGA-II algorithm in high-dimensional multi-objective optimization situation, this section compares it with the standard NSGA-II algorithm, r-NSGA-II algorithm (Ben Said et al., 2010) and NSGA-II algorithm based on fuzzy domination (He et al., 2014) (hereinafter referred to as f-NSGA-II). The reference point of r-NSGA-II algorithm is the same as nRa -NSGA-II. The threshold of nRa -NSGA-II, r-NSGA-II and f-NSGA-II are all taken as 0.3, the average value of the objective function results in this section are run independently ten times, and the average value is shown in Table 15. These results are also standardized by Equation (32), and shown in Figure 11.

[Take in Tables 15 and 16, and Figure 11 about here.]

From Figure 11 and Tables 14 and 15 we can see that, firstly, the solution set obtained by the proposed algorithm is better than other algorithms (shown in Figure 11), which reveals that the proposed algorithm can improve the performance of high-dimensional multi-objective optimization. Secondly, through the average expected order completion rate of the solution set obtained by different algorithms in each period, the proposed algorithm has a higher average expected order completion rate (shown in Table 16), ensuring more medical equipment demand can be met in the event of pandemic. Thirdly, from the perspective of solution set size, under the same conditions, the solution set size obtained by the proposed method is much smaller (shown in Table 15). This shows that the proposed algorithm can more effectively stratify individuals in high-dimensional multi-objective optimization, and can reflect the preferences of a decision-maker more effectively. Combined with the first two points, the solution set obtained by the proposed algorithm is superior to the average value of the objective function and the average expected order completion rate. In addition, this phenomenon shows that the larger the solution set, the more dispersed the solution set, which will affect the overall level of the solution set and reduce the beneficial result of the order allocation scheme. Therefore, the proposed algorithm can effectively obtain a more high-quality and centralized solution set, which can provide more effective decision-making support. In conclusion, considering the above three advantages, the proposed nRa-NSGA-II algorithm is more suitable for solving the SSS and order allocation problem under the condition of considering more comprehensive objectives and demanding higher expected order completion rate.

6. Discussion and managerial implication

6.1 Discussion

Firstly, as disruption risk has a great impact on the performance of supply chains (Esmaeili-Najafabadi et al., 2019), SSCs need resilience to deal with supply chain disruption (Rajesh and Ravi, 2015). Facing the huge disruption risk caused by the current pandemic, some pioneering studies explored the impact of the pandemic from different perspectives (e.g. Govindan et al., 2020; Li et al., 2021; Mahmoudi et al., 2021; Ivanov, 2020). Due to the unpredictability of the development and virus variation of

COVID-19 (Karmaker et al., 2021), it is recognized that the different stages of the pandemic have different characteristics and different impacts on SSCM, which have been ignored by existing studies. This research divides the development and spread of the pandemic into five stages from the perspective of the impact of supply disruption in SSCM, which enables the multi-period model constructed in this paper to fully capture these different features and impacts of the pandemic at different stages and to make appropriate SSS and order allocation decision-making.

Secondly, the pandemic requires multinational enterprises to consider not only the sustainability of suppliers, but also their resilience at the same time. However, most of the current research only considers traditional sustainability (e.g. Govindan et al., 2015; Cheraghalipour and Farsad, 2018; Harridan and Cheaitou, 2017) or resilience (e.g. Torabi et al., 2015; Mari et al., 2019), seperately. Meanwhile, disruption probability (risk) is only combined with other objectives, rather than considered as a separate objective in the existing research (Kaur and Prakash Singh, 2021). Furthermore, the different lockdown policies of various countries in the pandemic (Nikolopoulos et al., 2021) means multinational enterprises having to consider the geographical separation of suppliers. Thus, during the construction of the proposed model in Section 3.2, this research comprehensively considers the five objectives to ensure the low cost, high sustainability and resilience, low disruption probability and scattered supplier location of the procurement scheme. The illustrations in Section 4 show that the proposed model can ensure higher order completion rates during the whole process of the pandemic.

Thirdly, a suitable heuristic algorithm is required to solve the high-dimensional multi-objective optimization model. In this paper, the multi-objective optimization model is solved directly in order to avoid the local optimal solution when transforming multi-objective into a single objective (Hosseini et al., 2019). In order to effectively solve the high-dimensional multi-objective optimization model, to reflect decision-makers' preference for each objective, and to take the influence of different objective data types into account, this research proposes a novel nRa-NSGA-II algorithm based on Ra-

NSGA-II algorithm (Zou et al., 2020), which makes up for the shortages of existing algorithms (which are only suitable for low dimensional problems) (Cheraghalipour and Farsad, 2018). The illustrations in Section 4 demonstrate the effectiveness of the proposed algorithm. The sensitivity analysis in Section 5 also shows that the proposed algorithm can effectively reflect decision-makers' preferences and make the non-dominated solution set converge towards the preferred direction. In addition, comparative analysis shows that compared with other algorithms (e.g. Ben Said et al., 2010; He et al., 2014), the proposed algorithm can obtain the non-dominated solution set with better performances.

Finally, in order to cope with the lockdown policy of the pandemic (Hosseini et al., 2019), and reduce the risk of supply disruption caused by it, this research considers the characteristics of suppliers in different geographical locations and the importance of local procurement during the pandemic. Based on their different characteristics, this research divides potential suppliers into local, regional, international and global categories, while taking local procurement as an important constraint. The change of order allocation proportion of suppliers in different locations in different periods of the pandemic has been calculated in Section 4, which can guide decision-makers to make better purchasing plans to cope with the big challenges of pandemic.

6.2 Managerial implication

The research results can help multinational companies and SSCs which are affected by the pandemic to reconfigure their supplier selection and order allocation planning. In more detail, the application of the proposed model to Company B results in a quantitative analysis that can provide managers with the following managerial insights.

First, both decentralized and centralized procurement have their own advantages and disadvantages. Using decentralized procurement, SSCs can reduce the negative impacts of disruption caused by the pandemic and the corresponding regional or global lockdowns (Hosseini et al., 2019). Yet, under normal circumstances, decentralized procurement can cause monitoring difficulties and increased costs (Petersen et al., 2020). Thus, in order to avoid the negative impacts of the pandemic and similar global emergence events, appropriate decentralized procurement is more appropriate to ensure consistent supply when disruption events occur (e.g. Tables 10 and 11).

Second, from the result of the order allocation calculations, with the pandemic situation becoming more and more serious, local and regional procurement accounts for an increasing proportion of purchases (as shown in Figure 8). This important result reminds managers of the need to obtain as much information as possible about local suppliers who can meet the needs of their daily operations.

Third, in order to minimize the effect of transportation disruption when the disruption suddenly occurs, SSCs of multinational enterprises should try to separate the geographical location of suppliers when making procurement plans, and maintain good cooperation with local and regional suppliers, in order to ensure timely supply in case of pandemic occurs.

Fourth, the sensitivity analysis shows that decision-makers' preferences (the weights given to different objectives) leads the solution set to converge towards the preference objective. Thus, any change of weights must reflect the decision-makers' preference for different objective, especially under different decision-making situations. This requires the decision-maker to fully understand the demand preferences of companies for different objectives according to different characteristics in each decision-making period. Then, obtain an order allocation scheme that can meet the real needs of SSCs.

Fifth, decision-makers can control the region of interest size by intuitive parameter δ, the sensitivity analysis indicates that, to ensure the overall superiority of the non-dominated solution set, decision-makers should give a reasonable intuitive parameter δ. For example, the most appropriate value of the parameter is 0.2 to 0.4 in case of

Company B. Decision-makers can also adjust the parameter values interactively according to the needs of decision-making in SSS and order allocation process.

Finally, COVID-19 has variability, especially the Delta variant, which has been found all over the world (Bernal et al., 2021), making the pandemic repeated. In this case, decision makers need to judge the current stage according to the policy and pandemic development. At the same time, according to the actual situation, the parameters and priorities can be adjusted based on the five stages proposed in this paper, so as to deal flexibly with the impact of virus variants.

7. Conclusions

COVID-19 has brought unprecedented pressure to the global supply chains (Nikolopoulos et al., 2021). It results in shutdowns and production stoppages, regionally and globally, which are different from that caused by other natural disasters or human factors. At the same time, sustainability is still crucial to the operations of multinational enterprises (Zhu and Lia, 2019; Karmaker et al. 2021). Therefore, a specific SSS and order allocation method is urgently needed to deal with this new challenge. In the proposed framework, the development and spread of the pandemic is divided into five periods from the perspective of supply disruption in SSCM, while suppliers are categorized as either local, regional, international or global according to their geographical location. Taking the characteristics of the supply disruption caused by the pandemic into account, a novel multi-stage multi-objective optimization model is proposed, that considers more comprehensive objectives. To better solve the high-dimensional multi-objective optimization model, this paper improves the traditional NSGA-II algorithm by proposing the nRa-NSGA-II algorithm. The feasibility of the proposed model and algorithm is verified in an illustrative application. Sensitivity and comparative analysis also show that the average objective function performance of the solution set obtained by the proposed model is more in line with the decision-making objectives, for instance, the expected average order completion rate is larger using the proposed approach.

The contributions of this paper are summarized in the following four points. First, this research divides the development and spread of pandemic into five stages from the perspective of the impact of supply disruption in SSCM, which enables the multi-period model constructed in this paper to fully capture these different features and impacts of the pandemic at different stages. Second, a multi-period multi-objective SSS and order allocation model is constructed to deal with the supply disruption in SSCs of multinational enterprises caused by the pandemic, considering sustainability, resilience, geographical separation, disruption probability and related costs, comprehensively and simultaneously. The proposed model can ensure sustainability whilst reducing the vulnerability of the whole supply chain and improving the expected order completion rate. Third, a novel and more effective nRa-NSGA-II algorithm is proposed to solve the high-dimensional optimization problem, which makes up for the drawback that the existing order allocation algorithm is not suitable for high-dimensional optimization. The algorithm can obtain a better non-dominated solution set and reflect the preference of decision-makers in different decision-making situations. Fourth, this paper divides potential suppliers into four categories, whilst taking local procurement into account, which clarifies the characteristics of suppliers in different locations in each stage of the pandemic, and so ensures consistent supply. Furthermore, it can reflect the importance of different suppliers in each stage of the pandemic and greatly reduce the vulnerability of the whole SSCs.

There are also some shortcomings of this research. First, it is difficult to predict the impact of COVID-19 on SSC (Karmaker et al., 2021) and demand has great uncertainty (Alkahtani et al., 2021). Yet, one assumption of this research is that the customer demands of each stage are determined. Thus, the order allocation problem in the case of stochastic demand can be considered in future research. Furthermore, even if the algorithm proposed is also applicable to the case of a decrease of demand, further research considering this assumption is also an interesting question. Second, the focal company and its performance are affected not only by the first-tier suppliers, but also by the upstream multi-tier suppliers. The experience of COVID-19 shows that due to the failure of supply chain nodes, disruption will affect the whole supply chain network (Golan et al., 2020). As such, it is necessary to research the whole interconnected supply chain network. Thus, the influence of the second-tier and the third-tier suppliers from the perspective of supply disruption is also an interesting research question. Finally, the focus of this paper is to propose a SSS and order allocation model when considering disruption risk in SSCM caused by the pandemic. Additionally, the virus may mutate and cause other effects. What's more, supply disruptions also have other triggers, such as political factors, transportation interruptions, etc. In addition, enterprises may also choose not to purchase or make an unethical purchase when disruption occurs. These are all interesting topics for future research on SSS and order allocation under circumstances of disruption.

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Figures

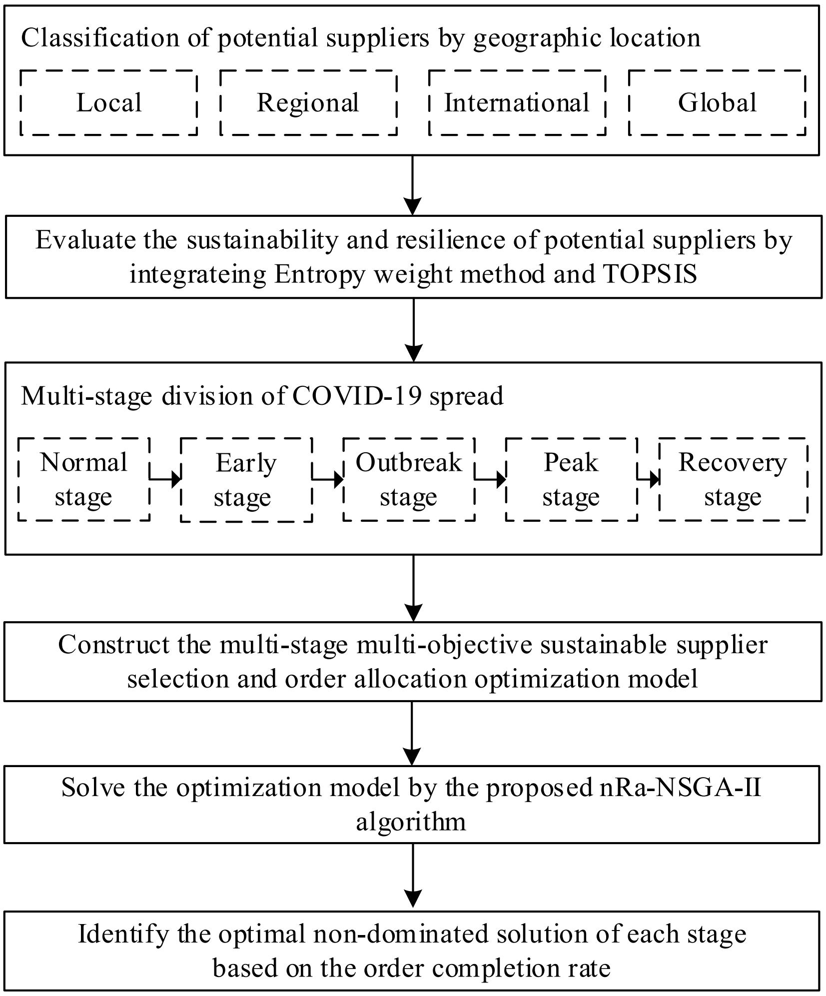


Figure 1: The proposed framework for sustainable supplier selection and order allocation

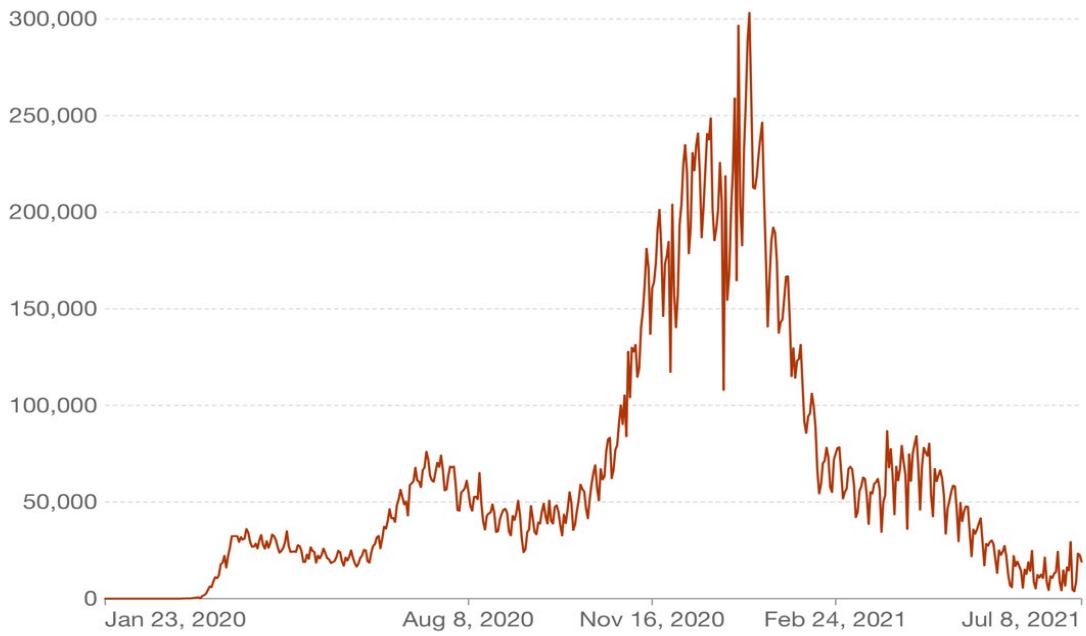


Figure 2: Daily new confirmed COVID -19 cases in the United States

Source: Our World Data website

https://ourworldindata.org/explorers/coronavirus-data-explorer

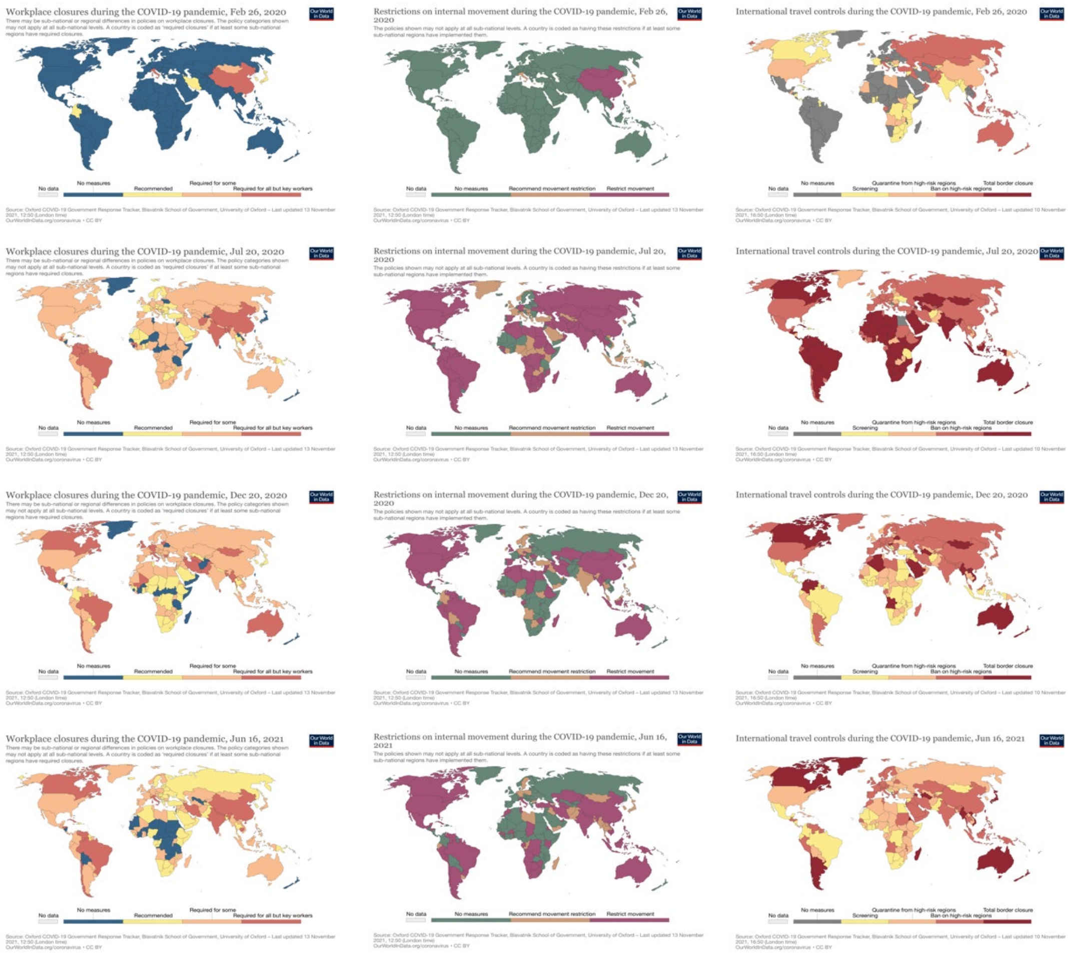


Figure 3: Map of changes of lockdown policy

Source: Our World Data website

https://ourworldindata.org/grapher/workplace-closures-covid

https://ourworldindata.org/grapher/internal-movement-covid

https://ourworldindata.org/grapher/international-travel-covid

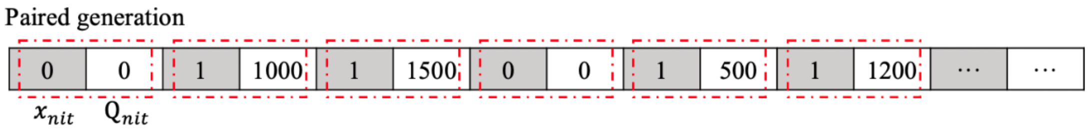


Figure 4: Schematic diagram of coding

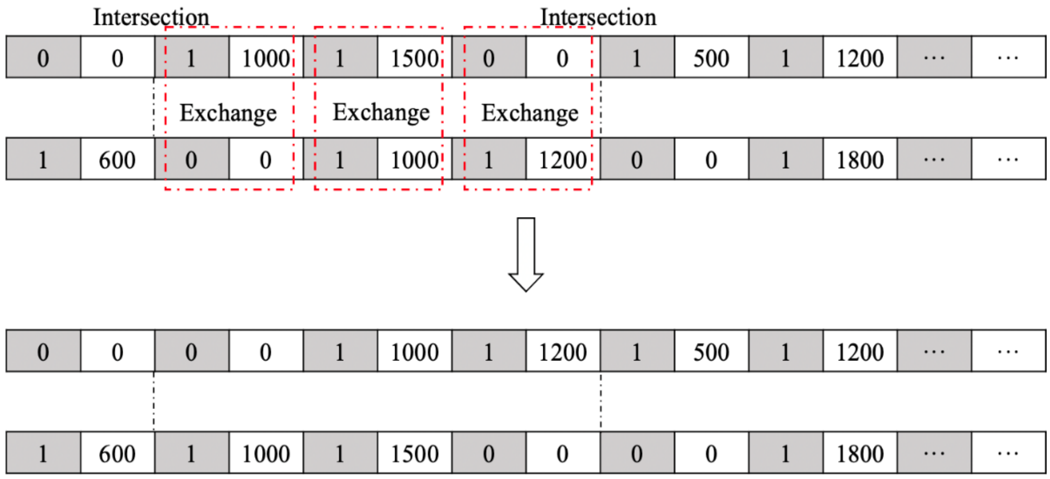


Figure 5: Schematic diagram of crossover operation

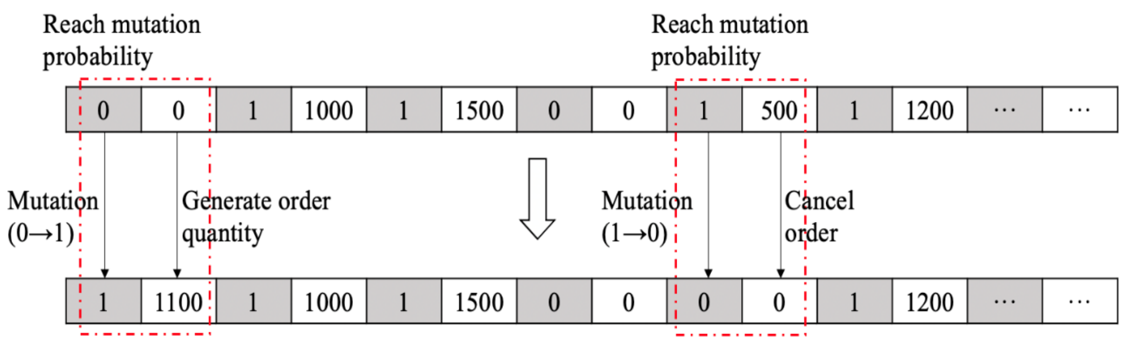


Figure 6: Schematic diagram of mutation operation

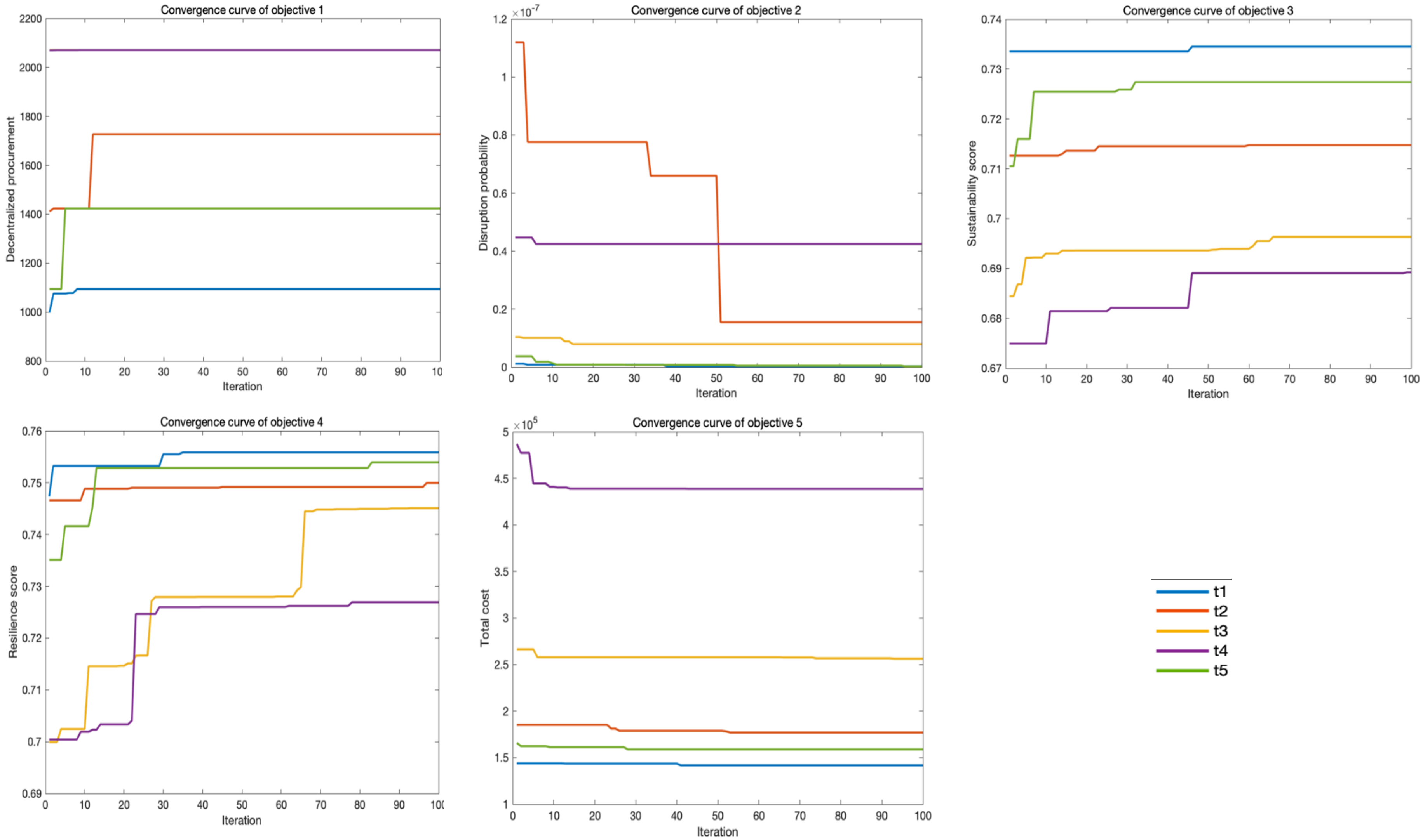


Figure 7: The evolution of objective function value of each period

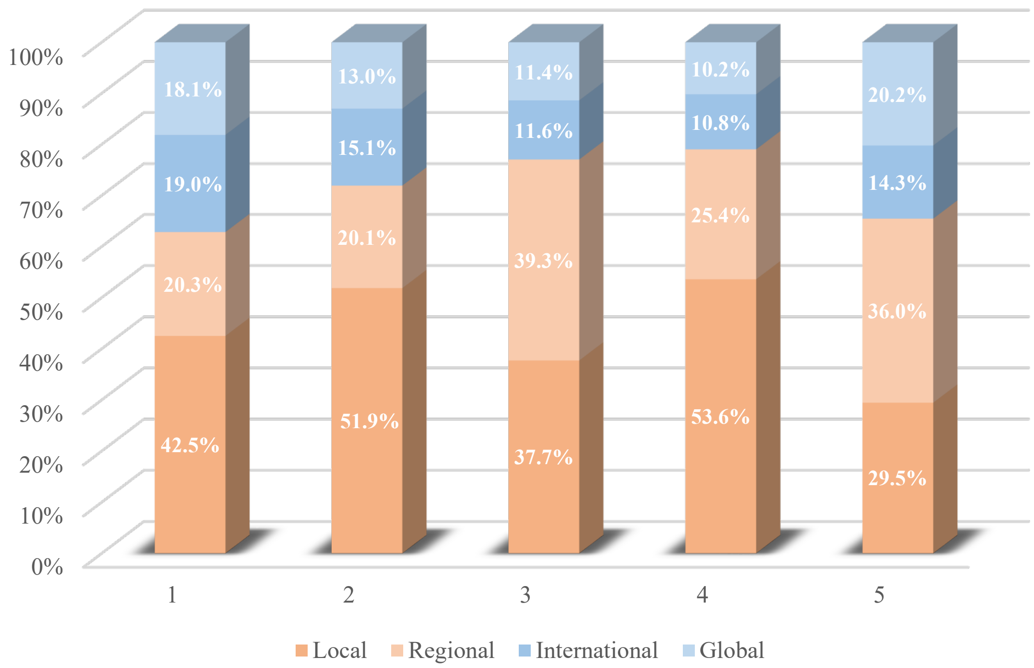


Figure 8: Proportion of procurement volume of suppliers in different geographical locations in each period

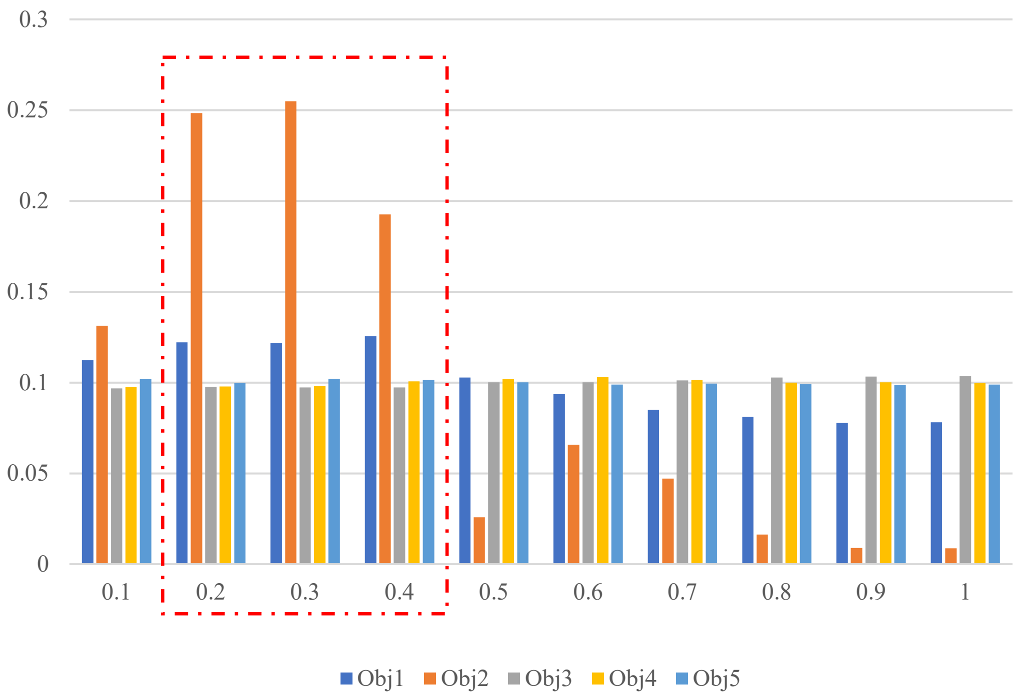
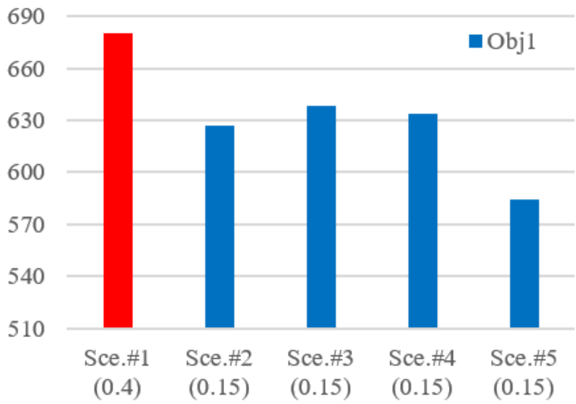
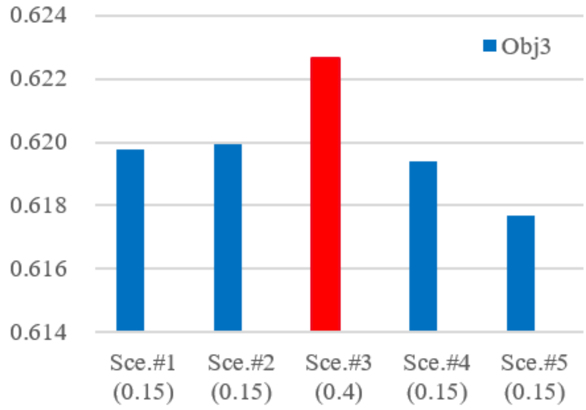
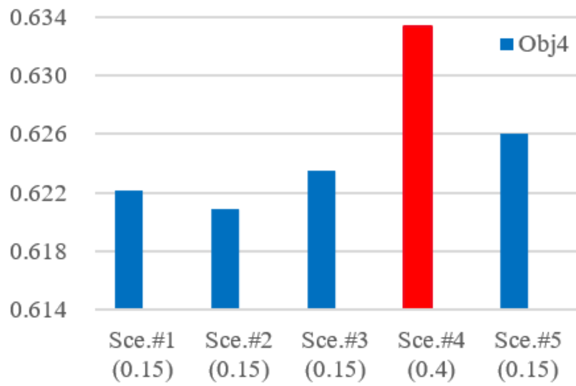


Figure 9: Standardized value of objective functions with different parameter δ

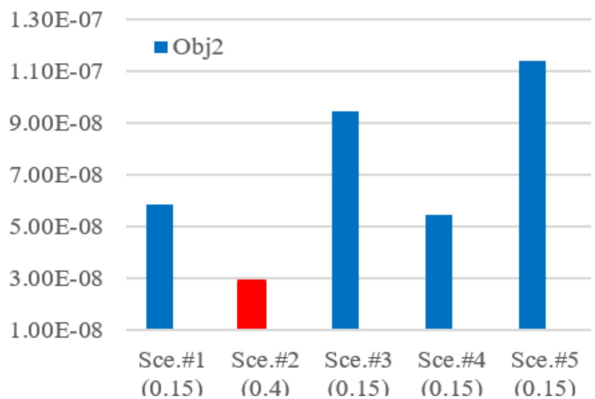
Benefit objectives (including Obj1, Obj3 and Obj4)

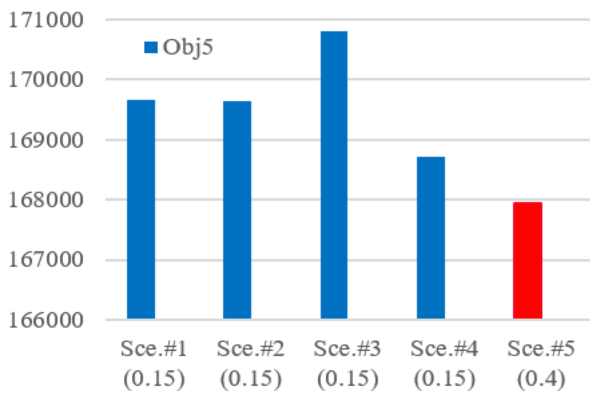






Cost objectives (including Obj2 and Obj5)





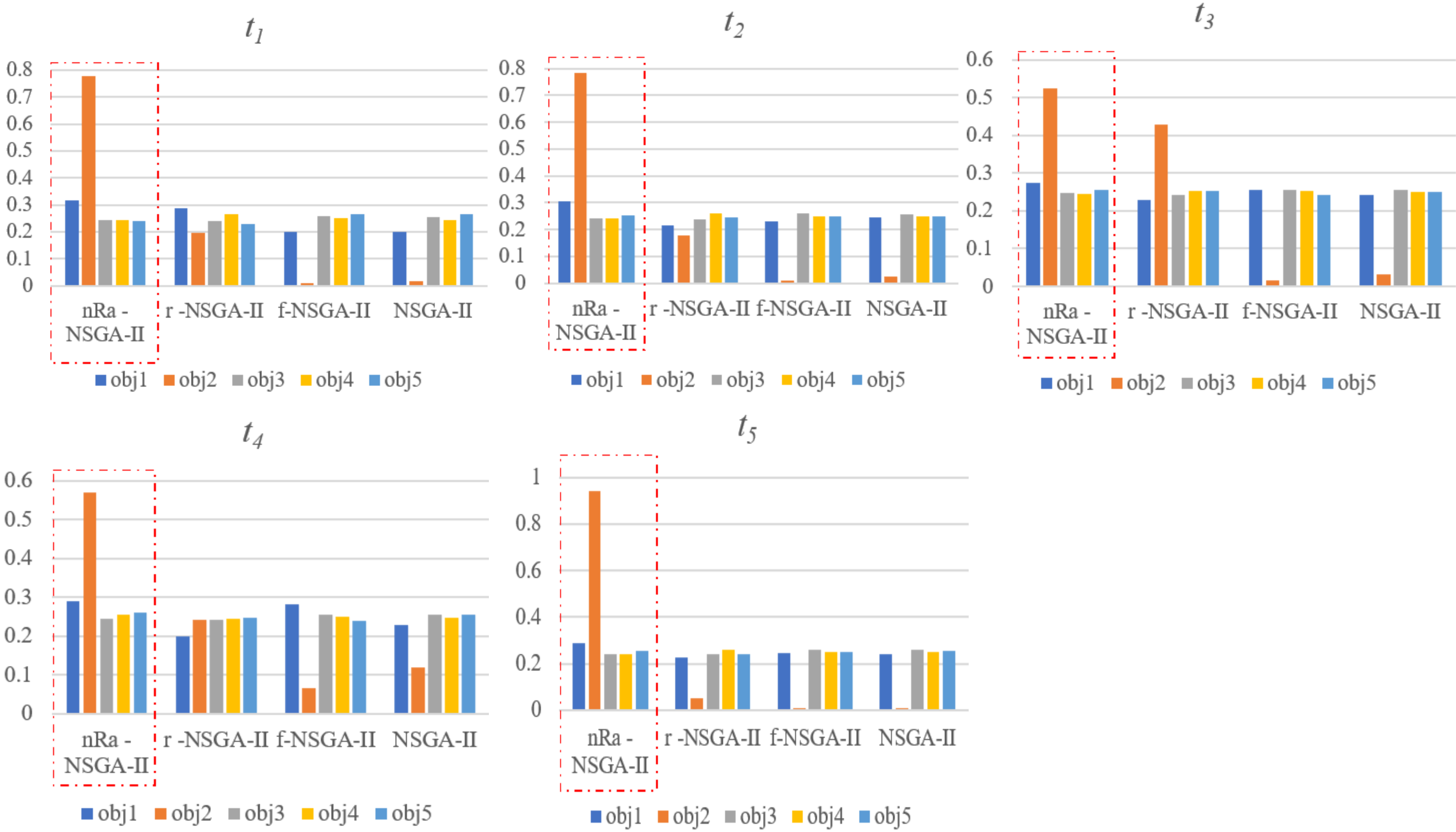


Figure 11: Standardized value of objective functions obtained by different algorithms

Tables

Table 1: Representative literature on sustainable supplier selection and order allocation

Authors/Year	Programming objectives					Sigle-Obj.	Multi -Obj.	Optimization methodology	Features
	Sus.	Res.	Geo.	Eco.	Dis.				
Kannan et al., (2013)				✓			✓	Linear programming, max-min method	Combining economic and green supplier selection criteria.
Torabi et al., (2015)		✓		✓		✓		ε-constraint, differential evolution algorithm	Operational & disruption risk are considered at the same time.
Meena and Sarmah, (2015)				✓	✓	✓		Stepwise procedure	Compensation based on supplier failure risk and quantity discount are considered.
Govindan et al., (2015)	✓			✓			✓	MOHEV algorithm	A new metaheuristic algorithm is proposed.
Cheraghalipour and Farsad, (2018)	✓			✓	✓		✓	Multi-Choice Goal Programming	Two types of quantity discount are considered and a novel hybrid MCDM-MILP approach is proposed.
PrasannaVenkatesan and Goh, (2016)				✓	✓		✓	Multi-objective PSO	The conflict between the total cost considering interruption loss and purchase value is balanced.
Harridan and Cheaitou, (2017)	✓			✓			✓	Integer liner programming model	Multi objective configuration and bi-objective configuration are compared.
Vahidi et al., (2018)	✓	✓		✓	✓	✓		ε-constraint, differential evolution algorithm	Objective of sustainability and elasticity score is constructed.
Mari et al., (2019)		✓		✓			✓	Fuzzy programming	The quantitative resilience criterion is proposed.
Hosseini et al., (2019)			✓	✓	✓	✓		ε-constraint, Mixed integer programming	Quantifying the geographical separation of suppliers.
Kaur and Prakash Singh, (2021)				✓	✓	✓		Mixed integer programming	Different of disruption risk are considered for uncertain demand.
The proposed model	✓	✓	✓	✓	✓		✓	nRa-NSGA-II	Considering resilience and sustainable objectives at the same time, a new high-dimensional multi-objective optimization method is proposed.

Notes: Sus.: Sustainability; Res.: Resilience; Geo.: Geographic separation; Eco.: Economic; Dis.: Disruption probability

Table 2: The five periods of the pandemic and their specific characteristics

Period	Description	Demand level	Lockdown situations				Probability of disruption	Priority of supply chain operations management
			Local	Regional	International	Global		
t_1	Normal stage	Normal	0	0	0	0	Very low	Costs, decentralized sourcing, disruption, sustainability, resilience
t_2	Early stage	Rise slightly	0	0	1	1	Medium	Sustainability, disruption, decentralized sourcing, resilience, costs
t_3	Outbreak stage	Rise sharply	2	2	3	3	High	Sustainability, disruption, decentralized sourcing, resilience, costs
t_4	Peak stage	Rise sharply	3	3	4	4	Very high	Sustainability, disruption, resilience, decentralized sourcing, costs
t_5	Recovery stage	Normal	1	1	2	2	Low	Cost, decentralized sourcing, sustainability, resilience, disruption

Notes: 0-4 respectively indicates the severity of the lockdown policy, 0 indicates no lockdown policy, and 4 indicates that the lockdown is very serious.

Table 3: The notations used in the proposed model

Notations	Illustrations
Li	i^{th} local supplier
Ri	i^{th} region supplier
Ii	i^{th} international supplier
Gi	i^{th} global supplier
L, R, I, G	The set of local, region, international, and global suppliers
t	t^{th} period
Decision variables	
x_{ni}	If supplier *ni* is selected, 1; 0, otherwise.
Q_{nit}	Order quantity from supplier *ni* during period *t*.
Parameters	
D_t	Demand during period *t*.
f_{ni}	Fixed ordering cost for supplier *ni*. ($n = L, R, I, G$)
u_{ni}	Unit cost for supplier *ni*. ($n = L, R, I, G$)
α_{ni}	Transportation cost for supplier *ni* per unit.
h	The unit holding cost.
d_{ninj}	Distance between supplier *ni, nj*. ($n = L, R, I, G$)
d_{ni}	Distance between supplier *ni* and firm. ($n = L, R, I, G$)
β	Unit penalty cost.
C_{nit}	Maximum supply capacity of supplier *ni* during period *t*.
M_{nt}	Impact of logistics disruption of *n* during period *t*. ($n = L, R, I, G$)
ζ_{ni}	Sustainable score of supplier *ni*. ($n = L, R, I, G$)
η_{ni}	Resilience score of supplier *ni*. ($n = L, R, I, G$)
θ_{nit}	Supplier *ni* disruption probability during period *t*. ($n = L, R, I, G$)
σ	Minimum order completion rate.
τ	The minimum purchase proportion of a single supplier.
φ	Maximum number of suppliers selected.
ε	Minimum number of local suppliers

Table 4: Numerical variables and corresponding IFNs

Linguistic terms	IFNs
Very good (VG)	(0.90,0.05,0.05)
Good (G)	(0.75,0.15,0.10)
Medium good (MG)	(0.60,0.25,0.15)
Medium (M)	(0.50,0.40,0.10)
Medium poor (MP)	(0.40,0.50,0.10)
Poor (P)	(0.25,0.65,0.10)
Very poor (VP)	(0.10,0.80,0.10)

Table 5: Resilience evaluation criteria and illustrations

	Criteria	Illustrations	Reference
RC_1	Rerouting	The ability to change the mode and route of transportation in case of disruption.	Amindoust (2018); Hosseini and Al Khaled (2019)
RC_2	Restorative capacity	Timely resumption of normal production after supply interruption.	Amindoust (2018); Hosseini and Al Khaled (2019)
RC_3	Risk awareness	The ability to predict and reduce potential risks of suppliers.	Rajesh and Ravi (2015)
RC_4	Surplus inventory	The amount of inventory used by suppliers in daily production to cope with disruption risk.	Amindoust (2018)

Table 6: Sustainable evaluation criteria and illustrations

Criteria		Sub-criteria	Illustrations	Reference
Economic	SC_1	Quality	Reliability of production quality.	Li et al. (2019) Tong et al. (2020)
	SC_2	Delivery	Timeliness and reliability of suppliers' delivery.	Li et al. (2019) Jain and Singh (2020)
	SC_3	Service	Service provided during and after purchasing.	Jain and Singh (2020) Hendiani et al. (2020)
	SC_4	Technology capability	The application of new production technology.	Tong et al. (2020) Jain and Singh (2020)
Environment	SC_5	Resource and energy consumption	The consumption of resources and energy in the production process.	Tong et al. (2020)
	SC_6	Eco-design	Design to reduce environmental impact throughout the product life cycle.	Jain and Singh (2020)
	SC_7	Environmental management system	Environmental standards and organizational structure that the supplier complies with and obtains certification, such as ISO 14001.	Jain and Singh (2020)
Social	SC_8	Labor safety & healthy	Production plans to protect the safe and health of their employees.	Li et al., (2019) Tong et al., (2020) Jain and Singh (2020) Hendiani et al. (2020)
	SC_9	Staff training	Training level of knowledge and skills for employees.	Tong et al., (2020) Hendiani et al., (2020)
	SC_{10}	Social responsibility	The level of corporate investment in social responsibility activities.	Jain and Singh (2020)

Table 7: Sustainability score and flexibility score of each supplier

	L_1	L_2	L_3	L_4	R_1	R_2	R_3	I_1	I_2	I_3	G_1	G_2
ζ_{ni}	0.62	0.63	0.80	0.56	0.55	0.71	0.59	0.57	0.67	0.62	0.69	0.65
η_{ni}	0.54	0.51	0.68	0.61	0.79	0.54	0.74	0.74	0.38	0.78	0.53	0.73

Table 8: Reference point g of each period

	Obj_1	Obj_2	Obj_3	Obj_4	Obj_5
t_1	600	5.00E-06	0.6	0.6	180000
t_2	800	5.00E-06	0.6	0.6	220000
t_3	900	5.00E-08	0.6	0.6	420000
t_4	900	5.00E-07	0.6	0.6	600000
t_5	600	5.00E-06	0.6	0.6	200000

Table 9: Weight ω_i of each period

	Obj_1	Obj_2	Obj_3	Obj_4	Obj_5
t_1	0.20	0.15	0.15	0.10	0.40
t_2	0.18	0.22	0.29	0.16	0.15
t_3	0.17	0.25	0.28	0.17	0.13
t_4	0.13	0.28	0.30	0.19	0.10
t_5	0.20	0.10	0.20	0.15	0.35

Table 10: Sustainable supplier selection and order allocation results

	L_1	L_2	L_3	L_4	R_1	R_2	R_3	I_1	I_2	I_3	G_1	G_2
t_1	0	2124	0	3106	0	0	2499	2341	0	0	2229	0
t_2	2183	2078	0	3888	3153	0	0	0	2366	0	0	2041
t_3	2833	2674	0	2643	2382	2816	3297	2499	0	0	2457	0
t_4	3136	2446	2932	3550	3299	0	2428	0	2426	0	0	2291
t_5	2094	1927	0	0	2414	2498	0	0	0	1953	2757	0

Table 11: Objective function value and expected out of stock of each period

	Obj_1	Obj_2	Obj_3	Obj_4	Obj_5	Out of stock
t_1	510.18	7.20E-09	0.60	0.63	175068.69	22
t_2	874.75	2.40E-07	0.61	0.60	235584.72	105
t_3	921.32	2.04E-08	0.62	0.63	423389.85	875
t_4	1243.95	7.00E-08	0.63	0.63	550290.22	3452
t_5	432.99	8.52E-10	0.64	0.61	215183.70	44

Table 12: Weight adjustment of each scenario

	Obj_1	Obj_2	Obj_3	Obj_4	Obj_5
Scenario #1	0.40	0.15	0.15	0.15	0.15
Scenario #2	0.15	0.40	0.15	0.15	0.15
Scenario #3	0.15	0.15	0.40	0.15	0.15
Scenario #4	0.15	0.15	0.15	0.40	0.15
Scenario #5	0.15	0.15	0.15	0.15	0.40

Table 13: The average value of the objective function and the size of the solution set

δ	Obj_1	Obj_2	Obj_3	Obj_4	Obj_5	Solution set size
0.1	552.74	1.45E-07	0.62	0.63	173354.99	9
0.2	601.62	7.67E-08	0.62	0.63	177208.38	12
0.3	599.34	7.47E-08	0.62	0.63	173018.06	15
0.4	617.59	9.89E-08	0.62	0.65	174419.98	38
0.5	506.29	7.37E-07	0.64	0.66	176529.27	63
0.6	461.09	2.90E-07	0.64	0.66	178710.63	95
0.7	418.33	4.04E-07	0.64	0.65	177809.20	100
0.8	399.54	1.17E-06	0.65	0.64	178322.88	100
0.9	383.23	2.14E-06	0.66	0.64	178843.73	100
1.0	384.51	2.16E-06	0.66	0.64	178782.62	100

Table 14: The average value of the objective function in different scenarios

	Obj_1	Obj_2	Obj_3	Obj_4	Obj_5
Scenario #1	680.653	5.86E-08	0.620	0.622	169655.654
Scenario #2	626.769	2.92E-08	0.620	0.621	169637.496
Scenario #3	638.589	9.44E-08	0.623	0.623	170811.743
Scenario #4	633.682	5.44E-08	0.619	0.633	168711.673
Scenario #5	584.027	1.14E-07	0.618	0.626	167936.468

Table 15: The average value of the objective function and the size of the solution set by different optimization algorithms

		Obj_1	Obj_2	Obj_3	Obj_4	Obj_5	Solution set size
t_1	nRa -NSGA-II	599.34	7.47E-08	0.62	0.63	173018.06	15
	r -NSGA-II	540.55	2.95E-07	0.61	0.69	183026.09	36
	f-NSGA-II	375.14	6.02E-06	0.66	0.65	156142.29	73
	NSGA-II	374.51	3.25E-06	0.65	0.63	157193.00	100
t_2	nRa -NSGA-II	775.68	6.81E-07	0.61	0.61	223585.61	20
	r -NSGA-II	549.24	2.98E-06	0.61	0.66	227880.08	24
	f-NSGA-II	587.06	4.58E-05	0.66	0.63	224914.55	75
	NSGA-II	623.35	2.14E-05	0.65	0.64	225060.07	100
t_3	nRa -NSGA-II	1153.79	1.04E-07	0.63	0.63	408667.03	11
	r -NSGA-II	961.77	1.28E-07	0.61	0.64	412558.87	78
	f-NSGA-II	1076.07	3.51E-06	0.65	0.64	427550.46	74
	NSGA-II	1024.73	1.72E-06	0.65	0.64	414889.55	100
t_4	nRa -NSGA-II	1499.37	2.06E-07	0.62	0.66	519610.18	14
	r -NSGA-II	1022.68	4.83E-07	0.61	0.63	547240.60	38
	f-NSGA-II	1452.77	1.78E-06	0.65	0.64	564482.20	76
	NSGA-II	1181.27	9.76E-07	0.65	0.64	529387.32	100
t_5	nRa -NSGA-II	659.21	3.42E-08	0.61	0.62	194434.68	21
	r -NSGA-II	524.88	6.22E-07	0.61	0.67	206262.84	30
	f-NSGA-II	565.98	1.40E-05	0.66	0.64	199513.13	71
	NSGA-II	547.91	5.45E-06	0.65	0.64	195770.41	100

Table 16: The expected order completion rate of different allocation schemes

	nRa -NSGA-II	r -NSGA-II	f-NSGA-II	NSGA-II
t_1	93.84%	90.88%	84.28%	86.72%
t_2	89.28%	87.46%	82.27%	85.09%
t_3	88.27%	87.54%	80.14%	82.43%
t_4	79.72%	76.94%	78.18%	78.60%
t_5	91.37%	87.59%	83.18%	86.26%

Appendices

Appendix A: Location, related costs and production capacity of potential suppliers

	Longitude	Latitude	f_{ni}	u_{ni}	α_{ni}	Capacity
L_1	49.07	18.92	21	12.5	0.0033	3200
L_2	49.2	18.88	24	11.6	0.0038	2800
L_3	49.04	19.73	20	12.3	0.0042	3600
L_4	49.24	18.95	22	10.5	0.0043	4000
R_1	48.14	17.11	27	13.1	0.0039	3400
R_2	48.72	21.25	25	11.3	0.0031	3500
R_3	49	21.24	29	13.8	0.0041	3300
I_1	2.2	48.51	30	16.7	0.0088	2900
I_2	52.52	13.41	33	17.2	0.0091	3600
I_3	59.93	30.31	31	16.9	0.0082	3000
G_1	121.45	31.21	36	18.8	0.0094	3200
G_2	-118.15	34.04	37	19	0.0098	3100

Note: East longitude is positive and west longitude is negative.

The longitude and latitude of Company B's manufacturer is 49.22 and 18.74, respectively.

Appendix B: Disruption probability and impact of logistics disruption of each period

	Disruption probability					Impact parameters of disruption				
	t_1	t_2	t_3	t_4	t_5	t_1	t_2	t_3	t_4	t_5
L_1	0.010	0.050	0.080	0.096	0.012	1.0	1.0	1.3	1.5	1.0
L_2	0.015	0.056	0.076	0.090	0.016	1.0	1.0	1.3	1.5	1.0
L_3	0.020	0.055	0.070	0.089	0.022	1.0	1.0	1.3	1.5	1.0
L_4	0.010	0.051	0.068	0.091	0.013	1.0	1.0	1.3	1.5	1.0
R_1	0.020	0.080	0.120	0.145	0.024	1.0	1.1	1.5	1.8	1.1
R_2	0.010	0.090	0.110	0.147	0.014	1.0	1.1	1.5	1.8	1.1
R_3	0.030	0.070	0.130	0.150	0.032	1.0	1.1	1.5	1.8	1.1
I_1	0.040	0.120	0.160	0.190	0.130	1.0	1.3	1.9	2.3	1.2
I_2	0.035	0.140	0.170	0.200	0.140	1.0	1.3	1.9	2.3	1.2
I_3	0.040	0.130	0.165	0.195	0.120	1.0	1.3	1.9	2.3	1.2
G_1	0.040	0.150	0.180	0.210	0.110	1.0	1.5	2.3	2.7	1.3
G_2	0.030	0.150	0.190	0.230	0.120	1.0	1.5	2.3	2.7	1.3

Appendix C: Total demand of each period

Period	t_1	t_2	t_3	t_4	t_5
Total demand	12000	14500	20000	23000	13000

Appendix D: Sustainable evaluation of potential suppliers

	SC_1	SC_2	SC_3	SC_4	SC_5	SC_6	SC_7	SC_8	SC_9	SC_{10}
L_1	G	MG	VP	G	VG	MP	M	P	VG	G
L_2	MG	MP	VG	MG	M	P	VG	VP	VG	G
L_3	MG	MG	G	VG	VG	MG	G	M	G	VG
L_4	M	M	MG	P	MG	VP	VG	MP	VG	MG
R_1	VG	M	G	M	MP	MG	VP	M	G	P
R_2	G	G	MP	M	G	VG	MG	G	M	MG
R_3	MP	P	VG	G	G	M	MG	G	MG	VP
I_1	MG	VG	M	MG	VP	G	M	VG	P	MP
I_2	VG	VG	MG	MP	P	G	MG	G	MG	M
I_3	P	G	P	MG	VG	VG	MP	G	VP	VG
G_1	G	VP	VG	VG	G	MG	P	VG	MG	MG
G_2	VP	VG	G	VP	MG	VG	G	MG	MP	VG

Appendix E: Resilience evaluation of potential suppliers

	RC_1	RC_2	RC_3	RC_4
L_1	M	MG	VP	VG
L_2	MP	MG	VG	VP
L_3	MG	M	VG	M
L_4	VG	MP	P	G
R_1	VG	G	M	G
R_2	P	G	M	MG
R_3	M	VG	MG	G
I_1	G	VP	VG	VG
I_2	VP	M	G	P
I_3	G	VG	MG	MG
G_1	MG	P	MP	G
G_2	VG	MG	G	MP