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A general robust dynamic Bayesian network method for supply chain disruption risk estimation under ripple effect ⋆

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Abstract: Robust dynamic Bayesian network (DBN) is a valid tool for disruption propagation estimation in the supply chain under data scarcity. However, one of assumptions in robust DBN is that the Markov transition matrix is fixed and fully known, which is unpractical. To make up this deficiency, a novel and general robust DBN is, for the first time, proposed in this work to assess the worst-case oriented supply chain disruption risk under ripple effect. The study focuses on a supply chain with multiple suppliers and one manufacturer over a time horizon, in which only probability intervals of related probabilities are known. The objective is to obtain the worst-case supply chain disruption risk, measured by the probability of the manufacturer in the fully disrupted state in the final time period. For the problem, a new and general nonconvex programming model is established. Then, a case study is conducted to compare our approach with the classic DBN and robust DBN in the literature.

Keywords: supply chain, disruption risk estimation, ripple effect, robust dynamic Bayesian network, data scarcity.

1. INTRODUCTION

Due to the inherent structural complexity and increasing global scale, supply chains tend to be fragile under disruptions, such as natural and man-made disasters (Liu et al., 2021b). For example, in may 2017, production at BMW was disrupted due to a supply shortage of steering gears. BMW's 1st tier supplier, Bosch, was unable to provide the steering gears because an Italian 2nd tier supplier experienced production delays for certain steering parts as a consequence of internal machine breakdowns (Moetz et al., 2019). In another example, earthquake and tsunami in Japan in 2011 have disrupted multiple suppliers in the automotive industry, leading to production cease and material shortages worldwide (Ivanov et al., 2018). These facts portray the behavior of a disruption propagation along the supply chain, i.e., the ripple effect. The ripple effect, first introduced by Ivanov et al. (2014), denotes a disruption, rather than remaining localized or being contained to one part of the supply chain, cascades downstream and impacts the performance of the entire supply chain. It may result in adverse effects on the profitability of supply chain, such as lower revenues, delivery delays and loss of market share (Ivanov, 2019, 2020). To cope with the adverse consequences of ripple effect effectively, it is indispensable to develop appropriate mathematical models to estimate the disruption risk quantitatively.

Bayesian network (BN) is demonstrated to be a valid tool for this purpose. Referring to its natural directed acyclic graph structure, BN is capable of describing the ripple effect. Hosseini et al. (2020) first propose a dynamic BN (DBN) approach to quantify the ripple effect. In their work, complete probability distributions required by the DBN are assumed to be fully known. Liu et al. (2021b) argue that this assumption is unpractical due to data

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scarcity. Therefore, they propose a robust DBN approach, combining DBN with probability intervals, to assess the disruption risk in the supply chains. we agree that the robust DBN in disruption risk evaluation is efficient in cases of data scarcity. However, one of assumption in Liu et al. (2021b)'s work is that perfect information on Markov transition matrix can be obtained, which is also unpractical. Therefore, to make up for this deficiency, we relax this assumption and develop a general robust DBN approach. Specifically, in our work, only probability intervals of the entries in Markov transition matrix are known.

The main contributions of this paper include:

(1) A general robust DBN, in which only probability intervals of the entries in Markov transition matrix, is proposed.
(2) A new nonconvex model is developed to mathematically materialize the proposed method.
(3) A case study is conducted to compare our approach with the classic DBN and robust DBN.

The rest of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the studied problem in detail and formulates a new nonconvex optimization model. A case study is conducted in Section 4. Section 5 concludes this paper and outlines future research directions.

2. LITERATURE REVIEW

In this section, two major research areas (i.e., supply chain disruption risk management and probability intervals) are reviewed. Specifically, we first review supply chain disruption risk management methods with a particular focus on BN applications. Second, we briefly review the applications of probability intervals which can portray imperfect probability information.

2.1 Supply chain disruption risk management method

An extensive body of researches have been done on supply chain disruption risk management (Ivanov et al., 2014, 2015, 2017a,b, 2018; Sokolov et al., 2016; Kinra et al., 2020; Chen et al., 2019; Gupta and Ivanov, 2020; Sawik, 2011, 2013, 2016, 2017, 2018, 2019, 2020, 2021; Hosseini et al., 2016; Ojha et al., 2018; Hosseini et al., 2020; Lei et al., 2021; Dubey et al., 2021; Mishra et al., 2021; Chauhan et al., 2021; Ma et al., 2021; Özçelik et al., 2021; Azaron et al., 2021; Jahani et al., 2021; Gholami-Zanjani et al., 2021; Choi, 2021; Lee et al., 2021; Liu et al., 2021a,b,c). Ivanov et al. (2015) develop an optimal control framework combined with a mathematical programming approach to manage the resilience of supply chain. Based on Ivanov et al. (2015)'s work, Sokolov et al. (2016) investigate the ripple effect in the supply chain from the structural perspective. Sawik (2011, 2013, 2016, 2017, 2018, 2019, 2020, 2021) propose a portfolio approach (i.e., the stochastic mixed integer programming model) to mitigate the supply chain disruption risk.

Hosseini et al. (2016) propose a BN to measure the resilience of supply chain. A case study of sulphuric acid manufacturing plant is conducted to justify the BN approach. Ojha et al. (2018) also adopt the BN method, to assess the supply chain disruption risk under ripple effect. The disruption risk is evaluated using metrics like fragility, service level, inventory cost and lost sales. However, the temporal aspect of the disruption propagation behavior is not considered. To make up this deficiency, Hosseini et al. (2020) propose a dynamic BN (DBN) method to evaluate the disruption risk over a time horizon. Liu et al. (2021b) point out that obtaining perfect information on probability distributions required by the DBN is impractical due to data scarcity. They propose a robust DBN, combining DBN with probability intervals, to assess the disruption risk in supply chains, from the worst-case perspective. To overcome the computational difficulty in solving large-size problems, they further design a simulated annealing algorithm. Liu et al. (2021a) further propose a bounded deviation budget constraint, to build a bridge between DBN and robust DBN. With bounded deviation budget, decision makers can estimate the disruption risk according to their risk appetite. Based on Liu et al. (2021b)'s robust DBN, Liu et al. (2021c) propose a tabu search algorithm to improve the solution quality. Numerical experiments report that the proposed tabu search algorithm outperforms the SA algorithm.

2.2 Probability intervals

To describe imperfect probability distributions under data scarcity, a huge body of researches adopting probability intervals have been done (Qiu et al., 2008; Fallet et al., 2011; Guo and Tanaka, 2010; Jiang et al., 2013; Huang et al., 2017; Chen et al., 2017; Rocchetta et al., 2018; Liu et al., 2021b). Qiu et al. (2008) incorporate probability intervals into a system reliability model to portray imperfect probability distributions. The authors reveal that the probability interval is valid tool to represent imperfect probability information. Recently, in Liu et al. (2021b)'s work, the probability interval is used to describe the ambiguous probability in a certain state for a supplier in time period 1 and the entries of CPTs. Therefore, in this paper, we follow their work and adopt probability intervals to portray imperfect probability distributions.

3. PROBLEM DESCRIPTION AND FORMULATION

In this section, we first describe the studied problem in detail. Then a new nonconvex optimization model is established.

3.1 Problem description

Consider a supply chain with several suppliers and one manufacturer, where the business partner relationship is established between these supply chain members. When the suppliers undergo some natural or man-made disasters, the disruptions propagate from the suppliers to the manufacturer.

The disruption propagation in the supply chain can be viewed from both structural and temporal perspectives. For ease of explanation, Figure 1 is adapted to illustrate the disruption propagation relationships between supply chain members. From Figure 1, it can be observed that two disruptions hit two suppliers respectively, and these

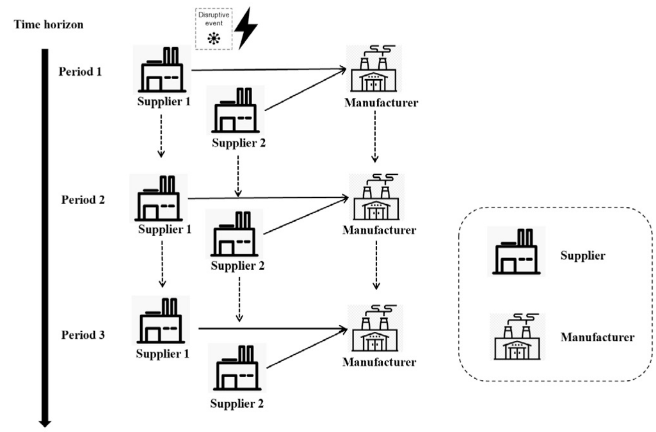

Fig. 1. Disruption propagation along a supply chain over a time horizon

disruptions propagate to the manufacturer along the supply chain structure and time. The dotted arrows denote the propagation direction of disruptions from the temporal aspect, while the solid arrows indicate the propagation direction in structure aspect.

Referring to Hosseini et al. (2020) and Liu et al. (2021b)'s works, we mathematically rephrase the DBN and robust DBN. Consider a supply chain with a set $\mathcal{J} = \{1, \cdots, j, \cdots, J\}$ of suppliers and a manufacturer, denoted as $J+1$, over a time horizon $\mathcal{T} = \{1, \cdots, t, \cdots, T\}$. Each supply chain member has a set of possible states $\mathcal{I} = \{1, \cdots, i, \cdots, I\}$. The states in the set $\mathcal{I}$ are sorted in an increasing order of disrupted magnitude.

According to the DBN proposed by Hosseini et al. (2020), the transition of the supplier j's state from i in the previous time period $t-1$ into i' in the current time period t can be represented via a probability $m_j^{ii'}$. All state transition relationships for the supplier j can be collected by a Markov transition matrix as follows:

$$\mathcal{M}_j = \begin{bmatrix} m_j^{11} & m_j^{12} & \cdots & m_j^{1I} \\ m_j^{21} & m_j^{22} & \cdots & m_j^{2I} \\ \vdots & \vdots & \ddots & \vdots \\ m_j^{I1} & m_j^{I2} & \cdots & m_j^{II} \end{bmatrix}, \quad \forall j \in \mathcal{J}$$

Therefore, the probabilities in different states for the supplier j in time period t can be calculated as follows:

$$(u_{j1}^t, \cdots, u_{jI}^t) = (u_{j1}^{t-1}, \cdots, u_{jI}^{t-1}) \cdot \mathbf{M}_j \quad \forall j \in \mathcal{J}, t \in \mathcal{T}/\{1\} \tag{1}$$

where $(u_{j1}^t, \cdots, u_{jI}^t)$ is the probability distribution of the supplier j in time period t.

As for the manufacturer, its state in the time period 1 only depends on all the suppliers' state in the same time period. However, from the time period 2, the manufacturer's state in the present time period t hinges on not only its state in the previous time period $t-1$, but also all the suppliers' state in the current time period t. Therefore, two different conditional probability tables (CPTs) are utilized. Specifically, according to Liu et al. (2021b)'s work, the DBN structure can be divided into one prior BN and (T-1) two-time BNs (2TBNs). Correspondingly, the CPT in the prior BN can be described as follow,

$$\mathrm{CPT}_{\mathrm{priorBN}} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1,I^J} \\ v_{21} & v_{22} & \cdots & v_{2,I^J} \\ \vdots & \vdots & v_{i\alpha} & \vdots \\ v_{I,1} & v_{I,2} & \cdots & v_{I,I^J} \end{bmatrix},$$

where the number of rows (i.e., I) indicates the number of possible states of the manufacturer, the number of columns (i.e., I^J) indicates the number of possible state combinations of all the suppliers, and $v_{i\alpha}$ is the conditional probability in i-th state for the manufacturer given the α-th state combination of all the suppliers (Liu et al., 2021b). For ease of exposition, we associate the state combination index with the α-th state combination. For the CPT in the prior BN, $\alpha \in \{1, 2, \cdots, I^J\}$. Clearly, there is a one-to-one correspondence relationship between a state-combination-index and a state combination (Liu et al., 2021b).

Following Liu et al. (2021b)'s work, we define a unique mapping $f(\cdot)$ to describe the one-to-one correspondence relationship. Let $f^{-1}(\cdot)$ represent the inverse mapping from a state-combination-index to a state combination. Let $f^{-1}(\alpha)(j)$ denote the state of supplier j in the α-th state combination. For brevity, let d_α denote the domain of the state-combination-index α, i.e., $d_\alpha = \{1, 2, \cdots, I^J\}$.

Therefore, the probability in i-th state for the manufacturer in the prior BN can be described as:

$$u_{(J+1)i}^1 = \sum_{\alpha \in d_\alpha} v_{i\alpha} \prod_{j \in J} u_{j,f^{-1}(\alpha)(j)}^1, \quad \forall i \in \mathcal{I} \tag{2}$$

where $u_{j,f^{-1}(\alpha)(j)}^1$ is the probability in state $f^{-1}(\alpha)(j)$ for supplier j in time period 1.

As for the CPTs in all 2TBNs, they are assumed to be identical in line with Hosseini et al. (2020) and Liu et al. (2021b)'s work, which can be described as:

$$\mathrm{CPT}_{\mathrm{2TBN}} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1,I^{J+1}} \\ w_{21} & w_{22} & \cdots & w_{2,I^{J+1}} \\ \vdots & \vdots & w_{i\beta} & \vdots \\ w_{I,1} & w_{I,2} & \cdots & w_{I,I^{J+1}} \end{bmatrix},$$

where the number of rows (i.e., I) implies the number of possible states for the manufacturer, the number of columns (i.e., I^{J+1}) denotes the number of all state combinations of all the suppliers in time period t and the manufacturer in time period $t-1$, and $w_{i\beta}$ indicates the conditional probability in i-th state for the manufacturer given the β-th state combination (Liu et al., 2021b).

Similarly, we define a unique mapping $g(\cdot)$ to represent the one-to-one correspondence relationship between a state combination and a state-combination-index. Let $g^{-1}(\cdot)$ indicate the inverse mapping of $g(\cdot)$. Let $g^{-1}(\beta)(j)$ denote the state of supplier j in the β-th state combination. Let d_β denote the domain of the state-combination-index β, i.e.$d_\beta = \{1, 2, \cdots, I^{J+1}\}$ (Liu et al., 2021b).

Therefore, the probability in i-th state for the manufacturer in each 2TBN can be described as:

$$u_{(J+1)i}^t = \sum_{\beta \in d_\beta} w_{i\beta} \prod_{j \in J} u_{j,g^{-1}(\beta)(j)}^t \cdot u_{J+1,g^{-1}(\beta)(J+1)}^{t-1} \quad \forall i \in \mathcal{I}, t \in \mathcal{T}/\{1\} \tag{3}$$

where $u_{J+1,g^{-1}(\beta)(J+1)}^{t-1}$ is the probability in state $g^{-1}(\beta)(J+1)$ for the manufacturer in time period $t-1$, and $u_{j,g^{-1}(\beta)(j)}^t$

is the probability in state $g^{-1}(\beta)(j)$ for supplier j in time period t.

In Liu et al. (2021b)'s robust DBN, only a probability interval in each state for each supplier j in time period 1 is known, i.e. $u^1_{ji} \in [\underline{u}^1_{ji}, \bar{u}^1_{ji}]$ where $j \in \mathcal{J}$, $i \in \mathcal{I}$. For the manufacturer, the entries of the CPT in the prior BN and those of the CPT in all 2TBNs are confined in probability intervals, i.e., $v_{i\alpha} \in [\underline{v}_{i\alpha}, \bar{v}_{i\alpha}]$, where $i \in \mathcal{I}$, $\alpha \in d_\alpha$, and $w_{i\beta} \in [\underline{w}_{i\beta}, \bar{w}_{i\beta}]$ where $i \in \mathcal{I}$, $\beta \in d_\beta$. Notably, Liu et al. (2021b) assume the entries $m^j_{ii'}$ in Markov transition matrix are fixed and fully known.

Our work is an extension of Liu et al. (2021b)'s robust DBN. In line with their work, in this paper, we further assume that the entries of the Markov transition matrix $m^j_{ii'}$ are restricted in probability intervals $[\underline{m}^j_{ii'}, \bar{m}^j_{ii'}]$, where $j \in \mathcal{J}$.

3.2 A nonconvex model

In this subsection, we first define input parameters and decision variables. Then, a general robust DBN formulation compared with the classic DBN and robust DBN is established.

Input parameters

- $\mathcal{J}$: set of suppliers, $\mathcal{J} = \{1, \cdots, J\}$, which is indexed by j. Especially, $J+1$ denotes the manufacturer;
- $\mathcal{T}$: set of periods, $\mathcal{T} = \{1, \cdots, T\}$, which is indexed by t;
- $\mathcal{I}$: set of states, $\mathcal{I} = \{1, \cdots, I\}$, which is indexed by i;
- d_α: the domain of the state-combination-index α, i.e., $d_\alpha = \{1, 2, \cdots, I^J\}$;
- d_β: the domain of the state-combination-index β, i.e., $d_\beta = \{1, 2, \cdots, I^{J+1}\}$;
- $f(\cdot)$: unique mapping in the prior BN which maps a state combination to a state-combination-index;
- $g(\cdot)$: unique mapping in each 2TBN which maps a state combination to a state-combination-index;
- $\underline{u}^1_{ji}$: the lower bound of the probability interval in the $i \in \mathcal{I}$-th state for the supplier $j \in \mathcal{J}$ in time period 1;
- $\bar{u}^1_{ji}$: the upper bound of the probability interval in the $i \in \mathcal{I}$-th state for the supplier $j \in \mathcal{J}$ in time period 1;
- $\underline{v}_{i\alpha}$: the lower bound of the probability interval in the $i \in \mathcal{I}$-th state for the manufacturer, conditional on the $\alpha \in d_\alpha$-th state combination in the prior BN;
- $\bar{v}_{i\alpha}$: the upper bound of the probability interval in the $i \in \mathcal{I}$-th state for the manufacturer, conditional on the $\alpha \in d_\alpha$-th state combination in the prior BN;
- $\underline{w}_{i\beta}$: the lower bound of the probability interval in the $i \in \mathcal{I}$-th state for the manufacturer, conditional on the $\beta \in d_\beta$-th state combination in each 2TBN;
- $\bar{w}_{i\beta}$: the upper bound of the probability interval in the $i \in \mathcal{I}$-th state for the manufacturer, conditional on the $\beta \in d_\beta$-th state combination in each 2TBN;
- $\underline{m}^j_{ii'}$ the lower bound of the probability interval for the supplier j's state from $i \in \mathcal{I}$ in the previous time period into $i' \in \mathcal{I}$ in the present time period, where $j \in \mathcal{J}$;
- $\bar{m}^j_{ii'}$ the upper bound of the probability interval for the supplier j's state from $i \in \mathcal{I}$ in the previous time period into $i' \in \mathcal{I}$ in the present time period, where $j \in \mathcal{J}$.

Decision variables

- $m^j_{ii'}$: the probability of the supplier j's state from $i \in \mathcal{I}$ in the previous time period into $i' \in \mathcal{I}$ in the present time period, where $j \in \mathcal{J}$;
- u^t_{ji}: the probability in the $i \in \mathcal{I}$-th state for the supplier $j \in \mathcal{J}$ or manufacturer $J+1$ in time period $t \in \mathcal{T}$;
- $v^t_{i\alpha}$: the probability in the $i \in \mathcal{I}$-th state for the manufacturer, conditional on the $\alpha \in d_\alpha$-th state combination in the prior BN;
- $w^t_{i\beta}$: the probability in the $i \in \mathcal{I}$-th state for the manufacturer, conditional on the $\beta \in d_\beta$-th state combination in each 2TBN.

The general robust DBN optimization model can be described as follow:

$$max \quad u^T_{J+1,I} \tag{4}$$

$$s.t. \quad (1)-(3)$$

$$\sum_{i' \in I} m^j_{ii'} = 1, \quad \forall j \in \mathcal{J}, i \in \mathcal{I} \tag{5}$$

$$\sum_{i \in I} u^1_{ji} = 1, \quad \forall j \in \mathcal{J} \tag{6}$$

$$\sum_{i \in I} v_{i\alpha} = 1, \quad \forall \alpha \in d_\alpha \tag{7}$$

$$\sum_{i \in I} w_{i\beta} = 1, \quad \forall \beta \in d_\beta \tag{8}$$

$$m^j_{ii'} \in [\underline{m}^j_{ii'}, \bar{m}^j_{ii'}], \quad \forall j \in \mathcal{J}, i, i' \in \mathcal{I} \tag{9}$$

$$u^1_{ji} \in [\underline{u}^1_{ji}, \bar{u}^1_{ji}], \quad \forall j \in \mathcal{J}, i \in \mathcal{I} \tag{10}$$

$$0 \leq u^t_{ji} \leq 1, \quad \forall j \in \mathcal{J} \cup \{J+1\}, i \in \mathcal{I}, t \in \mathcal{T}/\{1\} \tag{11}$$

$$v_{i\alpha} \in [\underline{v}_{i\alpha}, \bar{v}_{i\alpha}], \quad \forall i \in \mathcal{I}, \alpha \in d_\alpha \tag{12}$$

$$w_{i\beta} \in [\underline{w}_{i\beta}, \bar{w}_{i\beta}], \quad \forall i \in \mathcal{I}, \beta \in d_\beta \tag{13}$$

The objective function (4) aims to obtain the worst-case oriented supply chain disruption risk, i.e., the probability of the manufacturer in the fully disrupted state in the final time period. Constraint (1) denotes the Markov transition equation for each supplier $j \in \mathcal{J}$. Constraint (2)-(3) calculate the probability in each state for the manufacturer in the prior BN (or 2TBN). Constraint (5) implies that the sum of the probabilities in each row of the Markov matrix is equal to 1. Constraints (6)-(8) represent the second Kolmogorov axiom of probability. Constraints (9)-(13) limit the domains of decision variables.

Though the proposed model is a nonconvex programming formulation, it can be exactly solved via the commercial solver Gurobi 9.0 for small-size problems.

4. A CASE STUDY

In this section, the developed model is tested and compared with Hosseini et al. (2020)'s DBN and Liu et al. (2021b)'s robust DBN. The case study is adapted from Hosseini et al. (2020)'s case. Notably, in Hosseini et al. (2020)'s work, perfect information on probability distributions are assumed to be known. Nevertheless, in Liu et al.

(2021b)'s work, only probability interval information of each supplier in each state in time period 1 and the entries of the CPTs are known. In our study, based on Liu et al. (2021b)'s robust DBN, the entries of Markov transition matrix are also assumed to be uncertain and confined in probability intervals. The width for all probability intervals is set to be 0.01 according to Liu et al. (2021b)'s work. The numerical results obtained by three approaches are reported in Table 1. It can be observed that the disruption risk obtained by DBN, robust DBN and our approach are 2.61%, 3.15%, 3.20%, respectively. The results are reasonable because our approach relies on the least probability information and make the most conservative assessment. Decision makers can flexibly choose a certain approach to estimate the disruption risk according to actual condition. Specifically,

Table 1. Different disruption risk values obtained by three approaches

Approach	values(%)
DBN	2.61
robust DBN	3.15
Our approach	3.20

(1) If perfect information on probability distributions required by the DBN (i.e., the Markov transition matrix, the initial suppliers' states and the CPTs) can be obtained, the classic DBN is recommended.
(2) If only precise Markov transition matrix can be acquired, the robust DBN is preferable.
(3) If all related probabilities required by the DBN can not be estimated accurately, our general robust DBN is more suitable.

5. CONCLUSION

In this work, we investigate a supply chain disruption risk estimation problem under data scarcity. Specially, based on Liu et al. (2021b)'s robust DBN, we relax one of their problem assumptions (i.e., precise Markov transition matrix). We present a general robust DBN optimization model for the problem. Besides, a case study is conducted to compare our approach with the classic DBN and robust DBN.

Future research directions may include (i) designing more efficient algorithms to solve the large-scale problems; (ii) generalizing this model to multi-objective optimization model.

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