HAL open science

A New Robust Dynamic Bayesian Network Model with Bounded Deviation Budget for Disruption Risk Evaluation

Ming Liu, Tao Lin, Feng Chu, Feifeng Zheng, Chengbin Chu

To cite this version:

Ming Liu, Tao Lin, Feng Chu, Feifeng Zheng, Chengbin Chu. A New Robust Dynamic Bayesian Network Model with Bounded Deviation Budget for Disruption Risk Evaluation. IFIP International Conference on Advances in Production Management Systems (APMS), Sep 2021, Nantes, France. pp.681–688, 10.1007/978-3-030-85906-0_74 . hal-03360792

HAL Id: hal-03360792

https://hal.science/hal-03360792

Submitted on 23 Mar 2023

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.

A New Robust Dynamic Bayesian Network Model with Bounded Deviation Budget for Disruption Risk Evaluation

Ming Liu[1], Tao Lin[1], Feng Chu[2*], Feifeng Zheng[3], and Chengbin Chu[4]

[1] School of Economics & Management, Tongji University, Shanghai, People's Republic of China
[2] IBISC, Univ Évry, University of Paris-Saclay, Évry, France
feng.chu@univ-evry.fr
[3] Glorious Sun School of Business & Management, Donghua University, Shanghai, People's Republic of China
[4] Laboratoire d'Informatique Gaspard-Monge (LIGM), UMR 8049, Univ Gustave Eiffel, ESIEE Paris, 93162 Noisy-le-Grand Cedex, France

Abstract. Dynamic Bayesian network (DBN), combining with probability intervals, is a valid tool to estimate the risk of disruptions propagating along the supply chain (SC) under data scarcity. However, since the approach evaluate the risk from the worst-case perspective, the obtained result may be too conservative for some decision makers. To overcome this difficulty, a new robust DBN model, considering bounded deviation budget, is first time to be developed to analyse the disruption risk properly. We first formulate a new robust DBN optimization model with bounded deviation budget. Then a linearization technique is applied to linearize the nonlinear bounded deviation budget constraint. Finally, a case study is conducted to demonstrate the applicability of the proposed model and some managerial insights are drawn.

Keywords: supply chain · dynamic bayesian network · bounded deviation budget.

1 Introduction

The COVID-19 epidemic causes extreme disturbances for people's daily life. Supply chain (SC) is no exception. Especially, due to high structural complexity and increasing global scale, supply chain is fragile under disruptions, such as natural or man-made disasters. One example comes from the Japanese tsunami in 2011, which affected the production of auto parts' suppliers, leading to the reduce of production of auto companies [5]. Another example comes from the explosion and subsequent fires of BASF facility in Ludwigshafer, the disaster stops the production of raw materials, and its downstream manufacturer has a great difficulty to maintain production. According to [1], the propagation of the disruption results in a revenue loss of 10-15% compared to the previous year. All these facts embody the impact of a disruption along the supply chain, i.e.

the ripple effect. The ripple effect introduced by [9] means the disruption risk of upstream partners in the SC propagates to downstream partners. Due to the adverse consequences of ripple effects, the disruption risk propagation along the SC is the most notorious challenge that each enterprise must confront.

To mitigate the adverse results of ripple effects and maintain competitiveness for enterprises, disruption risk assessment has been given a high priority in SCM [10,7]. It is indispensable to adopt appropriate optimization methods to estimate the disruption risk quantitatively. Bayesian network (BN), first introduced by [3], is an outstanding representative. The BN describe the ripple effect via a directed acyclic graph. However, the temporal nature of the disruption propagation is not studied in his work. Considering the dynamics of the disruption risk propagation over a time horizon, [5] propose a dynamic Bayesian network (DBN). [11] indicate further that the probability distribution of each supplier's state and the disruption propagation in the SC can not be perfectly known under data scarcity. Thus they propose a new robust DBN approach, integrating the DBN and probability intervals, to evaluate the worst-case oriented disruption risk under data scarcity. However, [11]'s model focus on the worst-case situation in given probability intervals, which is too conservative for some decision makers. Therefore, in this work, we incorporate a bounded deviation budget constraint into [11]'s model.The bounded deviation budget constraint denotes the total sum of deviation (i.e., the part of decision variables deviates from the mean value of given intervals) no greater than the budget, which can reduce the robust properly. Moreover, the SC structure is built on partner relationships following [11]'s work. This study aims to aid decision makers to properly assess SC risk with bounded deviation budget. The main contributions of this paper include:

(1) To the best of our knowledge, we are first to combine DBN with bounded deviation budget, to evaluate the disruption risk propagation along th SC.
(2) A new robust DBN optimization formulation considering bounded deviation budget is developed.
(3) The linearization technique is applied to linearize the nonlinear constraint.

The rest of this paper is organized as follows. In Section 2, a brief literature review is given. Section 3 describes the addressed problem in detail and formulate a new robust DBN model for the worst-case oriented disruption risk estimation considering bounded deviation budget. In Section 4, the linearization technique is applied to linearize the nonlinear constraint. A case study is conducted in Section 5. Section 6 concludes this paper and outlines future research directions.

2 Literature review

Since our study falls within the scope of SC disruption risk management problems, only most related works are reviewed.

The ripple effect is first introduced by [9]. [8] proposed an optimal control framework combined with a mathematical programming method to perform

planning and execution control for SC resilience. Based on [8]'s work, [13] investigate the ripple effect in the SC from the structural perspective. [6] consider the structural and operational vulnerabilities of the SC under ripple effect simultaneously. [12] formulates a stochastic programming moodel and proposes multiple SC management strategy to mitigate the disruption risks under ripple effect.

Based on the dependence relationships between suppliers and manufactures, [2] propose a Bayesian network (BN) approach for measuring the resilience of SCs. Based on the BN approach, [4] propose a metric for quantifying the resilience of the SC. [5] joint consider the structural and temporal nature of the disruption propagation under ripple effect, and propose a dynamic BN (DBN) approach to analyze the disruption propagation in an SC. [11] develop a new robust DBN model for SC risk assessment under data scarcity.

Concluding, to the best of our knowledge, there is no result for evaluating SC disruption risks considering bounded deviation budget under data scarcity in the literature.

3 Problem description and formulation

For the addressed problem, we study an SC with multiple suppliers and one manufacturer, and the SC structure is based on partner relationships. When disruptions occur in suppliers, the disruptions propagate from the suppliers to the manufacturer. To emulate the disruption and recovery of each SC member, the Markov process is utilized to describe the temporal propagation of disruptions. We mathematically restate the DBN method proposed by [5] and adopt the same notation developed by [11]. We study an SC with a set $\mathcal{I} = \{1, \cdots, i, \cdots, I\}$ of suppliers and a manufacturer, denoted as $I+1$, over a time horizon $\mathcal{T} = \{1, \cdots, t, \cdots, T\}$. When an SC member suffers a disruption, its state can be represented by one in the set $\mathcal{S}_i = \{s_{i1}, \cdots, s_{ij}, \cdots, s_{in_i}\}$ of possible states, where $i \in \{1, \cdots, I, I+1\}, j \in \{1, \cdots, n_i\}$, and n_i is the number of possible states of SC member or partner i. The states in the set $\mathcal{S}_i$ are sorted in an increasing order of severity degree, i.e., s_{i1} signifies a fully operational state and s_{in_i} denotes a fully disrupted state. The states of the suppliers and the manufacturer in time period $t \in \mathcal{T}$ are denoted as $X_1^t, \cdots, X_I^t$ and X_{I+1}^t, respectively. For notation simplicity, the probability of random event $X_i^t = s_{ij}$ is denoted as x_{ij}^t (i.e., $x_{ij}^t = P\{X_i^t = s_{ij}\}$).

According to the DBN introduced by [5], the transition of the supplier i's state from s_{ij} in the previous time period $t-1$ into $s_{ij'}$ in the present time period t can be described by a probability $m_{s_{ij}s_{ij'}}$, where $t \in \{2, \cdots, T\}, j, j^{'} \in \{1, \cdots, n_i\}$. All state transition relationships for the supplier i can be represented by a Markov transition matrix $\boldsymbol{M}_i$. In general, the probabilities in different states for the supplier i in time period t can be calculated as follows:

$$(x_{i1}^t, \cdots, x_{in_i}^t) = (x_{i1}^1, \cdots, x_{in_i}^1) \cdot (\boldsymbol{M}_i)^{t-1}, \quad \forall i \in \{1, \cdots, I\}, t \in \mathcal{T}/\{1\} \quad (1)$$

where $(x_{i1}^1, \cdots, x_{in_i}^1)$ and $(x_{i1}^t, \cdots, x_{in_i}^t)$ are the probability distribution of the supplier i in time period 1 and time period t, respectively.

Besides, the DBN structure consists of T sub-BNs, i.e., one prior BN and $(T-1)$ two-time temporal Bayesian networks (2TBNs). The state transition relationships for the manufacturer can be described by a conditional probability table (CPT). Especially, there are two types of CPTs, i.e., the $\mathrm{CPT}_{\mathrm{priorBN}}$ and $\mathrm{CPT}_{\mathrm{2TBNs}}$. Accordingly, the probability in jth state for the manufacturer $I+1$ in the prior BN and 2TBN can be described as formula (2) and (3), respectively.

$$x^1_{(I+1)j} = \sum_{c \in dom(c)} y_{jc} \cdot \prod_{i=1}^{I} x^1_{i,C^{-1}(c)(i)}, \quad \forall j \in \{1, \cdots, n_{I+1}\} \tag{2}$$

$$x^t_{(I+1)j} = \sum_{g \in dom(g)} z_{jg} \cdot \prod_{i=1}^{I} x^t_{i,G^{-1}(g)(i)} \cdot x^{t-1}_{(I+1),G^{-1}(g)(I+1)}, \quad \forall j \in \{1, \cdots, n_{I+1}\}, t \in \mathcal{T}/\{1\} \tag{3}$$

The detailed notations and problem variables are defined as follows. Moreover, we formulate a novel robust DBN model with bounded deviation budget.

Input parameters

- $\mathcal{I}$: the set of suppliers, $\mathcal{I} = \{1, \cdots, I\}$, indexed by i;
- $I+1$: the manufacturer;
- $\mathcal{T}$: the set of periods, $\mathcal{T} = \{1, \cdots, T\}$, indexed by t;
- $\boldsymbol{M}_i$: Markov transition matrix of supplier i, where $i \in \mathcal{I}$;
- $dom(c)$: the domain of the state-combination-index c, i.e. $dom(c) = \{1, 2, \cdots, n_1 \cdot n_2 \cdot \cdots n_I\}$;
- $C(\bullet)$: unique bijection mapping $\mathcal{S}_1 \times \cdots \times \mathcal{S}_I \xrightarrow{C(\bullet)} dom(c)$ in the prior BN which maps a state combination to a state-combination-index;
- $C^{-1}(\bullet)$: the inverse mapping of $\boldsymbol{C}(\bullet)$;
- $C^{-1}(c)(i)$: the corresponding state of supplier i for a given state-combination-index c (in the CPT) in the prior BN;
- $dom(g)$: the domain of the state-combination-index g, i.e. $dom(g) = \{1, 2, \cdots, n_1 \cdot n_2 \cdots n_I \cdot n_{I+1}\}$;
- $G(\bullet)$: unique bijection mapping $\mathcal{S}_1 \times \cdots \times \mathcal{S}_I \times \mathcal{S}_{I+1} \xrightarrow{\boldsymbol{G}(\bullet)} dom(g)$ in each 2TBN which maps a state combination to a state-combination-index;
- $G^{-1}(\bullet)$: the inverse mapping of $G(\bullet)$;
- $G^{-1}(g)(i)$: the corresponding state of supplier (or manufacturer) $i, i \in \mathcal{I} \cup \{I+1\}$, for a given state-combination-index g (in the CPT) in each 2TBN;
- $\underline{x}^1_{ij}, \bar{x}^1_{ij}$: the lower and upper bound of the probability interval in the jth state for the supplier i in time period 1, where $i \in \{1, \cdots, I\}, j \in \{1, \cdots, n_i\}$;
- $\underline{y}_{jc}, \bar{y}_{jc}$: the lower and upper bound of the probability interval in the jth state for the manufacturer, conditional on the cth state combination in the prior BN, where $j \in \{1, \cdots, n_{I+1}\}, c \in dom(c)$;
- $\underline{z}_{jg}, \bar{z}_{jg}$: the lower and upper bound of the probability interval in the jth state for the manufacturer, conditional on the gth state combination in each 2TBN, where $j \in \{1, \cdots, n_{I+1}\}, g \in dom(g)$;

budget: the deviation budget.

Decision variables

x_{ij}^t: the probability in the jth state for the supplier or manufacturer i in time period t, where $i \in \mathcal{I} \cup \{I+1\}, j \in \{1, \cdots, n_i\}, t \in \mathcal{T}$;

y_{jc}: the probability in the jth state for the manufacturer, conditional on the cth state combination (in the CPT) in the prior BN, where $j \in \{1, \cdots, n_{I+1}\}, c \in dom(c)$;

z_{jg}: the probability in the jth state for the manufacturer, conditional on the gth state combination (in the CPT) in each 2TBN, where $j \in \{1, \cdots, n_{I+1}\}, g \in dom(g)$.

$$\begin{aligned} max \quad & x_{(I+1),n_{I+1}}^T \\ s.t. \quad & (1) - (3) \end{aligned} \tag{4}$$

$$\sum_{j=1}^{n_i} x_{ij}^1 = 1, \quad \forall i \in \mathcal{I} \tag{5}$$

$$\sum_{j=1}^{n_{I+1}} y_{jc} = 1, \quad \forall c \in dom(c) \tag{6}$$

$$\sum_{j=1}^{n_{I+1}} z_{jg} = 1, \quad \forall g \in dom(g) \tag{7}$$

$$\begin{aligned} \sum_{j=1}^{n_i} \sum_{i \in \mathcal{I}} \left| x_{ij}^1 - \frac{1}{2}(\underline{x}_{ij}^1 + \bar{x}_{ij}^1) \right| + \sum_{j=1}^{n_{I+1}} \sum_{c \in dom(c)} \left| y_{jc} - \frac{1}{2}(\underline{y}_{jc} + \bar{y}_{jc}) \right| + \\ \sum_{j=1}^{n_{I+1}} \sum_{g \in dom(g)} \left| z_{jg} - \frac{1}{2}(\underline{z}_{jg} + \bar{z}_{jg}) \right| \leq budget \end{aligned} \tag{8}$$

$$x_{ij}^1 \in [\underline{x}_{ij}^1, \bar{x}_{ij}^1], \quad \forall i \in \mathcal{I}, j \in \{1, \cdots, n_i\} \tag{9}$$

$$0 \leq x_{ij}^t \leq 1, \quad \forall i \in \mathcal{I}, j \in \{1, \cdots, n_i\}, t \in \mathcal{T}/\{1\} \tag{10}$$

$$0 \leq x_{(I+1)j}^t \leq 1, \quad \forall j \in \{1, \cdots, n_{I+1}\}, t \in \mathcal{T} \tag{11}$$

$$y_{jc} \in [\underline{y}_{jc}, \bar{y}_{jc}], \quad \forall j \in \{1, \cdots, n_{I+1}\}, c \in dom(c) \tag{12}$$

$$z_{jg} \in [\underline{z}_{jg}, \bar{z}_{jg}], \quad \forall j \in \{1, \cdots, n_{I+1}\}, g \in dom(g) \tag{13}$$

The objective function (4) is to estimate the worst-case disruption risk, i.e., to evaluate the robustness of the manufacturer in the final time period T under disruptions. Constraint (1) denotes the Markov transition equation for each supplier i. Constraint (2) and (3) calculate the probability in each state for the manufacturer in the prior BN and each 2TBN, respectively. Constraint (5) - (7) guarantee the second Kolmogorov axiom of probability, i.e., the sum of probabilities for a supplier or the manufacturer is equal to 1. Constraint (8) ensure the total sum of deviation no greater than the budget. Constraint (9) - (13) give the domains of probabilities in each state (in all time periods).

4 Solution method

The above proposed model can not be solved by off-the-shelf solver, due to the Constraint (8). Therefore, we equivalently transform this constraint into a set of linear constraints which can be solved by GUROBI.

We first introduce a variable α_{ij}, where $\alpha_{ij} \geq 0, i \in \mathcal{I}, j \in \{1, \cdots, n_i\}$. Since we want to delete $|\bullet|$ notation, we let $\alpha_{ij} = |x^1_{ij} - \frac{1}{2}(\underline{x}^1_{ij} + \bar{x}^1_{ij})|$, so we have

$$\alpha_{ij} \geq x^1_{ij} - \frac{1}{2}(\underline{x}^1_{ij} + \bar{x}^1_{ij}), \quad \forall i \in \mathcal{I}, j \in \{1, \cdots, n_i\} \tag{14}$$

$$\alpha_{ij} \geq -x^1_{ij} + \frac{1}{2}(\underline{x}^1_{ij} + \bar{x}^1_{ij}), \quad \forall i \in \mathcal{I}, j \in \{1, \cdots, n_i\} \tag{15}$$

Notably, as the objective value wants us to minimize the value of α_{ij}, $\alpha_{ij} = |x^1_{ij} - \frac{1}{2}(\underline{x}^1_{ij} + \bar{x}^1_{ij})|$ can be guaranteed. Likely, given the auxiliary variables β_{jc} and γ_{jg}, where $\beta_{jc}, \gamma_{jg} \geq 0, j \in \{1, \cdots, n_{I+1}\}, c \in dom(c), g \in dom(g)$. We let $\beta_{jc} = |y_{jc} - \frac{1}{2}(\underline{y}_{jc} + \bar{y}_{jc})|$ and $\gamma_{jg} = |z_{jg} - \frac{1}{2}(\underline{z}_{jg} + \bar{z}_{jg})|$, and we can induce

$$\beta_{jc} \geq y_{jc} - \frac{1}{2}(\underline{y}_{jc} + \bar{y}_{jc}), \quad \forall j \in \{1, \cdots, n_{I+1}\}, c \in dom(c) \tag{16}$$

$$\beta_{jc} \geq -y_{jc} + \frac{1}{2}(\underline{y}_{jc} + \bar{y}_{jc}), \quad \forall j \in \{1, \cdots, n_{I+1}\}, c \in dom(c) \tag{17}$$

$$\gamma_{jg} \geq z_{jg} - \frac{1}{2}(\underline{z}_{jg} + \bar{z}_{jg}), \quad \forall j \in \{1, \cdots, n_{I+1}\}, g \in dom(g) \tag{18}$$

$$\gamma_{jg} \geq -z_{jg} + \frac{1}{2}(\underline{z}_{jg} + \bar{z}_{jg}), \quad \forall j \in \{1, \cdots, n_{I+1}\}, g \in dom(g) \tag{19}$$

A new model can be developed as follow.
New decision variables

α_{ij}: auxiliary variables, where $i \in \mathcal{I}, j \in \{1, \cdots, n_i\}$;
β_{jc}: auxiliary variables, where $j \in \{1, \cdots, n_{I+1}\}, c \in dom(c)$;
γ_{jg}: auxiliary variables, where $j \in \{1, \cdots, n_{I+1}\}, g \in dom(g)$;

$$max \quad x^T_{(I+1),n_{I+1}} \tag{20}$$

$$s.t. \quad (1) - (7), (9) - (19),$$

$$\sum_{j=1}^{n_i} \sum_{i \in \mathcal{I}} \alpha_{ij} + \sum_{j=1}^{n_{I+1}} \sum_{c \in dom(c)} \beta_{jc} + \sum_{j=1}^{n_{I+1}} \sum_{g \in dom(g)} \gamma_{jg} \leq budget \tag{21}$$

$$\alpha_{ij} \geq 0, \quad \forall i \in \mathcal{I}, j \in \{1, \cdots, n_i\} \tag{22}$$

$$\beta_{jc}, \gamma_{jg} \geq 0, \quad \forall j \in \{1, \cdots, n_{I+1}\}, c \in dom(c), g \in dom(g) \tag{23}$$

Though the constructed model is still a nonlinear programming formulation, it can be solved by using the commercial solver GUROBI.

5 A case study

In this section, an illustrative example is presented to demonstrate the applicability of the proposed model. The model are coded in PYTHON 3.7 and combined with GUROBI 9.0 solver. Numerical experiments are conducted on a personal computer with Core I5 and 2.11 GHz processor and 16 GB RAM under windows 10 operating system.

Especially, we focus on the situation that the SC has three suppliers and one manufacturer, and the number of periods is set to be three. Each supplier and the manufacturer has two states, i.e., state 1 denotes a fully operational state and state 2 signifies a fully disrupted state. The Markov transition matrix of supplier i and the lower bound and upper bound of probability intervals are shown as follows.

$$\boldsymbol{M}_i = \begin{bmatrix} 0.549 & 0.715 \\ 0.451 & 0.285 \end{bmatrix}, \forall i \in \{1,2,3\} \quad \underline{x}_{ij}^1 = \begin{bmatrix} 0.209 & 0.360 \\ 0.000 & 0.151 \\ 0.073 & 0.046 \end{bmatrix} \quad \bar{x}_{ij}^1 = \begin{bmatrix} 0.718 & 0.513 \\ 0.775 & 0.718 \\ 0.710 & 0.665 \end{bmatrix}$$

$$\underline{y}_{jc} = \begin{bmatrix} 0.275 & 0.354 & 0.145 & 0.255 & 0.446 & 0.448 & 0.063 & 0.104 \\ 0.026 & 0.220 & 0.015 & 0.228 & 0.325 & 0.139 & 0.338 & 0.295 \end{bmatrix}$$

$$\bar{y}_{jc} = \begin{bmatrix} 0.984 & 0.774 & 0.986 & 0.857 & 0.849 & 0.608 & 0.988 & 0.503 \\ 0.626 & 0.717 & 0.890 & 0.599 & 0.931 & 0.992 & 0.582 & 0.799 \end{bmatrix}$$

Table 1. Different disruption risk probabilities obtained by different deviation budgets

budget	5	6	7	8	9	10
obj	0.239	0.252	0.261	0.267	0.268	0.268

The different disruption risk probabilities obtained by different deviation budgets are reported in Table 1. *budget* denotes the deviation budget and *obj* means the disruption risk probabilities. We can observe that with the increase of *budget*, *obj* increases first and remains unchanged later. It is natural that the worst-case risk estimations with large deviation budget are greater than those with small one. The experimental results are useful, since decision makers can adopt different deviation budget in line with their risk preferences to evaluate the disruption risk probability properly.

Acknowledgments

The authors are grateful for the valuable comments from the reviewers. This work was supported by the National Natural Science Foundation of China (NSFC) under Grants 72021002, 71972146, 71771048, 71432007, 71832001 and 72071144.

References

1. Dolgui, A., Ivanov, D., Sokolov, B.: Ripple effect in the supply chain: an analysis and recent literature. International Journal of Production Research **56**(1-2), 414–430 (2018)
2. Hosseini, S., Al Khaled, A., Sarder, M.: 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)
3. Hosseini, S., Barker, K.: A bayesian network model for resilience-based supplier selection. International Journal of Production Economics **180**, 68–87 (2016)
4. Hosseini, S., Ivanov, D.: A new resilience measure for supply networks with the ripple effect considerations: A bayesian network approach. Annals of Operations Research pp. 1–27 (2019)
5. 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)
6. Ivanov, D.: 'a blessing in disguise'or 'as if it wasn't hard enough already': reciprocal and aggravate vulnerabilities in the supply chain. International Journal of Production Research **58**(11), 3252–3262 (2020)
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., Hartl, R., Dolgui, A., Pavlov, A., Sokolov, B.: Integration of aggregate distribution and dynamic transportation planning in a supply chain with capacity disruptions and the ripple effect consideration. International Journal of Production Research **53**(23), 6963–6979 (2015)
9. Ivanov, D., Sokolov, B., Dolgui, A.: The ripple effect in supply chains: trade-off 'efficiency-flexibility-resilience'in disruption management. International Journal of Production Research **52**(7), 2154–2172 (2014)
10. Ivanov, D., Sokolov, B., Solovyeva, I., Dolgui, A., Jie, F.: Dynamic recovery policies for time-critical supply chains under conditions of ripple effect. International Journal of Production Research **54**(23), 7245–7258 (2016)
11. 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)
12. Sawik, T.: On the risk-averse optimization of service level in a supply chain under disruption risks. International Journal of Production Research **54**(1), 98–113 (2016)
13. Sokolov, B., Ivanov, D., Dolgui, A., Pavlov, A.: Structural quantification of the ripple effect in the supply chain. International Journal of Production Research **54**(1), 152–169 (2016)