



HAL
open science

Stochastic Integrated Supplier Selection and Disruption Risk Assessment Under Ripple Effect

Ming Liu, Zhongzheng Liu, Feng Chu, Feifeng Zheng, Chengbin Chu

► **To cite this version:**

Ming Liu, Zhongzheng Liu, Feng Chu, Feifeng Zheng, Chengbin Chu. Stochastic Integrated Supplier Selection and Disruption Risk Assessment Under Ripple Effect. IFIP International Conference on Advances in Production Management Systems (APMS), Sep 2021, Nantes, France. pp.689–696, 10.1007/978-3-030-85906-0_75 . hal-03360839

HAL Id: hal-03360839

<https://hal.science/hal-03360839v1>

Submitted on 1 Oct 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License



This document is the original author manuscript of a paper submitted to an IFIP conference proceedings or other IFIP publication by Springer Nature. As such, there may be some differences in the official published version of the paper. Such differences, if any, are usually due to reformatting during preparation for publication or minor corrections made by the author(s) during final proofreading of the publication manuscript.

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

Ming Liu¹, Zhongzheng Liu¹, Feng Chu², Feifeng Zheng³, and Chengbin Chu⁴

¹ School of Economics & Management, Tongji University, Shanghai 200092, China
mingliu@tongji.edu.cn
1830351@tongji.edu.cn

² IBISC, Univ Évry, Université of Paris-Saclay, 91025 Évry, France
feng.chu@univ-evry.fr

³ Glorious Sun School of Business & Management Donghua University, Shanghai 200051, China
ffzheng@dhu.edu.cn

⁴ ESIEE Paris, Université Paris-Est, 93162 Noisy-le-Grand, France
chengbin.chu@gmail.com

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]).

^{*} Supported by the National Natural Science Foundation of China (NSFC) under Grants 72021002, 71771048, 71432007, 71832001 and 72071144.

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 $\mathcal{I} = \{1, \dots, i, \dots, I\}$ 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 $\mathcal{J}_i = \{J_{i1}, \dots, J_{ij}, \dots, J_{in_i}\}$. 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 $G(\cdot)$ be a unique bijection mapping $\mathcal{J}_1 \times \dots \times \mathcal{J}_I \xrightarrow{G(\cdot)} \{1, \dots, n_1 \cdot n_2 \cdot \dots \cdot n_I\}$. $G^{-1}(\cdot)$ 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., $\{1, \dots, n_1 \cdot n_2 \cdot \dots \cdot n_I\} \xrightarrow{G^{-1}(\cdot)} \mathcal{J}_1 \times \dots \times \mathcal{J}_I$. Let $G^{-1}(s)(i)$ denote the state of supplier i in the s th potential scenario. For brevity, let \mathcal{S} denote the domain of the scenario s , i.e., $\mathcal{S} = \{1, 2, \dots, n_1 \cdot n_2 \cdot \dots \cdot n_I\}$. Therefore, the probability of disruption scenario s realized is

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

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, \dots, X_I, X_{I+1} can be expressed as

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

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

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

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 , $r \in \{1, \dots, 2^I\}$, which be represented as follow:

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

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

is less than $|\mathcal{S}|$. Therefore, to encapsulate the actual CPT informations into CPT^r with fixed matrix size (i.e., $n_{I+1} \times |\mathcal{S}|$), the elements of CPT^r matrix are reorganized by the following rule: $\mathbb{P}(X_{I+1}|X_{i_1}, \dots, X_{i_k})$ is stored in $\mathbb{P}(X_{I+1}|X_{i_1}, \dots, X_{i_k}, X_{i'_1} = J_{i'_1}, \dots, X_{i'_{I-k}} = J_{i'_{I-k}})$. 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 supplier 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 j th 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:

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

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

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

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

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

$$\sum_{r=1}^{2^I} \nu_r = 1 \quad (6)$$

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

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

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

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

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

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

$$\nu_r \in \{0, 1\}, \quad r \in \{1, \dots, 2^I\} \quad (13)$$

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

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

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.

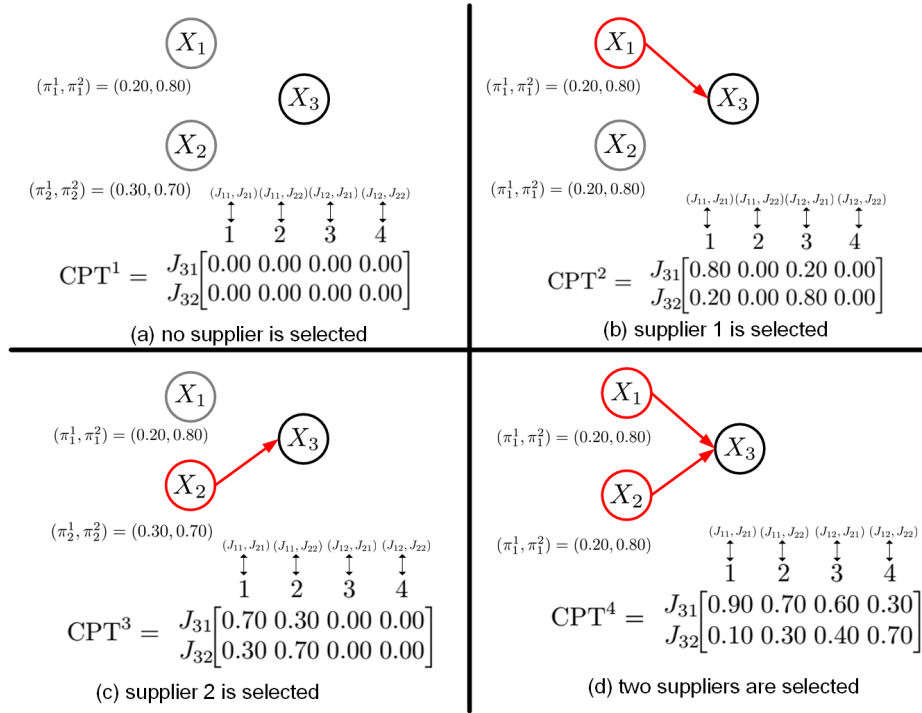


Fig. 1. The BN informations based on our notations of the illustrative example.

References

- Ivanov, D., Dolgui, A.: OR-methods for coping with the ripple effect in supply chains during COVID-19 pandemic: Managerial insights and research implications. *International Journal of Production Economics*, **232**, 107921 (2021).
- Ivanov, D., Das, A.: Coronavirus (COVID-19/SARS-CoV-2) and supply chain resilience: A research note. *International Journal of Integrated Supply Management*, **13**(1), 90–102 (2020).
- Queiroz, M. M., Ivanov, D., Dolgui, A., Wamba, S. F.: Impacts of epidemic outbreaks on supply chains: mapping a research agenda amid the COVID-19 pandemic through a structured literature review. *Annals of Operations Research* (2020). DOI: 10.1007/s10479-020-03685-7.
- Ivanov, D.: Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/ SARS-CoV-2) case. *Transportation Research Part E*, **136**, 101922 (2020).
- Dolgui, A., Ivanov, D., Rozhkov, M.: Does the ripple effect influence the bullwhip effect? An integrated analysis of structural and operational dynamics in the supply chain. *International Journal of Production Research*, **58**(5), 1285–1301 (2020).
- Ivanov, D., Dolgui, A., Sokolov, B.: *Handbook of Ripple Effects in the Supply Chain*. 2019. Springer International Publishing.

7. Ivanov, D., Dolgui, A., Sokolov, B., Ivanova, M.: Literature review on disruption recovery in the supply chain, *International Journal of Production Research*, **55**(20), 6158–6174 (2017).
8. Ivanov, D., Dolgui, A.: A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0, *Production Planning & Control*, (2020). DOI: 10.1080/09537287.2020.1768450.
9. Pavlov, A., Ivanov, D., Werner, F., Sokolov, B.: Integrated detection of disruption scenarios, the ripple effect dispersal and recovery paths in supply chains. *Annals of Operations Research* (2019). DOI: 10.1007/s10479-019-03454-1.
10. Dolgui, A., Ivanov, D.: Ripple effect and supply chain disruption management: new trends and research directions, *International Journal of Production Research*, **59**(1), 102–109 (2021).
11. Tang, C. S.: Perspectives in supply chain risk management. *International Journal of Production Economics*, **103**(2), 451–488 (2006).
12. Sawik, T.: Disruption mitigation and recovery in supply chains using portfolio approach. *Omega*, **84**, 232–248 (2019).
13. Sawik, T.: Selection of resilient supply portfolio under disruption risks. *Omega*, **41**(2), 259–269 (2013).
14. Kinra, A., Ivanov, D., Das, A., Dolgui, A.: Ripple effect quantification by supplier risk exposure assessment, *International Journal of Production Research*, **58**(18), 5559–5578 (2020).
15. Hosseini, S., Khaled, A. A., Sarder, M. D.: A general framework for assessing system resilience using Bayesian networks: A case study of sulfuric acid manufacturer. *Journal of Manufacturing Systems*, **41**, 211–227 (2016).
16. Hosseini, S., Ivanov, D.: A new resilience measure for supply networks with the ripple effect considerations: A Bayesian network approach. *Annals of Operations Research*, (2019). DOI: 10.1007/s10479-019-03350-8.
17. Hosseini, S., Ivanov, D., Dolgui, A.: Ripple effect modelling of supplier disruption: integrated Markov chain and dynamic Bayesian network approach. *International Journal of Production Research*, **58**(11), 3284–3303 (2020).
18. Liu, M., Liu, Z., Chu, F., Zheng, F., Chu, C.: A new robust dynamic Bayesian network approach for disruption risk assessment under the supply chain ripple effect. *International Journal of Production Research*, **59**(1), 265–285 (2021).
19. Sawik, T.: A cyclic versus flexible approach to materials ordering in make-to-order assembly. *Mathematical and computer modelling*, **42**(3–4), 279–290 (2005).
20. Sawik, T.: Single vs. multiple objective supplier selection in a make to order environment. *Omega*, **38**(3–4), 203–212 (2010).
21. Sawik, T.: Selection of supply portfolio under disruption risks. *Omega*, **39**(2), 194–208 (2011).
22. Sawik, T.: Integrated supply chain scheduling under multi-level disruptions. *IFAC-PapersOnLine*, **48**(3), 1515–1520 (2015).
23. Sawik, T.: A portfolio approach to supply chain disruption management. *International Journal of Production Research*, **55**(7), 1970–1991 (2017).
24. Sawik, T.: On the risk-averse selection of resilient multi-tier supply portfolio. *Omega*, **101**, 102267 (2021).