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▶ **To cite this version:**

Ming Liu, Hao Tang, Feng Chu, Feifeng Zheng, Chengbin Chu. A Tabu Search Heuristic for the Robust Dynamic Bayesian Network Optimisation Problem Under the Supply Chain Ripple Effect. International Conference on Advances in Production Management Systems (APMS 2021), Sep 2021, Nantes, France. pp.673-680, 10.1007/978-3-030-85906-0_73 . hal-03360830

HAL Id: hal-03360830

https://hal.science/hal-03360830v1

Submitted on 15 Feb 2023

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A Tabu Search Heuristic for the Robust Dynamic Bayesian Network Optimisation Problem Under the Supply Chain Ripple Effect

Ming Liu[1], Hao Tang[1], Feng Chu[2(✉)], Feifeng Zheng[3], and Chengbin Chu[4]

[1] School of Economics and 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 and 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. Due to the impact of the global COVID-19, supply chain (SC) risk management under the ripple effect is becoming an increasingly hot topic in both practice and research. In our former research, a robust dynamic bayesian network (DBN) approach has been developed for disruption risk assessment, whereas there still exists a gap between the proposed simulated annealing (SA) algorithm and commercial solver in terms of solution quality. To improve the computational efficiency for solving the robust DBN optimisation model, a tabu search heuristic is proposed for the first time in this paper. We design a novel problem-specific neighborhood move to keep the search in feasible solution space. The computational experiments, conducted on randomly generated instances, indicate that the average gap between our approach and commercial solver is within 0.07%, which validates the performance of the proposed method.

Keywords: Ripple effect · Robust DBN · Tabu search

1 Introduction

In recent years, supply chain (SC) risk management has been a widely discussed topic in both industry and academia as a result of severe impact of the COVID-19 epidemic and some other natural or man-made disasters on SCs. Due to the growth structural complexity and increasing global scale of SC networks, the disruption of a supplier caused by these unpredictable disasters will probably propagate to the downstream manufacturers located in disaster-free areas. For example, the Japanese tsunami and earthquake in 2011 disrupted the production

of auto parts and image sensors suppliers, leading to the cease of production of auto companies and smart electronic devices manufacturers in other countries due to the shortage of necessary parts [7]. In another recent example, the sudden Texas winter storm strikes chip foundries, such as South Korea's Samsung Electronics Co., one of the world's biggest chip makers with about 28% of its overall production capacity in Austin facilities[1]. The impact of the disruption in the fragile chip industry, caused by the global COVID-19 epidemic and winter storm, propagates to auto automobile, mobile phone, game consoles and other downstream industries. These above facts embody the impact of a disruption or a series of disruptions along the SCs, i.e. the ripple effect. The ripple effect is introduced by Ivanov et al. [9], meaning the disruption risk of upstream partners in the SCs propagating to downstream partners. For a comprehensive review of this research area, interested readers may refer to surveys by Hosseini et al. [6] and Dolgui et al. [3].

To reduce adverse impact of the ripple effect and mitigate it at minimal costs, it is crucial to measure quantitatively the risk of disruptions propagating along SCs. Bearing this in mind, more and more researchers have proposed novel mathematical models and optimization methods to estimate adverse consequences of ripple effects [2]. Among these techniques, bayesian network (BN), capable of describing the ripple effect via a directed acyclic graph, is introduced for the disruption risk evaluation by Hosseini and Barker [5]. Due to the complexity of global SCs, it is worth noting that the disruptions of source suppliers have continuous effect, which can affect the SCs over several time periods [8]. To assess the disruption risk in a SC with two suppliers and one manufacturer over a time horizon with several periods, Hosseini et al. [7] further propose a simulation model based on a dynamic bayesian network (DBN). In their work, the inputs of DBN (i.e. the corresponding probability distributions) are assumed to be perfectly known. To overcome data scarcity in some real situations, Liu et al. [10] propose a new robust DBN optimisation model utilising the probability intervals to evaluate the worst-case disruption risk.

The new robust DBN approach opens a new perspective for disruption risk assessment, whereas the proposed algorithm in the former work can be improved in terms of both solution quality and computational time. Besides, as a result of the high level of complexity and uncertainty of global SC network, the state of SC may change at any time. Accurate and timely decisions will make a difference for mitigating the impact of disruptions. Motivated by the above two reasons, it is necessary to design efficient solution algorithm that can obtain risk assessment results within a reasonable amount of time.

As a main contribution of this paper, we propose a tabu search (TS) heuristic for solving the robust DBN optimisation model efficiently, which can provide

[1] Asa Fitch, 2021. Texas Winter Storm Strikes Chip Makers, Compounding Supply Woes. The Wall Street Journal. https://www.wsj.com/articles/texas-winter-storm-strikes-chip-makers-compounding-supply-woes-11613588617?mod=searchresults_pos3&page=1.

higher quality solutions within a shorter run time compared to that obtained by the simulated annealing (SA) algorithm developed in our former work.

The remainder of this paper is organized as follows. In Sect. 2, the robust DBN optimisation model is briefly presented for review. In Sect. 3, an efficient TS heuristic is designed for solving the problem, and computational experiments are conducted to evaluate its performance in Sect. 4.

2 Problem Formulation

In this section, we only restate the robust DBN optimisation formulation introduced in the paper [10] for simplicity. For a comprehensive description of the robust DBN approach, readers may refer to Liu et al. [10] and Hosseini et al. [7].

The notations and problem variables are defined the same as former research as follows:

Parameters

$\mathcal{I}$: the set of suppliers, $\mathcal{I} = \{1, \ldots, I\}$, indexed by i;
$I + 1$: the manufacturer;
$\mathcal{T}$: the set of periods, $\mathcal{T} = \{1, \ldots, T\}$, indexed by t;
$\mathcal{S}_i$: the set of states for the supplier or manufacturer i, $\mathcal{S}_i = \{s_{i1}, \ldots, s_{ij}, \ldots, s_{in_i}\}$, indexed by j, where n_i is the number of possible states of SC member $i \in \mathcal{I} \cup \{I + 1\}$;
s_{ij}: the jth state of the supplier or the manufacturer i, where $s_{ij} \in \mathcal{S}_i$, $i \in \mathcal{I} \cup \{I + 1\}$, $j \in \{1, \ldots, n_i\}$;
$\mathbf{M}_i$: Markov transition matrix of supplier i, where $i \in \mathcal{I}$;
$dom(c)$: the domain of the state-combination-index c, i.e. $dom(c) = \{1, 2, \ldots, n_1 \cdot n_2 \cdots n_I\}$;
$\mathrm{C}(\bullet)$: unique bijection mapping $\mathcal{S}_1 \times \cdots \times \mathcal{S}_I \xrightarrow{\mathrm{C}(\bullet)} dom(c)$ in the prior BN which maps a state combination to a state-combination-index;
$\mathrm{C}^{-1}(\bullet)$: the inverse mapping of $\mathrm{C}(\bullet)$, $dom(c) \xrightarrow{\mathrm{C}^{-1}(\bullet)} \mathcal{S}_1 \times \cdots \times \mathcal{S}_I$, which maps a state-combination-index to a state combination;
$\mathrm{C}^{-1}(c)(i)$: the corresponding state of supplier i, $i \in \mathcal{I}$, for a give state-combination-index c in the prior bayesian network (BN);
$dom(g)$: the domain of the state-combination-index g, i.e. $dom(g) = \{1, 2, \ldots, n_1 \cdot n_2 \cdots n_I \cdot n_{I+1}\}$;
$\mathrm{G}(\bullet)$: unique bijection mapping $\mathcal{S}_1 \times \cdots \times \mathcal{S}_I \times \mathcal{S}_{I+1} \xrightarrow{\mathrm{G}(\bullet)} dom(g)$ in each two-time bayesian network (2TBN) which maps a state combination to a state-combination-index;
$\mathrm{G}^{-1}(\bullet)$: the inverse mapping of $\mathrm{C}(\bullet)$, $dom(g) \xrightarrow{\mathrm{G}^{-1}(\bullet)} \mathcal{S}_1 \times \cdots \times \mathcal{S}_I \times \mathcal{S}_{I+1}$, which maps a state-combination-index to a state combination;
$\mathrm{G}^{-1}(g)(i)$: the corresponding state of supplier (or the manufacturer) i, $i \in \mathcal{I} \cup \{I + 1\}$, for a give state-combination-index g in each 2TBN;
$\underline{x}^1_{ij}$: the lower bound of the probability interval in the jth state for the supplier i in time period 1, where $i \in \mathcal{I}$, $j \in \{1, \ldots, n_i\}$;

$\bar{x}^1_{ij}$: the upper bound of the probability interval in the jth state for the supplier i in time period 1, where $i \in \mathcal{I}$, $j \in \{1, \ldots, n_i\}$;

$\underline{y}_{jc}$: the lower bound of the probability interval in the jth state for the manufacturer, conditional on the cth state combination in the prior BN, where $j \in \{1, \ldots, n_{I+1}\}$, $c \in dom(c)$;

$\bar{y}_{jc}$: the upper bound of the probability interval in the jth state for the manufacturer, conditional on the cth state combination in the prior BN, where $j \in \{1, \ldots, n_{I+1}\}$, $c \in dom(c)$;

$\underline{z}_{jg}$: the lower bound of the probability interval in the jth state for the manufacturer, conditional on the gth state combination in each 2TBN, where $j \in \{1, \ldots, n_{I+1}\}$, $g \in dom(g)$;

$\bar{z}_{jg}$: the upper bound of the probability interval in the jth state for the manufacturer, conditional on the gth state combination in each 2TBN, where $j \in \{1, \ldots, n_{I+1}\}$, $g \in dom(g)$;

Problem Variables

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

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

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

The robust DBN optimisation model can be formulated as follows:

$$[\text{Robust DBN}]: \ \max \left\{ \sum_{g \in dom(g)} z_{n_{I+1},g} \cdot \prod_{i \in \mathcal{I}} x^T_{i,G^{-1}(g)(i)} \cdot x^{T-1}_{I+1,G^{-1}(g)(I+1)} \right\} \quad (1)$$

Subject to:

$$\left(x^t_{i1}, \ldots, x^t_{in_i}\right) = \left(x^1_{i1}, \ldots, x^1_{in_i}\right) \cdot (\mathbf{M}_i)^{t-1}, \quad \forall i \in \{1, \ldots, I\}, t \in \mathcal{T}/\{1\} \quad (2)$$

$$x^1_{(I+1)j} = \sum_{c \in dom(c)} y_{jc} \cdot \prod_{i=1}^{I} x^1_{i,\mathrm{C}^{-1}(c)(i)}, \quad \forall j \in \{1, \ldots, n_{I+1}\} \quad (3)$$

$$x^t_{(I+1)j} = \sum_{g \in dom(g)} z_{jg} \cdot \prod_{i=1}^{I} x^t_{i,G^{-1}(g)(i)} \cdot x^{t-1}_{(I+1),G^{-1}(g)(I+1)}, \quad \forall j \in \{1, \ldots, n_{I+1}\}, t \in \mathcal{T}/\{1\} \quad (4)$$

$$\sum_{j \in \{1,\ldots,n_i\}} x^1_{ij} = 1, \quad \forall i \in \mathcal{I} \quad (5)$$

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

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

$$x_{ij}^1 \in \left[\underline{x}_{ij}^1, \bar{x}_{ij}^1\right], \quad \forall i \in \mathcal{I}, j \in \{1,\ldots,n_i\} \tag{8}$$

$$0 \le x_{ij}^t \le 1, \quad \forall i \in \mathcal{I}, j \in \{1,\ldots,n_i\}, t \in \mathcal{T}/\{1\} \tag{9}$$

$$0 \le x_{(I+1)j}^t \le 1, \quad \forall j \in \{1,\ldots,n_{I+1}\}, t \in \mathcal{T} \tag{10}$$

$$y_{jc} \in \left[y_{jc}, \bar{y}_{jc}\right], \quad \forall j \in \{1,\ldots,n_{I+1}\}, c \in dom(c) \tag{11}$$

$$z_{jg} \in \left[\underline{z}_{jg}, \bar{z}_{jg}\right], \quad \forall j \in \{1,\ldots,n_{I+1}\}, g \in dom(g) \tag{12}$$

The objective function (1) is to maximise the worst-case disruption risk, i.e. to estimate the robustness of the manufacturer in the final period T under disruptions. Constraint (2) represents the Markov transition equation for each supplier i. Constraints (3) describes the probability in each state for the manufacturer in the prior BN. Constraint (4) calculates the probability in each state for the manufacturer in each 2TBN. Constraints (5)–(7) guarantee the second Kolmogorov axiom of probability, i.e., the sum of probabilities in all states for a supplier or the manufacturer is equal to 1. Constraints (8)–(12) are the domains of probabilities in each state in all periods.

3 Solution Approach

Tabu search (TS) is an efficient iterative metaheuristic for finding optimal or near-optimal solution via memory structures and exploration strategies that can help escape from local optima [4]. Because of its outstanding performance, TS has become a popular tool for solving various difficult problems in many research fields. In the field of SC management and optimisation, researchers have applied TS for production and distribution planning problem [1] and multi-product, multi-echelon and multi-objective SC network design problem [11,12].

To solve the robust DBN optimisation model more efficiently, we devise a TS heuristic based on the characteristics of the model. In the following, the main components of the proposed TS heuristic are presented.

3.1 Solution Representation

From constraint (2), we know that the values of variables x_{ij}^t, where $t \in \mathcal{T}/\{1\}$, can be obtained once variables x_{ij}^1 have been determined. Thus, only variables x_{ij}^1, y_{jc}, and z_{jg} are encoded for representing the solution.

3.2 Initial Solution Generation

According to constraints (8), (11) and (12), the initial variables are randomly generated between their lower and upper bounds. Note that the solution may be infeasible due to violations of constraints (5)–(7) in the random generation process. Therefore, to guarantee feasibility of initial solution, the probability correction procedure proposed in paper [10] is applied after random generation.

3.3 Neighborhood and Move

As the number of suppliers gets larger, the number of variables increases exponentially due to the increase of the number of state-combinations in the prior BN and 2TBN. All neighborhoods of the incumbent solution, therefore, cannot be enumerated in bounded time. Besides, it has also been indicated that exploring complete neighborhoods may not be an efficient use of computing resources [13]. Thus, we merely generates partial neighboring solutions in each iteration.

Take the neighborhood move for variable x^1_{ij} as an example. Two variables $x^1_{ij_1}$ and $x^1_{ij_2}$ for each supplier i are randomly selected and the values of them are changed as follows:

$$\begin{cases} x^1_{ij_1} = x^1_{ij_1} + \alpha \\ x^1_{ij_2} = x^1_{ij_2} - \alpha \end{cases} \tag{13}$$

where $\alpha = \min\left\{\beta \cdot x^1_{ij_1}, \bar{x}^1_{ij_1} - x^1_{ij_1}, x^1_{ij_2} - \underline{x}^1_{ij_2}\right\}$, and β is the adjustment rate, which is set to be 0.2 after initial experiments. The variation α will keep the neighborhood move within the feasible solution space. Likewise, for each state-combination c (g), the neighborhood move for variable y_{jc} (z_{jg}) is conducted by randomly selecting two variables $y_{j_1,c}$ and $y_{j_2,c}$ ($z_{j_1,g}$ and $z_{j_2,g}$), and changing their values in a similar way. Therefore, the number of neighboring solutions in each iteration is $I + n_1 \cdot n_2 \cdots n_I + n_1 \cdot n_2 \cdots n_I \cdot n_{I+1}$.

3.4 Tabu List Management and Aspiration Criterion

Based on initial experiments, the length of tabu list is set to be $|\mathcal{S}_{I+1}| \cdot I^2$, which is dependent on problem size. In the iterative procedure, tabu list is managed in a cyclical way using the first-in-first-out (FIFO) strategy. Besides, as a special case, whenever a move in tabu list yields a candidate solution better than the best solution so far, the new solution will be accepted and this move will be replaced at the end of the tabu list.

3.5 Stop Criterion

The search procedure stops when it reaches the maximum number of iterations or the maximum number of iterations without improving the best solution.

4 Computational Results

In this section, computational results on randomly generated instances are reported to demonstrate the performance of the solution method. The proposed TS heuristic is programmed in Python, and the commercial solver Yalmip (using Gurobi and Matlab built-in functions to compute lower bound and upper bound) is called in Matlab 2019a as a comparison. The computational experiments have been conducted on a personal computer with 2.4 GHz Core i5 and 16 GB Ram.

We generated 12 random instances with 1 manufacturer, 2–4 suppliers and 2–5 time periods, as the same way in our former research [10]. The numerical results are as follows:

Table 1. The Computational results.

		Yalmip		TS		
Number of suppliers	Number of periods	Objective	Time (sec.)	Objective	Time (sec.)	gap(%)
2	2	0.3512	3.60	0.3512	1.06	0.00
	3	0.2782	7.61	0.2782	1.76	0.00
	4	0.3710	13.96	0.3710	3.90	0.00
	5	0.2353	21.41	0.2353	3.97	0.00
3	2	0.3548	52.13	0.3548	16.49	0.00
	3	0.3327	176.68	0.3327	33.15	0.00
	4	0.3310	200.03	0.3310	45.21	0.00
	5	0.2932	278.40	0.2932	58.70	0.00
4	2	0.3511	414.14	0.3502	181.34	0.26
	3	0.3248	2038.50	0.3242	264.68	0.18
	4	0.3107	3356.10	0.3097	467.40	0.32
	5	–	3600.00	0.3445	439.84	–
Average	0.3213	596.60	0.3230	126.46		0.07*

'–': means Yalmip cannot output solutions within a time limit of 3600 s;
'*': the average gap is calculated except the '–' cases.

From Table 1, we can observe that the TS heuristic can provide almost the same solutions with an average gap of only 0.07% compared to the commercial solver Yalmip. In terms of computational time, our approach outperforms the commercial solver clearly. Especially when the solver cannot output optimal solution for the instance with 4 suppliers and 5 periods in 3600 s, the TS heuristic still can obtain good solution.

Compared with the SA proposed in former work [10], whose average gap with Yalmip on the same sized problems is 6.56%, the new solution approach proposed in this paper can provide better disruption risks assessment for SC managers to make better decisions to reduce adverse impact of the ripple effect.

Acknowledgement. This work was supported by the National Natural Science Foundation of China (NSFC) under Grants 72021002, 71972146, 71771048, 71432007, 71832001 and 72071144.

References

1. Armentano, V.A., Shiguemoto, A.L., Løkketangen, A.: Tabu search with path relinking for an integrated production-distribution problem. Comput. Oper. Res. **38**(8), 1199–1209 (2011)
2. Badurdeen, F., et al.: Quantitative modeling and analysis of supply chain risks using Bayesian theory. J. Manuf. Technol. Manag. **25**(5), 631–654 (2014)
3. Dolgui, A., Ivanov, D., Sokolov, B.: Ripple effect in the supply chain: an analysis and recent literature. Int. J. Prod. Res. **56**(1–2), 414–430 (2018)
4. Glover, F.: Tabu search: a tutorial. Interfaces **20**(4), 74–94 (1990)
5. Hosseini, S., Barker, K.: A Bayesian network model for resilience-based supplier selection. Int. J. Prod. Econ. **180**, 68–87 (2016)
6. Hosseini, S., Ivanov, D., Dolgui, A.: Review of quantitative methods for supply chain resilience analysis. Transp. Res. Part E Logist. Transp. Rev. **125**, 285–307 (2019)

7. Hosseini, S., Ivanov, D., Dolgui, A.: Ripple effect modelling of supplier disruption: integrated Markov chain and dynamic Bayesian network approach. Int. J. Prod. Res. **58**(11), 3284–3303 (2020)
8. Ivanov, D., Dolgui, A., Sokolov, B., Ivanova, M.: Literature review on disruption recovery in the supply chain. Int. J. Prod. Res. **55**(20), 6158–6174 (2017)
9. Ivanov, D., Sokolov, B., Dolgui, A.: The ripple effect in supply chains: trade-off 'efficiency-flexibility-resilience' in disruption management. Int. J. Prod. Res. **52**(7), 2154–2172 (2014)
10. 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. Int. J. Prod. Res. **59**(1), 265–285 (2021)
11. Melo, M., Nickel, S., Saldanha-da Gama, F.: A Tabu search heuristic for redesigning a multi-echelon supply chain network over a planning horizon. Int. J. Prod. Econ. **136**(1), 218–230 (2012)
12. Mohammed, A.M., Duffuaa, S.O.: A Tabu search based algorithm for the optimal design of multi-objective multi-product supply chain networks. Expert Syst. Appl. **140**, 112808 (2020)
13. Reeves, C.R.: Improving the efficiency of Tabu search for machine sequencing problems. J. Oper. Res. Soc. **44**(4), 375–382 (1993)