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Stochastic integrated supplier selection and disruption risk assessment under ripple effect *

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Abstract. The impact of the COVID-19 pandemic in the supply chain (SC) evokes the need for valid measures to cope with the SC disruption risk. Supplier selection and disruption risk assessment, as valid measures, have received increasing attentions from academia. However, most of existing works focus on supplier selection and disruption risk assessment separately. This work investigates an integrated supplier selection and disruption risk assessment problem under ripple effect. The objective is to minimize the weighted sum of the disrupted probability and the total cost for the manufacturer. For the problem, a new stochastic programming model combined with Bayesian network (BN) is formulated. Then, an illustrative example is conducted to demonstrate the proposed method.

Keywords: Supply chain disruption risk · Supplier selection · Disruption risk assessment · Stochastic programming model· Bayesian network

1 Introduction

The outbreak of the COVID-19 pandemic, viewed as a new type of disruption, has greatly impacted the supply chain (SC) (Ivanov and Dolgui [1]; Ivanov and Das [2]; Queiroz et al. [3]; Ivanov [4]). The COVID-19 pandemic has triggered the SC ripple effect (Ivanov [4]). Dolgui et al. [5] state that ripple effect describes the disruption risk propagating from the upstream to the downstream in a multi-tier SC. Therefore, the SC disruption risk should be properly managed by enterprises under ripple effect (Ivanov et al. [6]; Ivanov et al. [7]; Ivanov and Dolgui [8]; Pavlov et al. [9]; Dolgui and Ivanov [10]).

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To mitigate the impact of the SC disruption risk under ripple effect, supplier selection, i.e., selection of supply portfolio, can be applied (Tang [11]; Sawik [12]). Moreover, supplier selection plays a crucial role for reducing ordering cost (Sawik [13]). Disruption risk assessment is to quantify the SC disruption risk. A huge body of researches have been done on SC disruption risk assessment problems (Kinra et al. [14]). Bayesian network (BN), as an important tool, is introduced to assess the SC disruption risk under ripple effect (Hosseini et al. [15]).

However, existing works mainly focus on supplier selection and disruption risk assessment separately. In this work, we consider a two-tier SC, and investigate a new stochastic integrated SC disruption risk assessment and supplier selection problem under ripple effect.

The remainder of this paper is organized as follows. The relevant literature is reviewed in Section 2. In Section 3, we develop a new nonlinear stochastic mixed integer programming model. In Sections 4, an illustrative example is conducted to illustrate the proposed method.

2 Literature Review

In this section, we review related studies from two aspects: SC disruption risk assessment under ripple effect, and supplier selection. The first aspect shows the significance of SC disruption risk assessment problem. The second aspect illustrates the supplier selection.

2.1 SC Disruption Risk Assessment under Ripple effect

There is a large number of studies about the disruption risk assessment under ripple effect. In this subsection, we only focus on related studies utilizing the BN approach, on which our model builds. Hosseini et al. [15] consider a SC resilience problem, and develop a BN approach. A case study is conducted to estimate the resilience of sulfuric acid manufacturer. Hosseini and Ivanov [16] consider a SC disruption risk assessment problem under ripple effect at disruption and recovery stages. The authors establish a new resilience measure based on a BN approach. Hosseini et al. [17] investigate a SC disruption risk assessment problem with different time periods. The authors propose a new model integrated a discrete-time Markov chain and a dynamic BN to estimate the SC disruption risk. Liu et al. [18] consider a SC disruption risk assessment problem in cases of data scarcity. The authors propose a new robust dynamic BN approach, and establish a nonlinear programming formulation.

2.2 Supplier Selection

Plenty of researches have been conducted on the supplier selection problems (e.g., Sawik [19]; Sawik [20]; Sawik [21]). Sawik [22] considers an integrated supplier selection and production and distribution scheduling in the context of the SC

disruption risk. The author formulates a stochastic mixed integer programming model with the objective of optimizing the weighted-sum aggregation. Sawik [23] studies an integrated supplier selection and production scheduling of finished products problem. The author proposes a new efficient portfolio approach combining decisions made before, during and after the disruption. Sawik [24] considers a risk-averse supplier selection problem with resilient supply and demand portfolios in a geographically dispersed multi-tier SC network under disruption risks. The author establishes a multi-portfolio approach and a scenario-based stochastic mixed integer programming model.

To the best of our knowledge, no studies have been reported to investigate a stochastic integrated supplier selection and disruption risk assessment problem.

3 Problem Formulation

In this section, we first describe the studied problem. Especially, BN approach is applied to establish the propagation of SC disruption risk. Then, we introduce some notations and construct a new nonlinear stochastic programming model.

3.1 Problem Description

Consider a two-tier SC network with multiple suppliers and one manufacturer. Let $\mathcal{I} = \{1, \cdots, i, \cdots, I\}$ be the set of suppliers and $I + 1$ denotes one manufacturer. The states of SC participant i, $i \in \mathcal{I} \cup I + 1$, can be represented by $\mathcal{J}_i = \{J_{i1}, \cdots, J_{ij}, \cdots, J_{in_i}\}$. The states in the set $\mathcal{J}_i$ are sorted in an increasing order of severity degree. Denotes by π_i^j the probability of supplier i in state j. Let P^s be the probability that scenario s is realized, $s \in \mathcal{S}$, where $\mathcal{S}$ denotes the set of all disruption scenarios. There are a total of $\prod_{i \in \mathcal{I}} n_i$ potential scenarios. To formalize the one-to-one correspondence relationship between state combination of suppliers and disruption scenario, we define the following mapping. Let $\mathrm{G}(\cdot)$ be a unique bijection mapping $\mathcal{J}_1 \times \cdots \times \mathcal{J}_I \xrightarrow{\mathrm{G}(\cdot)} \{1, \cdots, n_1 \cdot n_2 \cdots n_I\}$. $\mathrm{G}^{-1}(\cdot)$ represents the inverse mapping from a disruption risk scenario to a state combination (i.e., a set of states of suppliers), which is also unique, i.e., $\{1, \cdots, n_1 \cdot n_2 \cdots n_I\} \xrightarrow{\mathrm{G}^{-1}(\cdot)} \mathcal{J}_1 \times \cdots \times \mathcal{J}_I$. Let $\mathrm{G}^{-1}(s)(i)$ denote the state of supplier i in the sth potential scenario. For brevity, let $\mathcal{S}$ denote the domain of the scenario s, i.e., $\mathcal{S} = \{1, 2, \cdots, n_1 \cdot n_2 \cdots \cdot n_I\}$. Therefore, the probability of disruption scenario s realized is

$$P^s = \prod_{i=1}^{I} \pi_i^{\mathrm{G}^{-1}(s)(i)}.$$

To portray the propagation of SC disruption risk, the BN approach is applied, which can be represented as a graph with a set of nodes (random variables) and a set of arcs. X_i denotes the state random variable of SC participant i, $i \in \mathcal{I} \cup I + 1$. An arc from X_i to $X_{i'}$ denotes the dependence relationship.

According to the studied two-tier SC structure, the joint probability distribution of the BN consisting of variables $X_1, \cdots, X_I, X_{I+1}$ can be expressed as

$$\mathbb{P}(X_1, \cdots, X_I, X_{I+1}) = \prod_{i=1}^{I} \mathbb{P}(X_i) \cdot \mathbb{P}(X_{I+1}|X_1, \cdot, X_I),$$

where $\mathbb{P}(X_1, \cdots, X_I, X_{I+1})$ represents the joint probability distribution over X_1, $\cdots$, X_{I+1}. $\mathbb{P}(X_{I+1}|X_1, \cdots, X_I)$ denotes the conditional probability distribution, which can be represented as a conditional probability table (CPT). In our work, the CPT for $\mathbb{P}(X_{I+1}|X_1, \cdots, X_I)$ is represented as follows:

$$\text{CPT} = \begin{bmatrix} z_1^1 & \cdots & z_1^{|\mathcal{S}|} \\ \vdots & z_j^s & \vdots \\ z_{n_{I+1}}^1 & \cdots & z_{n_{I+1}}^{|\mathcal{S}|} \end{bmatrix},$$

where the number of rows corresponds to the number of possible states for the manufacturer $I+1$; the number of columns represents the number of state combinations of all suppliers; z_j^s represents the jth state probability of the manufacturer in scenario s (Note that, z_j^s will be adjusted to $z_{r,j}^s$ later.).

Based on the above notations, the disrupted probability of the manufacturer (i.e, $\pi_{I+1}^{n_{I+1}}$) can be expressed as follow:

$$\pi_{I+1}^{n_{I+1}} = \sum_{s \in \mathcal{S}} \Big(\prod_{i=1}^{I+1} \pi_i^{\mathrm{G}^{-1}(s)(i)} \cdot z_{n_{I+1}}^s \Big).$$

In our work, the supplier selection is considered, and the number of suppliers will be determined, which contributes to changing the BN structure accordingly. To adapt variable BN structure, the notation of CPT needs to be extended. The set of suppliers contains I suppliers, then the total combination number of selected suppliers is 2^I. Let r be the index of combinations of suppliers in the possible selection set (with 2^I elements). For clarity, we call r as the supplier-selection index. Let y_i be a binary variable, equal to 1 if supplier i is selected to supply material for the manufacturer. The supplier-selection index r can be calculated by $\left(\sum_{i=1}^{I} 2^{i-1} \cdot y_i + 1 \right)$ (That is, one-to-one correspondence between binary and decimal. For example, consider two suppliers. Supplier 1 is unselected, i.e., $y_1 = 0$, and supplier 2 is selected, i.e., $y_2 = 1$. Then, $r = 2 \cdot 1 + 1 \cdot 0 + 1 = 3$.). Therefore, an adjusted CPT, i.e., CPT^r, $r \in \{1, \cdots, 2^I\}$, which be represented as follow:

$$\text{CPT}^r = \begin{bmatrix} z_{r,1}^1 & \cdots & z_{r,1}^{|\mathcal{S}|} \\ \vdots & z_{r,j}^s & \vdots \\ z_{r,n_{I+1}}^1 & \cdots & z_{r,n_{I+1}}^{|\mathcal{S}|} \end{bmatrix}, \quad \forall r \in \{1, \cdots, 2^I\}$$

where $z_{r,j}^s$ represents the jth state probability of the manufacturer given the supplier-selection index r in scenario s. Note that, when k suppliers, i.e., $i_1, \cdots, i_k$, are selected, the number of columns of actual CPT, i.e., $|\mathcal{J}_{i_1}| \cdot |\mathcal{J}_{i_2}| \ldots \cdot |\mathcal{J}_{i_k}|$,

is less than $|\mathcal{S}|$. Therefore, to encapsulate the actual CPT informations into CPT^r with fixed matrix size (i.e., $n_{I+1} \times |S|$), the elements of CPT^r matrix are reorganized by the following rule: $\mathbb{P}(X_{I+1}|X_{i_1}, \cdots, X_{i_k})$ is stored in $\mathbb{P}(X_{I+1}|X_{i_1}, \cdots, X_{i_k}, X_{i'_1} = J_{i'_1 1}, \cdots, X_{i'_{I-k}} = J_{i'_{I-k} 1})$. At the same time, the other elements in CPT^r are set to be 0, as they are no meanings.

3.2 Nonlinear stochastic programming model

problem parameters:

$\mathcal{I}$: the set of suppliers, indexed by i;
$\mathcal{J}_i$: the set of states of supplier i, indexed by j;
$\mathcal{S}$: the set of scenarios, indexed by s;
D: the total materiel demands of the manufacturer;
b: the unit penalty cost of unfulfilled demand of the manufacturer;
o_i: the fixed cost of ordering materials from supplier i;
u_i: the unit cost of ordering materials from suppler i;
W_i^s: the supply capacity of supplier i in scenario s;
π_i^j: the probability of SC participant i at state j;
$z_{r,j}^s$: the jth state conditional probability of the manufacturer given the supplier-selection index r in scenario s;
P^s: the probability of scenario s;
δ: the weight coefficient of the disrupted probability of the manufacturer;
λ: the weight coefficient of the cost.

Decision variables:

x_{ij}^{sel}: continuous variable, denoting the probability of the supplier i in state j after the selection (the supplier i can be selected or not);
y_i: binary variable, equal to 1 if supplier i is selected to supply material for the manufacturer;
w_i^s: non-negative continuous variable, denoting the supply volume of supplier i in scenario s;
ν_r: binary variable, equal to 1 if the supplier-selection index r is realised;
h^s: non-negative continuous variable, representing the volume of unfulfilled supply in scenario s.

Nonlinear stochastic programming formulation:

$$\min \delta \cdot \Big[\sum_{s \in \mathcal{S}} \prod_{i=1}^{I} x_{i,\mathrm{G}^{-1}(s)(i)}^{sel} \cdot (\sum_{r=1}^{2^I} z_{r,n_{I+1}}^s \cdot \nu_r) \Big] + \lambda \cdot \Big[\sum_{s \in \mathcal{S}} P^s (b \cdot h^s + \sum_{i=1}^{I} u_i \cdot w_i^s) + \sum_{i=1}^{I} o_i \cdot y_i \Big] \tag{1}$$

$$w_i^s \leq M \cdot y_i, \quad i \in \mathcal{I}, s \in \mathcal{S} \tag{2}$$

$$0 \leq w_i^s \leq W_i^s, \quad i \in \mathcal{I}, s \in \mathcal{S} \tag{3}$$

$$D - \sum_{i=1}^{I} w_i^s \leq h_s, \quad s \in \mathcal{S} \tag{4}$$

$$\sum_{r=1}^{2^I} r \cdot \nu_r = \sum_{i=1}^{I} 2^{i-1} \cdot y_i + 1 \tag{5}$$

$$\sum_{r=1}^{2^I} \nu_r = 1 \tag{6}$$

$$x_{ij}^{sel} \leq \pi_i^j + M \cdot y_i, \quad \forall j \in \mathcal{J}_i \tag{7}$$

$$x_{ij}^{sel} \geq \pi_i^j - M \cdot y_i, \quad \forall j \in \mathcal{J}_i \tag{8}$$

$$x_{ij}^{sel} \leq 1 + M \cdot (1 - y_i), \quad \forall j \in \mathcal{J}_i \tag{9}$$

$$x_{ij}^{sel} \geq 1 - M \cdot (1 - y_i), \quad \forall j \in \mathcal{J}_i \tag{10}$$

$$x_{ij}^{sel} \in [0, 1], \quad \forall i \in \mathcal{I}, j \in \mathcal{J}_i \tag{11}$$

$$y_i \in \{0, 1\}, \quad \forall i \in \mathcal{I} \tag{12}$$

$$\nu_r \in \{0, 1\}, \quad r \in \{1, \cdots, 2^I\} \tag{13}$$

$$w_i^s \in \mathbb{R}^+, \quad i \in \mathcal{I}, s \in \mathcal{S} \tag{14}$$

$$h^s \in \mathbb{R}^+, \quad s \in \mathcal{S} \tag{15}$$

Formula (1) is the weighted objective function, i.e., minimizing the weighted sum of (i) disrupted probability of the manufacturer (i.e., n_{I+1}), and (ii) the total cost of the manufacturer. Constraint (2) guarantees that only the selected suppliers can supply materials for the manufacturer. Constraint (3) guarantees the supply capacity of supplier i in scenario s. Constraint (4) states that the unfulfilled material demand of the manufacturer. Constraints (5-6) guarantee that a specific CPT^r is utilized for the calculation of disrupted probability of the manufacturer. Constraints (7-10) ensure that the probability distributions of unselected suppliers are eliminated (i.e., the axioms of multiplication: for a specific number a, then $a \cdot 1 = a$). Constraints (11-15) are the ranges of variables.

4 An Illustrative Example

In this section, an illustrative example is conducted to illustrate the application of our method. Consider a SC with two suppliers and one manufacturer, of which have two states. Fig. 1 shows the acquired probability informations in the BN based on our notations. In addition, D, b, W_i^s, o_i, u_i, δ, and λ are set to be 100, 2, 120, 100, 4, 100, 1, respectively. This example is solved by YALMIP. The solution is that the supplier 1 is selected, and the objective value is 300.

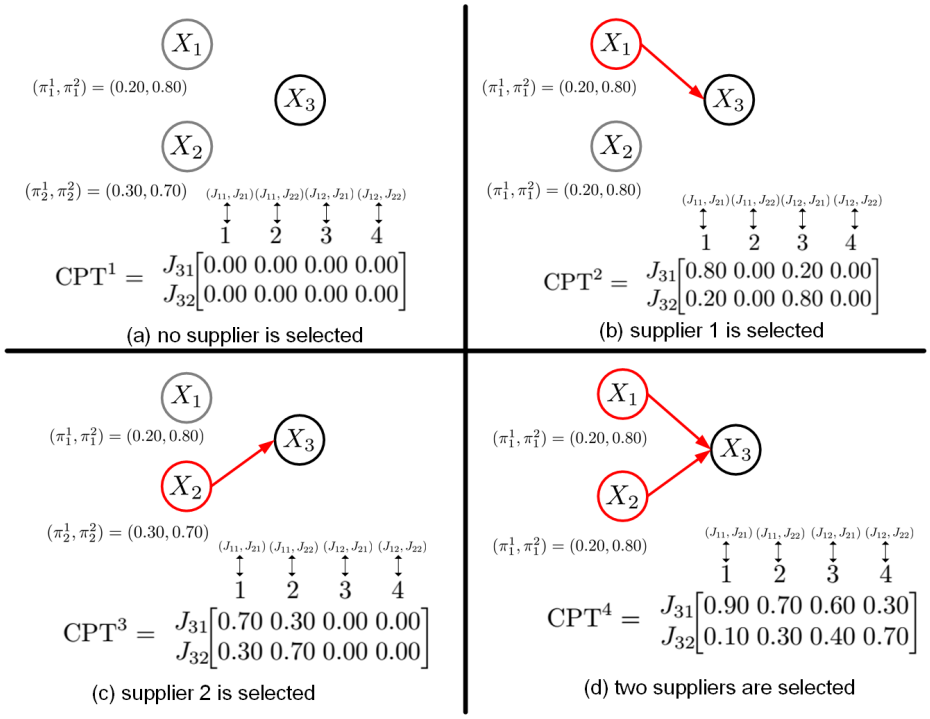

Fig. 1. The BN informations based on our notations of the illustrative example.

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