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Robust actions for improving supply chain resilience and viability ☆

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ABSTRACT

It is vital for supply chains (SCs) to survive the dramatic and long-term impacts from severe disruptive events, such as COVID-19 pandemic. SC viability, an extension of SC resilience, is increasingly attracting attention from both academics and practitioners. To improve SC viability, the government can perform a series of costly interventions on SCs. Due to data scarcity on unpredictable disruptive events, especially under the pandemic, the information related to SC partners may not be accurately obtained. In this paper, we investigate a novel SC resilience and viability improving problem under severe disruptive events, in which only the probability intervals of SC partners' states are known. The problem consists of the selection of appropriate intervention actions, respecting a limited capital budget. The objective is to minimize the worst-case disruption risk of the manufacturer. Specifically, Causal Bayesian Network (CBN) is applied to quantify the SC ripple effects; Do-calculus technique is used to measure the benefits of government intervention actions; and robust optimization is employed to minimize the disruption risk under the worst-case condition. For the problem, a new robust optimization model that combines the CBN and the Do-calculus is constructed. Based on analyses of problem features, an efficient problem-specific branch-and-bound (PS-BAB) algorithm is proposed to solve the problem exactly. Experimental results show the efficiency of our methodology and managerial insights are drawn.

1. Introduction

Disruptive events, such as natural or man-made events, can attack dramatically global supply chains (SCs). Severe disruptive events in SCs can further inflict serious damage on lives of people and the global economy. For example, during COVID-19, the shortage of approximately 880,000 medical ventilators in the global healthcare SC exposed the vulnerabilities of hospitals that rely heavily on such an oxygen supply equipment [1]. In 2022, Shanghai's lockdown caused Tesla manufacturing company to lose at least two billion dollars in revenue due to a shortage of raw materials [2]. Moreover, the propagation of disruptions, such as those caused by the COVID-19 pandemic, along the SC (i.e., ripple effects) can lead to an overall degradation of SC performance, and further result in negative economic, environmental, and social consequences to society [3–6]. Ivanov and Dolgui [7] state that the impacts of the pandemic will in a long term and seriously threaten the viability of SC. Viability is the "*ability of a supply chain to maintain itself and survive in a changing environment through a redesign of structures and replanning of performance with long-term impacts*" [8], which "*integrates resilience and sustainability through a combination of economical and societal components*" and "*refers not only to individual supply chains, but also to intertwined supply networks and ecosystems*" [9]. Today, the SC system is becoming more vulnerable due to its high structural complexity, and the increasing frequency and severity of various unpredictable disruptive events [10,11]. Therefore, improving the SC viability is the lifeblood for manufacturing and service industries [12–14]. As a dominant focus of SC viability, SC resilience refers to "*the ability to withstand a disruption (or a series of disruptions) and recover the performance*" [15]. Viability denotes the adaptation-based resilience perspective, so improving both SC viability and resilience attracts more and more attention from academics and practitioners [16].

Generally, there are two kinds of strategies to counter disruptive events, i.e., (preventive) mitigation strategy and (corrective) contingency strategy [3,17–19]. The mitigation strategy focuses on performing preventive actions before a disruptive event to reduce the disruption risk and its ripple effect, while the contingency strategy consists of

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restoring the system's performance after a disruption. Compared with the contingency strategy, the mitigation strategy is more fruitful in reducing major socio-economic impacts [20]. Thus, mitigation actions are typically taken to improve the viability [21] and resilience [22] of SCs. Mitigation actions are commonly taken from the following three prioritized perspectives: (1) disruption avoidance, (2) risk minimization, and (3) compensatory mitigation [23]. Completely avoiding unknown disruptive events is expensive. To make practical mitigation strategies under limited capital budget, the focus naturally shifts to the risk minimization.

To develop mitigation strategies for SCs, many researchers apply stochastic optimization (SO) approaches [24–27]. The existing SO approaches contribute a lot to SC risk management, but most of them ignore the critical role of government intervention actions for SC risk minimization. In practice, government interventions, such as financial and regulatory interventions, have been widely taken to enhance SC viability [9]. For example, the General Motors (GM) company received a $2 billion bailout from the government, and coupled with $100 million from its own resources, GM invested a total of $2.1 billion in its parts suppliers to help them survive the financial crisis [28]. In addition to financial support, many governments develop laws, regulations and national strategies for the response to, and future preparedness for, disruptive events (e.g., the COVID-19 pandemic) [29]. In the literature, most pieces of research focus on qualitatively evaluating the impact of government interventions [30–32], while only few studies quantitatively measure the impact. To the best of our knowledge, Liu et al. [21] is the first work on SC disruption risk minimization via cost-effective government interventions. For the studied problem, two stochastic optimization models are constructed by integrating Causal Bayesian Network (CBN) and Do-calculus technique. However, existing SO related works assume that the accurate information on the states of SC partners under disruptive events can be perfectly captured by joint probability distributions.

In real applications, due to data scarcity, only partial probability information of uncertain parameters can be accessed, especially for unpredictable disruptive events [33,34]. In such a data-scarce environment, the SO approaches are not appropriate for suggesting a guaranteed performance. Robust optimization (RO) is a well-known efficient tool for handling the worst-case situation, especially dealing with ambiguous information obtained under a data-scarce environment [35,36]. In the literature, some studies propose RO methods to develop mitigation strategies for SC network design and operations management problems, including the reliable facility location [37], the global SC network design [38], the reverse SC management under ripple effects [35], the resilient location-inventory for food SC [39], etc. These works enrich the literature of SC risk management, but the mechanism of disruption propagation (i.e., ripple effect) along the SC has not been explicitly modeled and incorporated in these works, although it is a key element to understand SC risks. To the best of our knowledge, Liu et al. [40] is the first work to portray ripple effects under data scarcity and assess the worst-case probability of the SC manufacturer's disrupted state. However, applying mitigation strategies to improve SC viability is ignored in their works.

In this paper, we investigate a new SC resilience and viability improving problem under data scarcity, i.e., only the probability intervals of states of SC partners are given. The problem consists of selecting appropriate government interventions, subject to a limited financial budget. The objective is to minimize the worst-case disruption risk of the manufacturer. For the problem, the CBN is applied to quantify the SC ripple effects; the Do-calculus technique is used to measure the benefits of government intervention actions. Based on problem characteristics, a robust optimization model is constructed from the worst-case perspective. A problem-specific branch-and-bound (PS-BAB) algorithm is proposed to efficiently solve the problem, thanks to efficient pruning rules and lower bound calculations. We note that the proposed approach can re-plan the SC performance (regarding viability) or restore the SC to an initial state (regarding resilience [9]) by intervening suppliers to different states. The main contributions of the work are summarized as follows:

1. A novel SC resilience and viability improving problem subject to a limited government intervention budget and data scarcity is first addressed.
2. To meet practical needs, a novel robust optimization model is established for the studied problem.
3. Based on the problem analysis, a problem-specific branch-and-bound (PS-BAB) algorithm is designed to solve such a complex problem, which includes efficient pruning rules and a fast-calculating lower bounding technique.
4. Numerical experiments are conducted to verify the efficiency of our methodology and managerial insights are drawn.

The rest of this paper is organized as follows. The literature review is presented in Section 2. In Section 3, the studied problem is described. The CBN approach and the Do-calculus technique are applied to characterize ripple effects and impacts of government interventions, respectively. Then the problem is formulated as a non-linear robust optimization model. In Section 4, a problem-specific exact algorithm is presented. In Section 5, computational experiments are conducted to evaluate the performance of the developed solution method and managerial insights are drawn. Finally, Section 6 presents conclusions and suggests future research directions.

2. Literature review

In the literature, there is abundant research on SC risk management. The interested readers can refer to the review of recent papers [17,41]. As the aim of this work is to develop efficient mathematical models and solution methods for improving SC resilience and viability under ripple effects, the section focuses on reviewing existing models and approaches for SC risk mitigation via stochastic optimization (SO) and robust optimization (RO) techniques, especially for SCs under the ripple effect/disruption propagation.

2.1. Stochastic optimization for SC risk mitigation

For SC under ripple effects, SO related techniques are widely applied to mitigate SC risks, especially for facility location, supplier selection, and inventory control under uncertain environments. Yılmaz et al. [26] investigate a reverse supply chain (RSC) design problem under ripple effects. The uncertain transportation distances and facility capacities are represented by a set of scenarios. The problem consists of minimizing the total facility location and transportation cost, confined to a desired emission level. For the problem, a two-stage SO model is constructed and solved by calling CPLEX. Gholami-Zanjani et al. [25] address a multi-echelon resilient food SC network design problem with uncertain demand and disruptive events, in which uncertain demand is portrayed by a set of scenarios, while the disruptive events and their ripple effects are associated with propagation probabilities. The problem consists of optimally determining manufacture and distribution center locations and allocating retailers to opened distribution centers. The objective is to maximize the revenue. For the problem, a two-stage SO optimization model is constructed, and an exact algorithm based on Benders decomposition is developed. Sindhwani et al. [42] study a pharmaceutical facility location problem under ripple effects. The problem is to determine the locations of backup factories (BFs), central distribution centers (CDCs) and regional distribution centers (RDCs), and the flow from suppliers or/and opened BFs to customers via opened CDCs and RDCs. The objective is to maximize the overall performance of the SC. For the problem, the Bayesian Network (BN) is firstly used to quantify ripple effects. Stochastic optimization and Lagrangian relaxation related techniques are used to find the best candidates of RDC. Then a SC network optimization model is constructed and solved by calling CPLEX. Pariazar et al. [43] consider a two-tier supplier chain design problem with correlated failures and inspections, in which disruption risks propagate from second-tier suppliers to first-tier suppliers and inspections are performed to mitigate the risk of supplier failures. The problem is to decide first-tier suppliers' locations, the flow from first-tier suppliers to customers and inspection actions. The objective is to minimize the total cost. For the problem, a two-stage SO model is constructed, and a Monte Carlo-based sample average approximation method is proposed. Hosseini et al. [24] investigate a bi-objective supplier selection and optimal order allocation problem under ripple effects and uncertain suppliers' capacities, in which the impacts of ripple effects are quantified by BN and uncertain suppliers' capacities are expressed by a set of scenarios. The first objective is to maximize the geographical segregation of suppliers, while the second is to minimize the total cost. The studied problem is formulated as a bi-objective stochastic mixed-integer optimization model and solved by a scenario reduction procedure and ϵ-constraint combined heuristic. Sawik [27] studies a resilient SC operation optimization problem under ripple effects and uncertain demand. The impacts of the disruption propagation are described by disruption durations and propagation delays, and uncertain demand is depicted by a set of scenarios. For the problem, two-stage stochastic mixed-integer optimization models are proposed and handled by GUROBI. Liu et al. [21] investigate a general SC risk management problem under ripple effects and government interventions to improve SC viability, where the disruption risks and their propagation are portrayed by CBN. The objective is to minimize the manufacturer's disruption risk. Two novel mixed-integer non-linear SO models are proposed to formulate the studied problem. Furthermore, a problem-specific genetic algorithm is developed for handling large-scale problem instances. To the best of our knowledge, Liu et al. [21] is the first work to quantitatively evaluate the impacts of government interventions in the SC risk management field.

In summary, the above works assume that the probability distribution of uncertain parameters is fully known, which is unsuitable for a data-scarce environment. Most of these researches apply commercial solvers or develop heuristics to address the proposed models, except the work of Gholami-Zanjani et al. [25], which devises an exact method.

2.2. Robust optimization for SC risk mitigation

RO is always used to address partial distribution information of uncertain parameters, especially in a data-scarce environment. In the SC risk mitigation related literature, existing RO researches focus mainly on facility location and operation management under ripple effects. Lim et al. [44] study a facility location problem with facility disruptions and additional investments for mitigating the disruption risk. The probabilities and correlation of disruptions are represented by intervals and a covariance matrix, respectively. The objective is to minimize the expected total cost, including facility, transportation, and penalty costs. For analyzing the impacts of estimation errors in the disruption probability, a RO model is constructed. Based on the analysis, a continuous approximation model integrating correlated disruptions is further proposed to examine the impacts of such errors in the disruption probability and correlation. Hasani and Khosrojerdi [38] investigate a robust global SC design problem considering correlated disruptions, uncertain demand and procurement cost of components. In particular, disruptions and uncertainties are expressed by probabilities of occurrence scenarios and intervals, respectively. The objective is to maximize the total profit. The problem is formulated as a robust optimization model based on six risk mitigation strategies and solved by a parallel Taguchi-based memetic algorithm. Özçelik et al. [35] propose a robust optimization formulation for RSC under uncertainties caused by ripple effects from the worst-case perspective, in which uncertain transportation distances of routes are characterized by intervals. The problem consists of determining facility usage, worker and vehicle assignments, and transportation of recovered products. The aim is to maximize the number of total recovered products. For the problem, a robust optimization model is proposed and solved by calling CPLEX. Lu et al. [37] study a reliable facility location problem with given marginal disruption probabilities. The objective is to minimize the worst-case total expected cost, including facility location, transportation and service penalty costs. The problem is formulated by a distributionally RO model and solved by calling CPLEX. Zhao and Freeman [45] investigate a multi-supplier selection and order allocation problem with correlated disruption risks in which marginal disruption probabilities are known. The aim is to seek an optimal sourcing strategy which maximizes the expected profit in the worst case. For the problem, a distributionally robust (DR) optimization model and a distributionally optimistic (DO) model are respectively constructed. Then, a general model hybriding the above two models is established. Numerical experiments are performed to analyze the sourcing strategy. Gholami-Zanjani et al. [39] focus on a joint location-inventory problem under ripple effects and uncertainties, originating from demand, capacity and inventory level. Ripple effects and uncertainties are characterized by a correlation matrix and a set of scenarios, respectively. The objective of the problem is to maximize the expected profit. For the problem, a comprehensive two-stage scenario-based mixed-integer linear programming model is constructed. Then, a solution approach combined with Monte Carlo scenario generation and a robust optimization model are designed for the problem. Recently, Liu et al. [40] apply a robust dynamic BN approach to evaluate the worst-case probability of the disrupted state for the SC, where only probability intervals of SC members' states are known. They develop a simulated annealing algorithm to solve the problem. For the same problem, Liu et al. [46] further develop an efficient Tabu search heuristic to assess disruption risks in large scales. However, [40] and [46] do not investigate the intervention actions. Regarding these RO related literature, we remark (1) all these studies ignore possible government interventions to mitigate the disruption risk, although it is becoming a common practice in many countries; (2) few researchers apply BN to express the impacts of ripple effects, despite its successful applications in many areas to quantify the impact; (3) there is no exact solution method developed, possibly due to the complexities of the problems.

In this work, the government intervention improves both SC viability and resilience under severe and long-term disruptions. For the problem, a new mathematical model that combines CBN, Do-calculus and RO is constructed under data scarcity and ripple effects. Then, an exact PS-BAB algorithm is developed. With the aim of minimizing the worst-case manufacturer's disruption risk, the proposed approach can re-plan the SC performance or restore the SC to an initial state by intervening suppliers to different states. Table 1 summarizes the main differences between our work and the related literature for SC disruption risk mitigation under ripple effects.

3. Problem description and modeling

In this section, the studied problem is described in Section 3.1. Then, Section 3.2 presents CBN to quantify the disruption propagation. Do-calculus is applied in Section 3.3 to calculate the impacts of government interventions on a disrupted SC. Finally, based on CBN and Do-calculus, a robust optimization model is developed to select appropriate government interventions under data scarcity in Section 3.4.

3.1. Problem description

This work focuses on finding optimal government interventions to minimize the disruption risk of the manufacturer in a multi-echelon SC under data scarcity and ripple effects. Considering the necessity of performing government interventions on a representative SC, we choose to study general multi-echelon acyclic SCs in the paper [47], which are common in manufacturing SCs [48], pharmaceutical SCs [49], and

Table 1
Comparison of our work to related literature for SC disruption risk mitigation under ripple effects.

Authors	Government intervention	SO	RO	BN	Do-calculus	Solution methods
Yılmaz et al. [26]		✓				CPLEX
Gholami-Zanjani et al. [25]		✓				Benders decomposition
Sindhwani et al. [42]		✓		✓		Lagrangian relaxation and CPLEX
Pariazar et al. [43]		✓				Sample average approximation
Hosseini et al. [24]		✓		✓		ϵ-constraint based heuristic
Sawik [27]		✓				GUROBI
Liu et al. [21]	✓	✓		✓	✓	Genetic algorithm
Lim et al. [44]			✓			Continuous approximation
Hasani and Khosrojerdi [38]			✓			Parallel memetic algorithm
Özçelik et al. [35]			✓			CPLEX
Lu et al. [37]			✓			CPLEX
Zhao and Freeman [45]			✓			–
Gholami-Zanjani et al. [39]			✓			Monte Carlo-based algorithm
Liu et al. [40]			✓	✓		Simulated annealing
Liu et al. [46]			✓	✓		Tabu search
This paper	✔		✔	✔	✔	Branch-and-bound algorithm

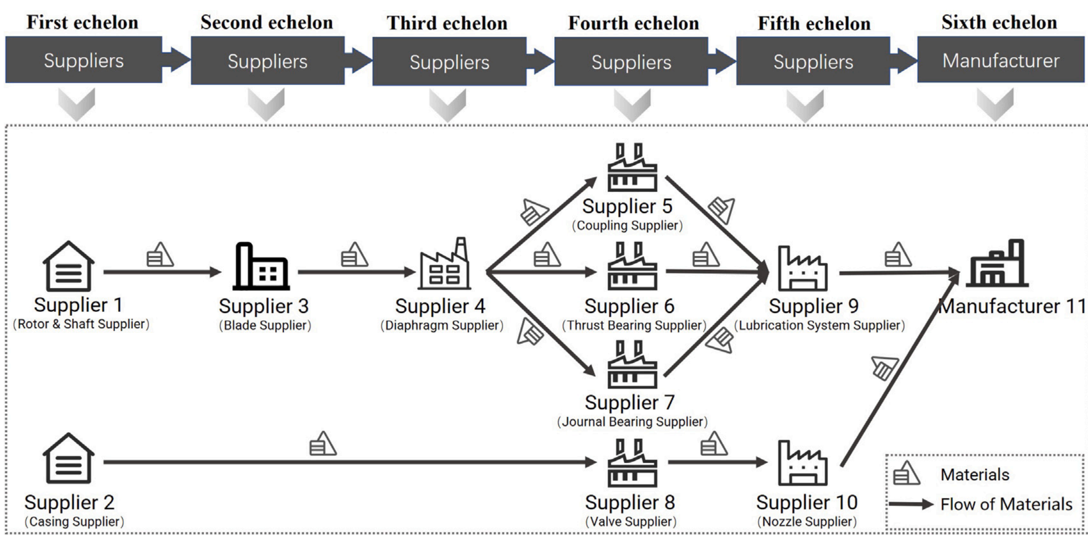

Fig. 1. A 6-echelon SC with 10 suppliers and 1 manufacturer.

food SCs [50], et al. In the following, the studied problem is formally presented.

Consider a multi-echelon SC network $(\mathcal{N}, \mathcal{L})$, where $\mathcal{N}$ is the set of SC partners (i.e., multiple suppliers and a manufacturer), and $\mathcal{L}$ is the relationships of material flows among the SC partners. Let set $\mathcal{K} = \{1, \ldots, k, \ldots, |\mathcal{K}|\}$ represent the set of echelons in the SC. $\mathcal{N}^k$ denotes the set of SC partners in echelon $k \in \mathcal{K}$. Specifically, the manufacturer locates in the $|\mathcal{K}|$th echelon, and it is denoted by $|\mathcal{N}|$. We have $\bigcup_{k\in\mathcal{K}} \mathcal{N}^k = \mathcal{N}$. To express the supplying relationships, let γ_j be the set of direct (or tier-one) suppliers of SC partner $j \in \mathcal{N}$. We have also $\bigcup_{j\in\mathcal{N}} \gamma_j = \mathcal{N} \backslash |\mathcal{N}|$. According to the SC in [48], a 6-echelon steam turbine manufacturing SC network with 10 suppliers and 1 manufacturer is illustrated in Fig. 1. Thus, we have $|\mathcal{K}| = 6$, $|\mathcal{N}| = 11$, and SC partners in each echelon are represented as $\mathcal{N}^1 = \{1, 2\}$, $\mathcal{N}^2 = \{3\}$, $\mathcal{N}^3 = \{4\}$, $\mathcal{N}^4 = \{5, 6, 7, 8\}$, $\mathcal{N}^5 = \{9, 10\}$, $\mathcal{N}^6 = \{11\}$. We have also the following sets of tier-one suppliers for each SC partner: $\gamma_1 = \gamma_2 = \emptyset$, $\gamma_3 = \{1\}$, $\gamma_4 = \{3\}$, $\gamma_5 = \{4\}$, $\gamma_6 = \{4\}$, $\gamma_7 = \{4\}$, $\gamma_8 = \{2\}$, $\gamma_9 = \{5, 6, 7\}$, $\gamma_{10} = \{8\}$, $\gamma_{11} = \{9, 10\}$. For example, SC partners 1 and 2 have no tier-one suppliers, and the tier-one suppliers of SC partner 11 are 9 and 10. Note that the casing supplier is in the third-echelon in [48]. Considering that the casing supplier has no tier-one suppliers, we adjust it to the first echelon for ease of explanation in subsequent sections.

In the study, we suppose that a SC partner has multiple possible states. For simplicity, we define S_j as the (ordered) index set of all possible states of SC partner $j \in \mathcal{N}$. The states from fully-operational to fully-disrupted with increasing order of disruption severity are indexed from 1 to $|S_j|$, respectively. Let r_{js} represent the sth state of SC partner $j \in \mathcal{N}$, where $s \in S_j$. Here, s is called the state-index. For example, r_{j1} means the fully-operational state for SC partner $j \in \mathcal{N}$. Let A_{js} be the probability of SC partner $j \in \mathcal{N}$ in state r_{js}, $s \in S_j$. Under data scarcity, we suppose that only the lower and upper bounds (denoted by $\underline{a}_{js}$ and $\overline{a}_{js}$ respectively) of uncertain state probability A_{js} of each SC partner in the first echelon are known, i.e., $A_{js} \in [\underline{a}_{js}, \overline{a}_{js}]$ for $j \in \mathcal{N}^1$ and $s \in S_j$. That is, we only know partial probability distribution information. The lower and upper bounds of state probabilities of SC partners in other echelons are unknown, but they can be deduced based on known information (which we will explain later). The state probability distribution of SC partner $j \in \mathcal{N}$ can be represented as a vector $\left(A_{j1}, \ldots, A_{js}, \ldots, A_{j|S_j|}\right)^{\top}$, which agrees with the probability axiom $\sum_{s=1}^{|S_j|} A_{js} = 1$.

For the manufacturer $|\mathcal{N}|$ in the SC, the state probability $A_{|\mathcal{N}||S_{|\mathcal{N}|}|}$ means the chance it is in the fully-disrupted state, which should be minimized [21]. The smaller the $A_{|\mathcal{N}||S_{|\mathcal{N}|}|}$ is, the more viable the SC is. In practice, government interventions can be performed to improve SC viability and reduce ripple effects, while the total cost of intervention actions should not exceed a given budget. The goal of the problem is to minimize the worst-case probability of the manufacturer in the fully-disrupted state under data scarcity. To this end, an optimal government

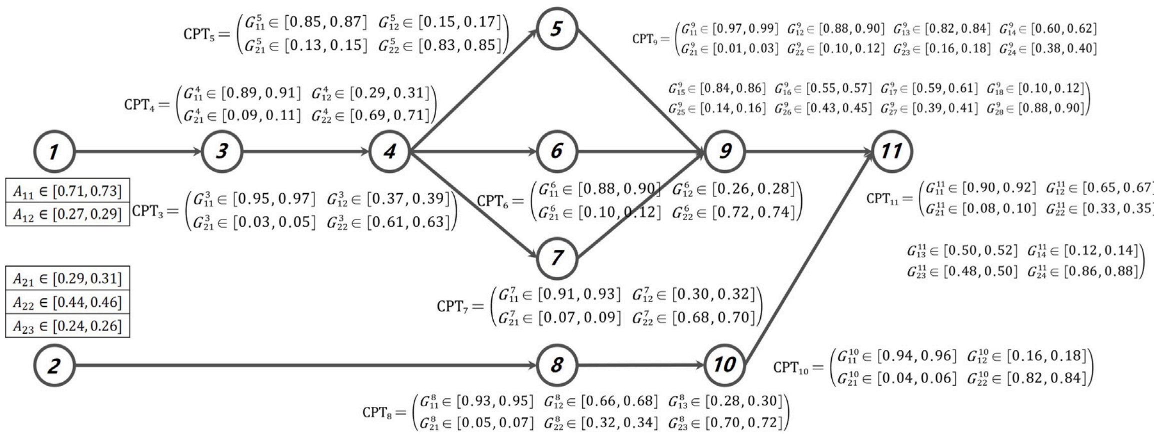

Fig. 2. State probability intervals for nodes in the first echelon and state conditional probability intervals for nodes from the second to the last echelons without disruptions.

intervention scheme should be decided subject to the limited budget under partial probability distribution information. In the following, before presenting the mathematical optimization model, CBN is applied to quantify the ripple effects, and the influences of government interventions are measured by Do-calculus.

3.2. Quantifying ripple effects via CBN

CBN is a directed acyclic graph formed by nodes and arcs to represent causal relationships [51]. Consider a CBN based on the studied SC network, states of SC partners can be represented as nodes, and relationships of the disruption propagation among these partners can be depicted by arcs [52]. For ease of notation, we also employ $(\mathcal{N}, \mathcal{L})$ to denote the CBN (which has been previously used in Section 3.1 to portray the SC network), where $\mathcal{N}$ represents the set of nodes and $\mathcal{L}$ the set of arcs between nodes. In the context of CBN, γ_j also means the set of parent nodes of node $j \in \mathcal{N}$.

For nodes from the second to the last echelons, their state probabilities can be determined by their parent nodes' state probabilities and their conditional probability tables (CPTs). The elements in CPT_j are called state conditional probabilities of node $j \in \mathcal{N} \backslash \mathcal{N}^1$. Let $\mathcal{M}_j$ be the (ordered) set of state combinations of node j's parent nodes, indexed by m which is referred to as the state-combination-index. Let G^j_{sm} denote the conditional probability of node $j \in \mathcal{N} \backslash \mathcal{N}^1$ in the sth state under the mth state combination of its parent nodes, where $s \in \mathcal{S}_j$ and $m \in \mathcal{M}_j$. Due to data scarcity, only the lower and upper bounds (represented by $\underline{g}^j_{sm}$ and $\overline{g}^j_{sm}$ respectively) of uncertain state conditional probability G^j_{sm} are assumed to be known, i.e., $G^j_{sm} \in [\underline{g}^j_{sm}, \overline{g}^j_{sm}]$ for $j \in \mathcal{N} \backslash \mathcal{N}^1$, $s \in \mathcal{S}_j$, and $m \in \mathcal{M}_j$. Note that the probability axiom $\sum_{s \in \mathcal{S}_j} G^j_{sm} = 1$ should be met as well for $j \in \mathcal{N} \backslash \mathcal{N}^1$ and $m \in \mathcal{M}_j$. Then, the conditional probability table CPT_j is defined as follows:

$$\mathrm{CPT}_j = \begin{pmatrix} G^j_{11} & \cdots & G^j_{1|\mathcal{M}_j|} \\ \vdots & G^j_{sm} & \vdots \\ G^j_{|\mathcal{S}_j|1} & \cdots & G^j_{|\mathcal{S}_j||\mathcal{M}_j|} \end{pmatrix}, \quad \forall j \in \mathcal{N} \backslash \mathcal{N}^1, s \in \mathcal{S}_j, m \in \mathcal{M}_j,$$

where the number of columns in CPT_j coincides with the number of state combinations of node j's parent nodes (i.e., $|\mathcal{M}_j|$), and the number of rows in CPT_j corresponds to the number of possible states of node j (i.e., $|\mathcal{S}_j|$).

Based on the example in Fig. 1, Fig. 2 shows state probability distributions (in the intervals) of nodes in the first echelon and CPTs (in the intervals) of nodes from the second to the last echelons without disruptions. In this example, for ease of illustration, node 2 is supposed to have three states (i.e., fully-operational state, semi-disrupted state, and fully-disrupted state, with respective indices 1, 2, and 3), and other nodes are assumed to have two states (i.e., fully-operational state and fully-disrupted state with respective indices 1 and 2, where node $j \in \{1, 3, 4, 5, 6, 7, 8, 9, 10, 11\}$). All CPTs have two rows. To explain the number of columns in a CPT, we take CPT_{11} as an example. Node 11 has two parent nodes (i.e., $\gamma_{11} = \{9, 10\}$), resulting in $2^2 = 4$ state combinations of parent nodes (i.e., $\mathcal{M}_{11} = \{(r_{91}, r_{101}), (r_{91}, r_{102}), (r_{92}, r_{101}), (r_{92}, r_{102})\}$). Thus CPT_{11} has four columns, and the state combinations are indexed by 1, 2, 3, and 4, respectively. In the first row of CPT_{11}, the elements are G^{11}_{11} and G^{11}_{12} which represent the conditional probabilities of node 11 in the first state (i.e., fully-operational state) under two different state combinations of its parent nodes (i.e., two elements in $\mathcal{M}_{11}$). Similarly, nodes 3, 4, 5, 6, 7, 8 and 10 has only one parent node, so CPT_3, CPT_4, CPT_5, CPT_6, CPT_7 and CPT_{10} have $2^1 = 2$ state combinations, and CPT_8 has $3^1 = 3$ state combinations. Especially, node 9 has 3 parent nodes, thus CPT_9 has $2^3 = 8$ state combinations, i.e., 8 columns.

Fig. 3(a) illustrates that uncertain disruptive events attack suppliers 1 and 10 and create ripple effects along the red arrows. The updated state probability intervals of node 1 and the updated state conditional probability intervals of node 10 (i.e., the intervals of each element in CPT_{10}) are illustrated with red color in Fig. 3(b). Without being affected by disruptive events, the state probability intervals of node 2 and the state conditional probability intervals of nodes 3, 4, 5, 6, 7, 8, 9 and 11 remain unchanged as in Fig. 2.

To calculate the state probabilities of nodes from the second to the last echelons, the mapping relationship between the set $\mathcal{M}_j$, $j \in \mathcal{N} \backslash \mathcal{N}^1$, and the state-combination-index $m \in \mathcal{M}_j$ should be established firstly [21]. Let $\mathrm{M}_j(\cdot)$ be a bijection mapping $\mathcal{M}_j \xrightarrow{\mathrm{M}_j(\cdot)} \left\{1, \ldots, m, \ldots, \left|\mathcal{M}_j\right|\right\}$, which represents that a state combination of node j's parent nodes is mapped to a state-combination-index of node $j \in \mathcal{N} \backslash \mathcal{N}^1$. Then the corresponding inverse mapping $\mathrm{M}^{-1}_j(\cdot)$ can be represented as $\left\{1, \ldots, m, \ldots, \left|\mathcal{M}_j\right|\right\} \xrightarrow{\mathrm{M}^{-1}_j(\cdot)} \mathcal{M}_j$. Let $\mathrm{M}^{-1}_j(m)(j')$ denote the state-index of parent node j' in the mth state combination, where $j \in \mathcal{N} \backslash \mathcal{N}^1$, $j' \in \gamma(j)$, $m \in \mathcal{M}_j$. Recalling in the previous example that $\mathcal{M}_{11} = \{(r_{91}, r_{101}), (r_{91}, r_{102}), (r_{92}, r_{101}), (r_{92}, r_{102})\}$, for example, $\mathrm{M}^{-1}_{11}(3)(9) = 2$ here means that parent node 9, given the state-combination-index 3, of node 11 is in the second state.

Next, we will use the above-defined variables to calculate the probability of the manufacturer in the fully-disrupted state, which represents the risk of the SC in our setting. Based on the state probability distribution $\left(A_{j1}, \ldots, A_{js}, \ldots, A_{j|\mathcal{S}_j|}\right)^{\top}$ of node $j \in \mathcal{N}^1$, and CPT_j of node $j \in \mathcal{N} \backslash \mathcal{N}^1$, the state probabilities of node $j \in \mathcal{N} \backslash \mathcal{N}^1$ can be calculated via the following equation [21]:

$$A_{js} = \sum_{m=1}^{\left|\mathcal{M}_j\right|} G^j_{sm} \prod_{j' \in \gamma_j} A_{j', \mathrm{M}^{-1}_j(m)(j')}, \quad j \in \mathcal{N} \backslash \mathcal{N}^1, s \in \mathcal{S}_j, \tag{1}$$

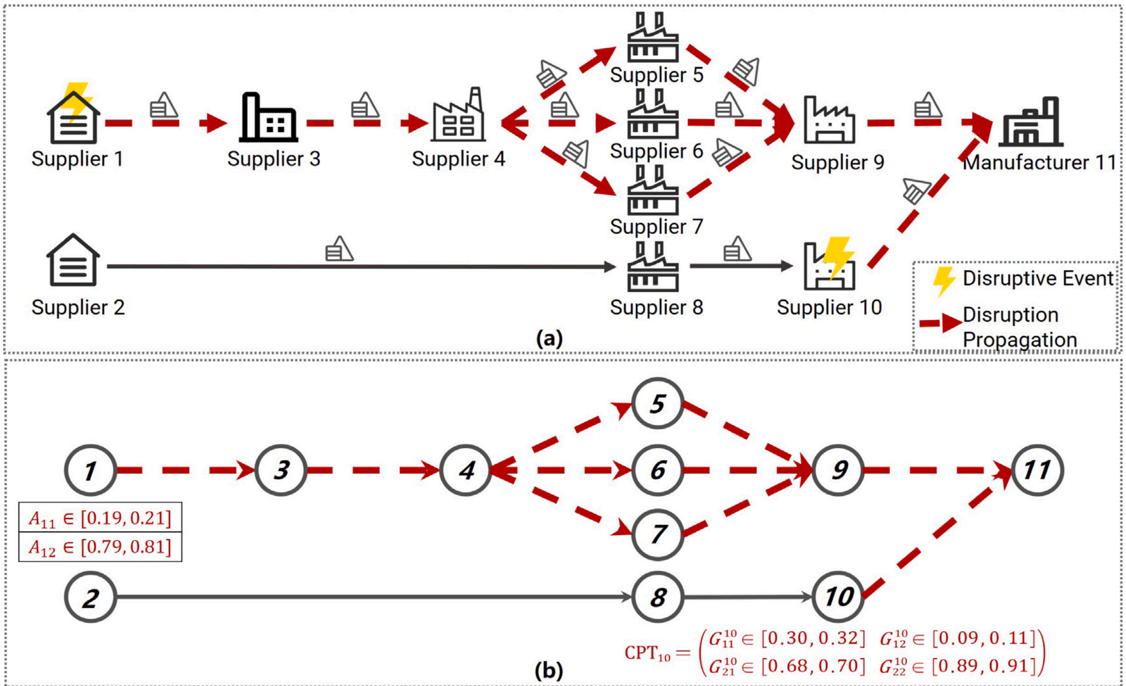

Fig. 3. (a) Suppliers 1 and 10 suffer disruptive events with ripple effects. (b) Updated state probability intervals of node 1 and state conditional probability intervals of node 10 under disruptions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

where $A_{j',\mathrm{M}_j^{-1}(m)(j')}$ means the probability of parent node $j' \in \gamma_j$ (of node $j \in \mathcal{N}\backslash\mathcal{N}^1$) in the $\mathrm{M}_j^{-1}(m)(j')$th state.

For example, in Fig. 3(b), we suppose that if the state probability distribution of node 1 is $\left(A_{11}, A_{12}\right)^\top = (0.20, 0.80)^\top$ and the elements in CPT_3 are given as $G_{11}^3 = 0.96$, $G_{12}^3 = 0.38$, $G_{21}^3 = 0.04$, and $G_{22}^3 = 0.62$, and then the state probabilities of node 3 can be calculated via Eq. (1) as:

$$A_{31} = G_{11}^3 \cdot A_{11} + G_{12}^3 \cdot A_{12} = 0.96 \cdot 0.20 + 0.38 \cdot 0.80 = 0.496,$$

$$A_{32} = G_{21}^3 \cdot A_{11} + G_{22}^3 \cdot A_{12} = 0.04 \cdot 0.20 + 0.62 \cdot 0.80 = 0.504.$$

3.3. Government interventions

Government intervention is a well-known strategy to reinforce SC viability under ripple effects [21], but the financial budget is always limited. Thus, it is important to quantitatively evaluate the impacts of government interventions, and to appropriately utilize the given budget. With Do-calculus technique [51], the impacts of interventions can be quantified through a mathematical tool called *do-operator*, denoted as $do(\cdot)$. In this paper, to show the effects of government interventions on ripple effects, only suppliers (i.e., node $j \in \mathcal{N}\backslash|\mathcal{N}|$) are allowed to be intervened.

Let R_j represent the state of node $j \in \mathcal{N}\backslash|\mathcal{N}|$, which is a random variable, and let $do(R_j = r_{js})$ denote an intervention such that node j is intervened to be state r_{js}, where $s \in \mathcal{S}_j$. Regarding where an intervention occurs, we distinguish the following two cases. (i) If node $j \in \mathcal{N}^1$ is intervened to be the sth state, $s \in \mathcal{S}_j$, then the state probability A_{js} is updated to be 1, and consequently, the probabilities of this node in the other states become 0. That is, when applying $do(R_j = r_{js})$, the state probability distribution of node $j \in \mathcal{N}^1$ becomes $\left(A_{j1}, \ldots, A_{js-1}, A_{js}, A_{js+1}, \ldots, A_{j|\mathcal{S}_j|}\right)^\top = (0, \ldots, 0, 1, 0, \ldots, 0)^\top$. (ii) If node $j \in \mathcal{N}\backslash\{\mathcal{N}^1, |\mathcal{N}|\}$ is intervened to be the sth state, $s \in \mathcal{S}_j$, then the state conditional probabilities in the sth row of CPT_j are updated to be 1, while those in the other rows of CPT_j become 0. That is, the CPT_j is updated as follows:

$$\mathrm{CPT}_j = \begin{pmatrix} G_{11}^j = 0 & \cdots & G_{1m}^j = 0 & \cdots & G_{1|\mathcal{M}_j|}^j = 0 \\ \vdots & & & & \vdots \\ G_{s1}^j = 1 & \cdots & G_{sm}^j = 1 & \cdots & G_{s|\mathcal{M}_j|}^j = 1 \\ \vdots & & & & \vdots \\ G_{|\mathcal{S}_j|1}^j = 0 & \cdots & G_{|\mathcal{S}_j|m}^j = 0 & \cdots & G_{|\mathcal{S}_j||\mathcal{M}_j|}^j = 0 \end{pmatrix},$$

where $j \in \mathcal{N}\backslash\{\mathcal{N}^1, |\mathcal{N}|\}$, $s \in \mathcal{S}_j$, $m \in \mathcal{M}_j$.

Fig. 4(a) and (b) illustrate the above two intervention cases such that nodes 1 and 4 are both intervened to be the first state, i.e., interventions $do(R_1 = r_{11})$ and $do(R_4 = r_{41})$ are performed. Consequently, the state probability distribution of node 1 is updated as $\left(A_{11}, A_{12}\right)^\top = (1, 0)^\top$. The state conditional probabilities in the first row of CPT_4 are updated to be 1, and the elements in the second row become 0. In this example, the updated CPT_4 is represented as:

$$\mathrm{CPT}_4 = \begin{pmatrix} 1 & 1 \\ 0 & 0 \end{pmatrix}.$$

According to the updated CPT_4, the probability of node 4 in the first state can be calculated via Eq. (1) and the probability axiom $\sum_{s=1}^{|\mathcal{S}_j|} A_{js} = 1$.

$$A_{41} = G_{11}^4 \cdot A_{11} + G_{12}^4 \cdot A_{12} = 1 \cdot A_{11} + 1 \cdot A_{12} = 1.$$

In addition, the probability of node 4 in the second state becomes 0. We have $\left(A_{41}, A_{42}\right)^\top = (1, 0)^\top$. In real applications, the budget for government interventions is always limited. For efficiently selecting appropriate interventions under data scarcity, we develop a robust optimization model in Section 3.4 to evaluate the probability of the manufacturer in the fully-disrupted state from the worst-case perspective.

3.4. Robust optimization model

In this subsection, a robust optimization model is established to minimize the manufacturer's probability in the fully-disrupted state

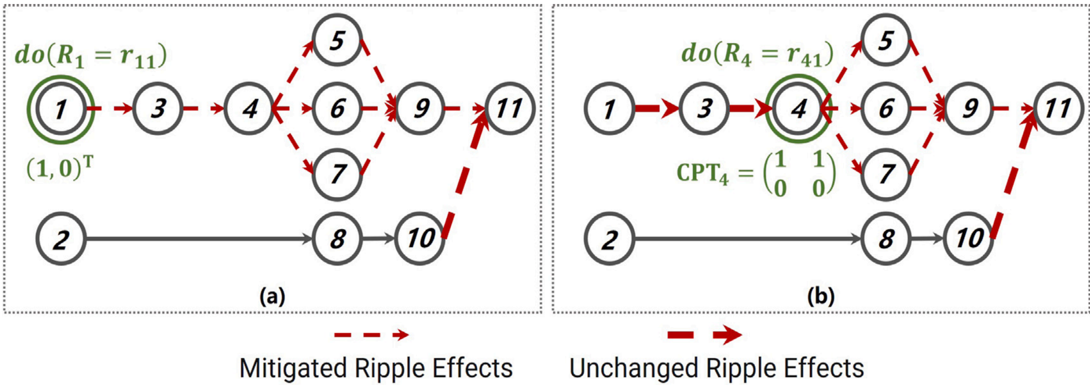

Fig. 4. (a) The intervention $do(R_1 = r_{11})$ on node 1. (b) The intervention $do(R_4 = r_{41})$ on node 4.

from the worst-case perspective. Before establishing the formulation, the problem assumptions are summarized as follows.

1. The studied SC comprises multiple echelons, and it is composed of several suppliers and one manufacturer [53]. There are no cycles or feedbacks in the SC network.
2. The disruptive events can hit any suppliers from the first to the penultimate echelons.
3. A SC partner has multiple possible states from the fully-operational state to the fully-disrupted state in the order of severity. The sum of state probabilities of node $j \in \mathcal{N}$ is equal to 1, i.e., the probability axiom $\sum_{s=1}^{|\mathcal{S}_j|} A_{js} = 1$ holds.
4. Under data scarcity, the lower and upper bounds of state probabilities of SC partners in the first echelon are known. The lower and upper bounds of state conditional probabilities of SC partners from the second to the last echelons are given.
5. Government interventions can be performed on several SC suppliers to mitigate ripple effects [21]. Consequently, their state conditional probabilities are updated.
6. The budget for government interventions is limited and must be respected. The cost of intervening a SC partner to be the fully-operational state is more expensive than that to other states [21].
7. A problem assumption is given according to the following proposition.

Proposition 1. *The government will not intervene SC suppliers to be the fully-disrupted state no matter how large the budget is.*

Proof. See Appendix A of the supplementary material. □

In the following, the probability of the manufacturer in the fully-disrupted state is also called its fully-disrupted probability, for simplicity. The purpose of the study is to minimize the disruption risk of the manufacturer from the worst-case perspective by considering all possible interventions under a limited budget. Given an intervention solution (i.e., a combination of interventions), the worst-case disruption risk of the manufacturer is mathematically modeled by maximizing the manufacturer's fully-disrupted probability under data scarcity, i.e., subject to known probability intervals. Thus, in this subsection, a minimax optimization formulation is designed to select an optimal intervention solution which minimizes the worst-case probability of the manufacturer in the fully-disrupted state.

Next, we first introduce the input parameters and decision variables, then detail the robust optimization model.

Input Parameters

$\mathcal{K}$: Set of echelons in the SC, indexed by k;
$\mathcal{N}$: Set of nodes (representing SC partners), indexed by j, where node $|\mathcal{N}|$ corresponds to the manufacturer and the other nodes represent all suppliers;
$\mathcal{N}^k$: Set of nodes in the kth echelon, $k \in \mathcal{K}$;
$\mathcal{S}_j$: Set of states for node j, indexed by s, $j \in \mathcal{N}$;
$\mathcal{M}_j$: Set of state combinations of node j's parent nodes, indexed by m, $j \in \mathcal{N} \setminus \mathcal{N}^1$;
γ_j: Set of parent nodes of node j, $j \in \mathcal{N}$;
$\underline{a}_{js}$: The lower bound of the probability of node j in the sth state, where $j \in \mathcal{N}^1$, $s \in \mathcal{S}_j$;
$\overline{a}_{js}$: The upper bound of the probability of node j in the sth state, where $j \in \mathcal{N}^1$, $s \in \mathcal{S}_j$;
$\underline{g}^j_{sm}$: The lower bound of the probability of node j in the sth state conditional on the mth state combination of its parent nodes, where $j \in \mathcal{N} \setminus \mathcal{N}^1$, $s \in \mathcal{S}_j$, $m \in \mathcal{M}_j$;
$\overline{g}^j_{sm}$: The upper bound of the probability of node j in the sth state conditional on the mth state combination of its parent nodes, where $j \in \mathcal{N} \setminus \mathcal{N}^1$, $s \in \mathcal{S}_j$, $m \in \mathcal{M}_j$;
$\mathrm{M}_j^{-1}(m)(j')$: The state-index of parent node j' for node j with given state-combination-index m, where $j' \in \gamma_j$, $j \in \mathcal{N} \setminus \mathcal{N}^1$, $m \in \mathcal{M}_j$;
C_{js}: The intervention cost to intervene node j to be the sth state, where $j \in \mathcal{N} \setminus |\mathcal{N}|$, $s \in \mathcal{S}_j$;
D: The total budget for the implementation of government interventions.

Decision variables

z_{js}: Equal to 1 if node j is intervened to be the sth state (i.e., $do(R_j = r_{js})$), 0 otherwise, where $j \in \mathcal{N} \setminus |\mathcal{N}|$, $s \in \mathcal{S}_j$;
A_{js}: The probability of node j in the sth state, where $j \in \mathcal{N}$, $s \in \mathcal{S}_j$;
G^j_{sm}: The conditional probability of node j in the sth state under the mth state combination of its parent nodes, where $j \in \mathcal{N} \setminus \mathcal{N}^1$, $s \in \mathcal{S}_j$, $m \in \mathcal{M}_j$.

Robust Optimization Model

$$\min_{z} \left\{ \max_{A,G} A_{|\mathcal{N}|,|\mathcal{S}_{|\mathcal{N}|}|} \right\} \tag{2}$$

s.t. Constraints (1)

$$\sum_{s=1}^{|\mathcal{S}_j|} z_{js} \le 1, \quad \forall j \in \mathcal{N} \setminus |\mathcal{N}| \tag{3}$$

$$\sum_{j=1}^{|\mathcal{N}|-1} \sum_{s=1}^{|\mathcal{S}_j|} C_{js} z_{js} \le D \tag{4}$$

$$A_{js} \le 2 - z_{js}, \quad \forall j \in \mathcal{N}^1, s \in \mathcal{S}_j \tag{5}$$

$$A_{js} \geq z_{js}, \quad \forall j \in \mathcal{N}^1, s \in \mathcal{S}_j \tag{6}$$

$$A_{js} \leq 1 + z_{js} - \sum_{s=1}^{|\mathcal{S}_j|} z_{js}, \quad \forall j \in \mathcal{N}^1, s \in \mathcal{S}_j \tag{7}$$

$$A_{js} \leq \bar{a}_{js} + \sum_{s=1}^{|\mathcal{S}_j|} z_{js}, \quad \forall j \in \mathcal{N}^1, s \in \mathcal{S}_j \tag{8}$$

$$A_{js} \geq \underline{a}_{js} - \sum_{s=1}^{|\mathcal{S}_j|} z_{js}, \quad \forall j \in \mathcal{N}^1, s \in \mathcal{S}_j \tag{9}$$

$$\sum_{s=1}^{|\mathcal{S}_j|} A_{js} = 1, \quad \forall j \in \mathcal{N}^1 \tag{10}$$

$$G^j_{sm} \leq 2 - z_{js}, \quad \forall j \in \mathcal{N} \backslash \{\mathcal{N}^1, |\mathcal{N}|\}, s \in \mathcal{S}_j, m \in \mathcal{M}_j \tag{11}$$

$$G^j_{sm} \geq z_{js}, \quad \forall j \in \mathcal{N} \backslash \{\mathcal{N}^1, |\mathcal{N}|\}, s \in \mathcal{S}_j, m \in \mathcal{M}_j \tag{12}$$

$$G^j_{sm} \leq 1 + z_{js} - \sum_{s=1}^{|\mathcal{S}_j|} z_{js}, \quad \forall j \in \mathcal{N} \backslash \{\mathcal{N}^1, |\mathcal{N}|\}, s \in \mathcal{S}_j, m \in \mathcal{M}_j \tag{13}$$

$$G^j_{sm} \leq \bar{g}^j_{sm} + \sum_{s=1}^{|\mathcal{S}_j|} z_{js}, \quad \forall j \in \mathcal{N} \backslash \{\mathcal{N}^1, |\mathcal{N}|\}, s \in \mathcal{S}_j, m \in \mathcal{M}_j \tag{14}$$

$$G^j_{sm} \geq \underline{g}^j_{sm} - \sum_{s=1}^{|\mathcal{S}_j|} z_{js}, \quad \forall j \in \mathcal{N} \backslash \{\mathcal{N}^1, |\mathcal{N}|\}, s \in \mathcal{S}_j, m \in \mathcal{M}_j \tag{15}$$

$$\sum_{s=1}^{|\mathcal{S}_j|} G^j_{sm} = 1, \quad \forall j \in \mathcal{N} \backslash \mathcal{N}^1, m \in \mathcal{M}_j \tag{16}$$

$$\underline{g}^{|\mathcal{N}|}_{sm} \leq G^{|\mathcal{N}|}_{sm} \leq \bar{g}^{|\mathcal{N}|}_{sm}, \quad \forall s \in \mathcal{S}_{|\mathcal{N}|}, m \in \mathcal{M}_{|\mathcal{N}|} \tag{17}$$

$$z_{j|\mathcal{S}_j|} = 0, \quad \forall j \in \mathcal{N} \backslash |\mathcal{N}| \tag{18}$$

$$0 \leq A_{js} \leq 1, \quad \forall j \in \mathcal{N}, s \in \mathcal{S}_j, m \in \mathcal{M}_j \tag{19}$$

$$0 \leq G^j_{sm} \leq 1, \quad \forall j \in \mathcal{N} \backslash \mathcal{N}^1, s \in \mathcal{S}_j, m \in \mathcal{M}_j \tag{20}$$

$$z_{js} \in \{0, 1\}, \quad \forall j \in \mathcal{N} \backslash |\mathcal{N}|, s \in \mathcal{S}_j \tag{21}$$

The objective function (2) is to minimize the worst-case probability of the manufacturer (i.e., node $|\mathcal{N}|$) in the fully-disrupted state, where $\boldsymbol{z}$ denotes all variables z_{js} for $j \in \mathcal{N} \backslash |\mathcal{N}|$ and $s \in \mathcal{S}_j$, $\boldsymbol{A}$ denotes all variables A_{js} for $j \in \mathcal{N}$ and $s \in \mathcal{S}_j$, and $\boldsymbol{G}$ denotes all variables G^j_{sm} for $j \in \mathcal{N} \backslash \mathcal{N}^1$, $s \in \mathcal{S}_j$, and $m \in \mathcal{M}_j$. Constraints (1) calculate the state probabilities for suppliers (except those in the first echelon) and the manufacturer. Constraints (3) guarantee that a supplier can only be intervened to be a specific state, if an intervention is performed on it. Constraint (4) ensures that the total intervention cost must respect the limited budget. Constraints (5)–(9) update the state probabilities of first-echelon supplier $j \in \mathcal{N}^1$ via intervention rules. Specifically, Constraints (5)–(6) mean that if first-echelon supplier $j \in \mathcal{N}^1$ is intervened to be the sth state (i.e., $z_{js} = 1$), where $s \in \mathcal{S}_j$, then the state probability A_{js} is updated to be 1; Constraints (7) signify that if first-echelon supplier $j \in \mathcal{N}^1$ is intervened, but the intervention is not on its sth state, where $s \in \mathcal{S}_j$, then its probability in the sth state is update to be 0, i.e., $A_{js} = 0$; and Constraints (8)–(9) ensure that the probability of first-echelon supplier $j \in \mathcal{N}^1$ in the sth state conforms with its state probability interval if it is not intervened, where $s \in \mathcal{S}_j$. Constraints (10) guarantee that the state probabilities of first-echelon supplier $j \in \mathcal{N}^1$ meet the probability axiom. Similarly, Constraints (11)–(15) update the state conditional probabilities of (non-first-echelon) supplier $j \in \mathcal{N} \backslash \{\mathcal{N}^1, |\mathcal{N}|\}$ via intervention rules. Constraints (16) guarantee that the state conditional probabilities of non-first-echelon SC partner $j \in \mathcal{N} \backslash \mathcal{N}^1$ satisfy the probability axiom. Constraints (17) ensure that the state conditional probabilities of the manufacturer $|\mathcal{N}|$ are within the upper and lower bounds. Constraints (18) ensure that suppliers are not intervened to be the fully-disrupted state according to Proposition 1. Constraints (19)–(21) give the domains of decision variables.

The minimax optimization model is a non-linear robust optimization model due to the objective function (2) and Constraints (1). The existing commercial optimization solvers cannot be applied to it, to the best of our knowledge. Thus, an exact problem-specific branch-and-bound (PS-BAB) algorithm is developed in the next section to solve the problem.

4. Solution method

The reformulation technique [54] and branch-and-bound (i.e., BAB) [55] are two main ways to find an optimal solution of the minimax optimization model. The former consists of transforming the minimax formulation into an equivalent minimization one via reforming the dual of its inner maximization such that the reformulated problem can be solved by classical optimal methods or by a commercial optimization solver. However, this technique is not applicable to the studied problem because Constraints (1) in the formulation in Section 3.4 are non-convex equality posynomial functions [56]. Thus, it cannot satisfy strong duality that is essential for applying the reformulation technique [57].

The principle of BAB describes the solution space via a tree structure, and searches for an optimal solution through exploring all branches. The branching scheme partitions the solution space into subspaces, where each non-leaf and leaf vertex often represents a *partial solution* and a *feasible solution*, respectively [58]. A non-leaf vertex is discarded by pruning rules if it cannot promise a better solution than the best one found so far. The algorithm continues until all branches are explored. In the study, a problem-specific branch-and-bound (PS-BAB) algorithm is developed by investigating the problem properties. Especially, pruning rules are developed and an initial upper bound (UB_c) is proposed via solving a non-convex SGP (signomial geometric programming) model (detailed in Section 4.1). The pruning rules include: (1) a dominance rule presented in Section 4.1, (2) an intervention cost checking procedure, and (3) a lower bound for each non-leaf vertex proposed by an efficient iterative-approximation-and-repair (IAR) algorithm (detailed in Section 4.2).

Fig. 5 illustrates the structure of the PS-BAB tree with $|\mathcal{N}|$ levels, where the index of levels l is in the set $\{0, 1, \dots, l, \dots, |\mathcal{N}| - 1\}$. The depth-first search strategy is used to ensure that all possible regions of the solution space are explored. Specifically, $Level\ l = 0$ locates the root vertex and $Level\ l = 1, 2, \dots, |\mathcal{N}| - 1$, represents various decisions made on SC partner $j = |\mathcal{N}| - 1, |\mathcal{N}| - 2, \dots, 1$, respectively. We know $l + j = |\mathcal{N}|$. Let $\mathcal{V}_l$ denote the set of vertices in $Level\ l$, where $l \geq 0$. Recall that $\mathcal{S}_j$, $j \in \mathcal{N}$, represents the set of state-index of SC partner j, and $|\mathcal{S}_j|$ is the number of j's states. In $Level\ l \geq 1$ of our PS-BAB tree, the set $\mathcal{V}_l$ is detailed as $\mathcal{V}_l = \{v^0_l, v^1_l, \dots, v^{|\mathcal{S}_j|-1}_l\}$, where elements in $\mathcal{V}_l$ are explained as follows. The first vertex v^0_l in $Level\ l$ records the intervention decision "0", which means that SC partner j is not intervened. From the second to the last vertices in $Level\ l$, each vertex v^s_l records the intervention decision "s", representing that SC partner j is intervened to be the sth state, where $s \in \mathcal{S}_j \backslash |\mathcal{S}_j|$. When a SC partner $j \in \mathcal{N} \backslash |\mathcal{N}|$ is intervened to be the sth state, its probability in this state becomes 1. Consequently, the probability of SC partner j in the s'th state is equal to 0, where $s' \in \mathcal{S}_j \backslash \{s, |\mathcal{S}_j|\}$. Note that there is no need to intervene SC partner $j \in \mathcal{N} \backslash |\mathcal{N}|$ to be the $|\mathcal{S}_j|$th state according to Proposition 1 in Section 3.4. Thus, the corresponding vertices are not included in the PS-BAB tree.

At the beginning of searching the PS-BAB tree, it is first checked whether the budget is equal to or greater than the upper limit proposed in Theorem 1. If it is (i.e., the condition of Theorem 1 is satisfied), then the optimal government intervention solution can be obtained directly from this theorem and the algorithm stops.

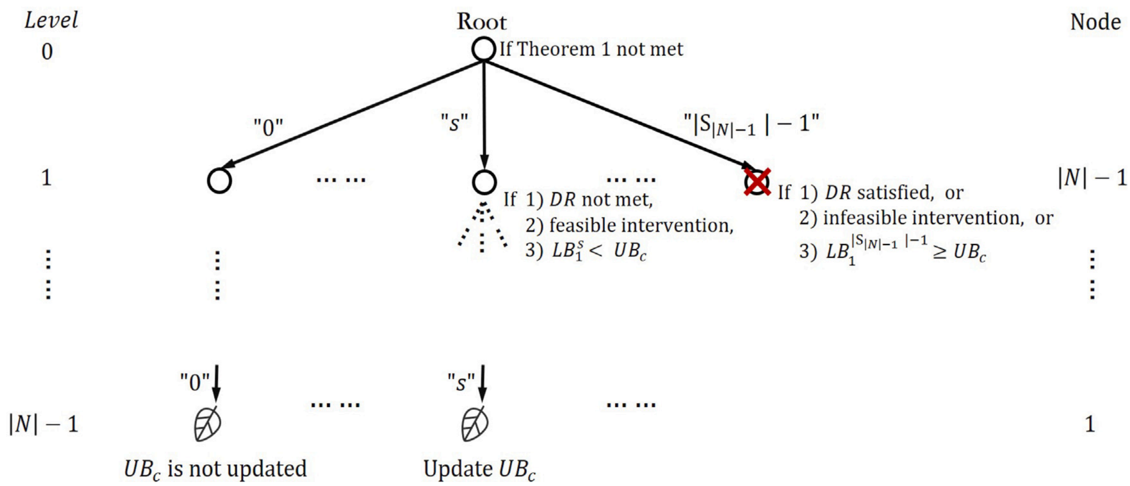

Fig. 5. The framework of the PS-BAB tree (the notation DR means dominance rule).

Theorem 1. *The manufacturer's minimum worst-case disruption risk can be achieved by intervening all of the manufacturer's tier-one SC partners to be the fully-operational state, except those that are already completely in fully-operational state. The corresponding total intervention cost can be seen as the upper limit of the budget. That is, if the budget is equal to or larger than the upper limit, then an optimal solution can be output.*

Proof. See Appendix B of the supplementary material. □

If the budget is less than the upper limit proposed in Theorem 1 (i.e., Theorem 1 is not met), then for a non-leaf vertex v_l^s, $s \in \mathcal{S}_j \backslash |\mathcal{S}_j|$, in $Level\ l$ (i.e., $l = |\mathcal{N}|-j$), a dominance rule (DR) is examined firstly. If the dominance rule is met, the vertex v_l^s is cut. Secondly, the feasibility of an intervention is checked. If the accumulated intervention cost of explored SC partners in vertex v_l^s is greater than the budget, then this vertex will be pruned. Thirdly, the lower bound of vertex v_l^s (denoted as LB_l^s) is calculated (detailed in Section 4.2). If the lower bound LB_l^s is not smaller than the current upper bound (denoted as UB_c), i.e., $LB_l^s \geq UB_c$, no better feasible solution can be found from this vertex, and thus the vertex v_l^s is cut. If the above pruning rules are not met, branches will be developed from vertex v_l^s to explore the invention possibilities for $Level\ l+1$ corresponding to SC partner $j-1$, due to $l+j = |\mathcal{N}|$. For each leaf vertex, UB_c is updated according to the method proposed in Section 4.1. The process continues until all branches are explored.

4.1. The characteristics of the PS-BAB algorithm

In the subsection, a dominance rule (DR) is proposed to reduce the solution space, and a SGP (signomial geometric programming) model is established to obtain an upper bound.

4.1.1. Dominance rule

Recall that the PS-BAB tree explores intervention possibilities from SC partners $|\mathcal{N}| - 1$ to 1. According to the Proposition 1 (page 9) in [21], for a SC partner $j \in \mathcal{N} \backslash |\mathcal{N}|$, the closer it is to the manufacturer $|\mathcal{N}|$, the higher the priority it has to be intervened. Obviously, in the CBN (where each node represents a SC partner), the child nodes have higher intervention priorities than their parent nodes. From the above observation, a dominance rule is established.

Dominance rule 1. If all children of SC partner $j \in \mathcal{N} \backslash |\mathcal{N}|$ in the CBN have been intervened, an intervention on SC partner j does not result in an optimal solution. Regarding the PS-BAB tree, for an unexplored vertex (associated with SC partner j, in $Level\ |\mathcal{N}| - j$), if all the ancestors (corresponding to SC partner j's children in the CBN) have been intervened, then all vertices in $Level\ |\mathcal{N}| - j$ except the first one (recording decision "0") will be cut.

Taking the example in Section 3, if SC partner 10 in Fig. 6(a) is intervened, then SC partners 2 and 8 will not be intervened. Thus, in $Level$ 3 (corresponding to node 8) of the PS-BAB tree, vertices v_3^1 (recording decision "1") and v_3^2 (recording decision "2") are cut. The corresponding PS-BAB tree can be found in Fig. 6(b), where the pruning of vertices in $Level$ 3 is illustrated.

4.1.2. Upper bound

For the PS-BAB tree, the initial UB_c and the UB_c at a leaf vertex can be calculated by solving a SGP model constructed based on the robust optimization model in Section 3.4. For the initial UB_c, there is no intervention for any SC partner j, thus each decision variable z_{js} in the robust optimization model can be fixed as 0, where $j \in \mathcal{N} \backslash |\mathcal{N}|$ and $s \in \mathcal{S}_j$. In a leaf vertex of the tree, the intervention decision on SC partner $j \in \mathcal{N} \backslash |\mathcal{N}|$ is known, thus z_{js} is fixed as 0 or 1. In the two cases, each variable z_{js} becomes a parameter denoted as Z_{js}, where $s \in \mathcal{S}_j \backslash |\mathcal{S}_j|$ and $j \in \mathcal{N} \backslash |\mathcal{N}|$. (Note that, we let $z_{j|\mathcal{S}_j|} = Z_{j|\mathcal{S}_j|} = 0$ based on Proposition 1, where $j \in \mathcal{N} \backslash |\mathcal{N}|$.) From the root vertex to each leaf vertex, accumulated intervention costs in non-leaf vertices do not exceed the budget. Constraint (4) is naturally satisfied. Thus, Constraint (4) does not need to appear in SGP model. The SGP model is built as follows, and it can be solved by calling a global optimization BMIBNB solver.

SGP Model

$$\max_{\boldsymbol{A},\boldsymbol{G}} A_{|\mathcal{N}|,|\mathcal{S}_{|\mathcal{N}|}|} \tag{22}$$

s.t. Constraints (1), (10), (16)–(17), (19)–(20)

$$A_{js} \leq 2 - Z_{js}, \quad \forall j \in \mathcal{N}^1, s \in \mathcal{S}_j \tag{5'}$$

$$A_{js} \geq Z_{js}, \quad \forall j \in \mathcal{N}^1, s \in \mathcal{S}_j \tag{6'}$$

$$A_{js} \leq 1 + Z_{js} - \sum_{s=1}^{|\mathcal{S}_j|} Z_{js}, \quad \forall j \in \mathcal{N}^1, s \in \mathcal{S}_j \tag{7'}$$

$$A_{js} \leq \overline{a}_{js} + \sum_{s=1}^{|\mathcal{S}_j|} Z_{js}, \quad \forall j \in \mathcal{N}^1, s \in \mathcal{S}_j \tag{8'}$$

$$A_{js} \geq \underline{a}_{js} - \sum_{s=1}^{|\mathcal{S}_j|} Z_{js}, \quad \forall j \in \mathcal{N}^1, s \in \mathcal{S}_j \tag{9'}$$

$$G_{sm}^j \leq 2 - Z_{js}, \quad \forall j \in \mathcal{N} \backslash \{\mathcal{N}^1, |\mathcal{N}|\}, s \in \mathcal{S}_j, m \in \mathcal{M}_j \tag{11'}$$

$$G_{sm}^j \geq Z_{js}, \quad \forall j \in \mathcal{N} \backslash \{\mathcal{N}^1, |\mathcal{N}|\}, s \in \mathcal{S}_j, m \in \mathcal{M}_j \tag{12'}$$

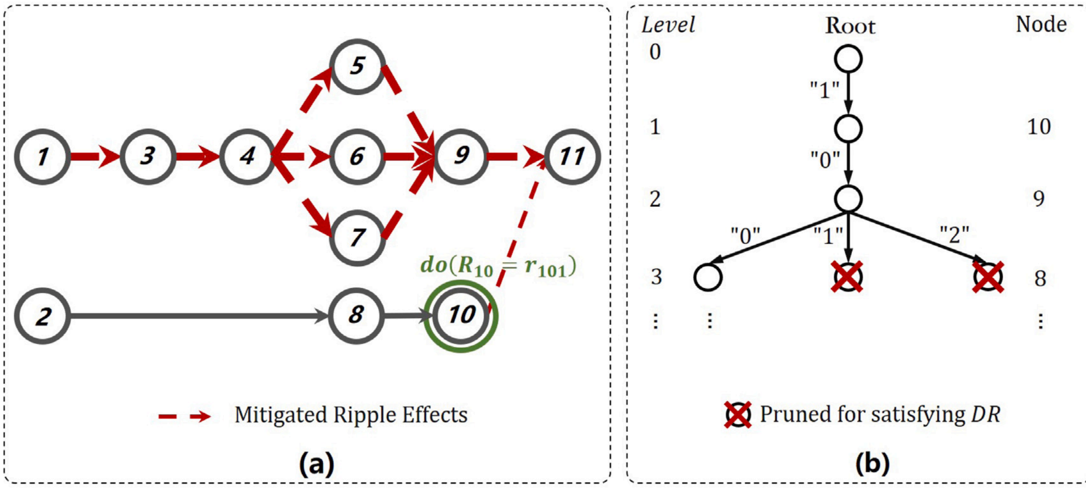

Fig. 6. Example of dominance rule.

$$G^j_{sm} \le 1 + Z_{js} - \sum_{s=1}^{|S_j|} Z_{js}, \quad \forall j \in \mathcal{N}\backslash\{\mathcal{N}^1, |\mathcal{N}|\}, s \in \mathcal{S}_j, m \in \mathcal{M}_j \tag{13'}$$

$$G^j_{sm} \le \overline{g}^j_{sm} + \sum_{s=1}^{|S_j|} Z_{js}, \quad \forall j \in \mathcal{N}\backslash\{\mathcal{N}^1, |\mathcal{N}|\}, s \in \mathcal{S}_j, m \in \mathcal{M}_j \tag{14'}$$

$$G^j_{sm} \ge \underline{g}^j_{sm} - \sum_{s=1}^{|S_j|} Z_{js}, \quad \forall j \in \mathcal{N}\backslash\{\mathcal{N}^1, |\mathcal{N}|\}, s \in \mathcal{S}_j, m \in \mathcal{M}_j \tag{15'}$$

4.2. Lower bounds of non-leaf vertices

In the subsection, the principle to construct the lower bounds (LBs) at non-leaf vertices is explained in Section 4.2.1. Then, the SGP model presented in Section 4.1.2 is used to calculate these LBs. Since the model is very time-consuming, an efficient iterative-approximation-and-repair (IAR) algorithm is developed in Section 4.2.2 to obtain LBs based on problem properties.

4.2.1. Definition of lower bounds

Recall that if the interventions from $Level$ 1 to l (i.e., SC partners from $|\mathcal{N}| - 1$ to j, where $l + j = |\mathcal{N}|$) are determined, then each intervention decision variable z_{js} in Section 3.4 can be fixed by the parameter $Z_{js} = 0$ or 1. The ideally best interventions at vertices from $Levels$ $l+1$ to $|\mathcal{N}| - 1$ can be performed (i.e., unexplored SC partners from $j-1$ to 1 are intervened to be the first state, denoted as $z_{j1} = 1$ and $z_{js} = 0$ for $s \in \mathcal{S}_j\backslash\{1\}$) if there is no budget limitation. That is, we relax the budget constraint, and make a conservative calculation. Consequently, the probability of SC partner j in the first state (resp. the s'th state for $s' \in \mathcal{S}_j\backslash\{1\}$) is equal to 1 (resp. 0). In this case, we calculate the corresponding LB at a non-leaf vertex through the SGP model by fixing z_{js} in the robust optimization model as follows:

(1) fix each intervention decision variable as $z_{js} = Z_{js}$, $j \in \{|\mathcal{N}| - 1, |\mathcal{N}| - 2, \dots, l\}$, $s \in \mathcal{S}_j$, and replace z_{js} by Z_{js} in related constraints.

(2) Relax the budget constraint, and best interventions can be implemented for SC partners from $j-1$ to 1, so $z_{j1} = 1$ and $z_{js} = 0$ for $s \in \mathcal{S}_j\backslash\{1\}$.

Theorem 2. *The optimal objective value of SGP model constructed at the non-leaf vertex v^s_l is a lower bound of the objective value at the vertex.*

Proof. The SGP model is constructed at v^s_l by relaxing the budget constraint such that all unexplored nodes from $Levels$ $l+1$ to $|\mathcal{N}| - 1$ are intervened to be the fully-operational state (i.e., the first state). The optimal solution of the constructed SGP model satisfies all constraints in the original robust optimization model, except the intervention budget constraint, thus the Theorem holds. □

4.2.2. Efficient calculation of lower bounds

With the SGP model and Theorem 2, the LBs at all non-leaf vertices can be obtained by calling BMIBNB solver. However, solving the SGP model is still time-consuming. Xu [59] develops an iterative heuristic based on a fast-solving GP (geometric programming) model to find a feasible solution of SGP one. The principle of the heuristic is: at the first iteration $I = 0$, find an initial feasible solution of SGP model by heuristics or designed strategies, and the solution is used to form $GP^{(1)}$. At iteration $I \ge 1$, $GP^{(I)}$ is optimally solved. If the difference between the two optimal solutions generated by $GP^{(I)}$ and $GP^{(I-1)}$ cannot met the predefined condition, some parameters are updated to form $GP^{(I+1)}$. Then, $GP^{(I+1)}$ is optimally solved at iteration $I+1$. The process continues until the stop criterion is met. The solution obtained at the last iteration is output as a feasible one for SGP model.

The disadvantage of the heuristic proposed by Xu [59] is that the obtained optimal solution of $GP^{(I)}$ during intermediate iterations may not be feasible for SGP model. In the study, we further augment a repair method at each iteration $I \ge 0$ such that the repaired solution is a feasible one for SGP model. The repair method is the adjustment procedure in [40]. The idea of this repair method is first to check if the solution output by $GP^{(I)}$ is a feasible one for SGP model. If not, the method alters values of variables within their probability intervals for each violated constraint until the repaired solution satisfies all constraints of SGP model. The repair method is detailed in Appendix C of the supplementary material.

Recall that $\boldsymbol{A}$ denotes all variables A_{js} for $j \in \mathcal{N}$ and $s \in \mathcal{S}_j$, and $\boldsymbol{G}$ denotes all variables G^j_{sm} for $j \in \mathcal{N}\backslash\mathcal{N}^1$, $s \in \mathcal{S}_j$, and $m \in \mathcal{M}_j$. In the following, we use $\widetilde{\boldsymbol{A}}$ and $\widetilde{\boldsymbol{G}}$ to represent the values of $\boldsymbol{A}$ and $\boldsymbol{G}$, respectively. Besides, we let $(\widehat{\boldsymbol{A}}, \widehat{\boldsymbol{G}})$ denote the repaired solution based on solution $(\widetilde{\boldsymbol{A}}, \widetilde{\boldsymbol{G}})$. At iteration $I = 0$, an initial solution is created and then repaired. To be specific, values of $\boldsymbol{A}$ and $\boldsymbol{G}$ in Constraints (5')–(7') and (11')–(13') can be easily determined as 0 or 1. While for variables $\boldsymbol{A}$ and $\boldsymbol{G}$ in Constraints (8')–(9') and (14')–(15'), their values are generated within given probability intervals randomly. Then, we can obtain an initial solution $(\widetilde{\boldsymbol{A}}^{(0)}, \widetilde{\boldsymbol{G}}^{(0)})$. To make the solution feasible for SGP model, we further repair $(\widetilde{\boldsymbol{A}}^{(0)}, \widetilde{\boldsymbol{G}}^{(0)})$ by calling the repair method in Appendix C of the supplementary material. The repair method is to satisfy Constraints (10) and (16) with $(\widehat{\boldsymbol{A}}^{(0)}, \widehat{\boldsymbol{G}}^{(0)})$. By doing this, other constraints in SGP model can be met as well [40]. Finally, the repaired solution $(\widehat{\boldsymbol{A}}^{(0)}, \widehat{\boldsymbol{G}}^{(0)})$ is utilized to form $GP^{(1)}$ model, and the objective value $\widehat{A}^{(0)}_{|\mathcal{N}|, |S_{|\mathcal{N}|}|}$ of SGP model can be updated with the feasible solution $(\widehat{\boldsymbol{A}}^{(0)}, \widehat{\boldsymbol{G}}^{(0)})$ via Eq. (1).

As GP model is a key element to obtain a feasible solution of SGP model. In the following, $GP^{(I)}$ and the parameter updating formulae to form $GP^{(I+1)}$ are presented. The process of approximating SGP model to GP model is detailed in Appendix D of the supplementary material. Next, we introduce the GP model at each iteration $I \geq 1$. The additional parameters and decision variables are defined.

Additional Parameters

- $\mathcal{T}$: Set of constraints that require approximation, indexed by t;
- $\mathcal{U}_t$: Set of positive monomial terms in the posynomial function in the tth constraint, indexed by u, where $t \in \mathcal{T}$;
- $w_t^{(I)}$: The tth positive weight coefficient obtained at iteration I, where $t \in \mathcal{T}$;
- $\beta_u^{(I)}$: The uth positive parameter obtained at iteration I, where $u \in \mathcal{U}_t$, $t \in \mathcal{T}$.

Additional Decision Variables

- f: Auxiliary variable for transforming the maximization objective function (22) into a minimization one (to satisfy the standard GP condition on the objective function);
- λ_t: The tth auxiliary relaxation variable, where $t \in \mathcal{T}$;
- α_u: The uth variable in the tth constraint, where $u \in \mathcal{U}_t$, $t \in \mathcal{T}$.

Then, GP model at the Ith iteration, $I \geq 1$, can be formulated as follows.

***GP*$^{(I)}$ Model**

$$\min \quad \left\{ \frac{1}{f} + \sum_{t=1}^{|\mathcal{T}|} w_t^{(I)}(\lambda_t - 1) \right\} \tag{23}$$

s.t. Constraints (5')–(9'), (11')–(15'), (17), (19)–(20)

$$\sum_{s=1}^{|S_j|} A_{js} \leq 1, \quad \forall j \in \mathcal{N}^1 \tag{24}$$

$$\sum_{s=1}^{|S_j|} G_{sm}^j \leq 1, \quad \forall j \in \mathcal{N} \backslash \mathcal{N}^1, m \in \mathcal{M}_j \tag{25}$$

$$f \geq A_{|\mathcal{N}|,|S_{|\mathcal{N}|}|} + 1 \tag{26}$$

$$\lambda_t^{-1} f \leq \prod_{u=1}^{|\mathcal{U}_t|} \left(\frac{\alpha_u}{\beta_u^{(I)}} \right)^{\beta_u^{(I)}}, \quad \forall t \in \mathcal{T} \tag{27}$$

$$A_{js} \geq \sum_{m=1}^{|\mathcal{M}_j|} G_{sm}^j \prod_{j' \in \gamma_j} A_{j',\mathrm{M}_j^{-1}(m)(j')}, \quad \forall j \in \mathcal{N} \backslash \mathcal{N}^1, s \in S_j \tag{28}$$

$$\lambda_t^{-1} A_{js} \leq \prod_{u=1}^{|\mathcal{U}_t|} \left(\frac{\alpha_u}{\beta_u^{(I)}} \right)^{\beta_u^{(I)}}, \quad \forall j \in \mathcal{N} \backslash \mathcal{N}^1, s \in S_j, t \in \mathcal{T} \tag{29}$$

$$\lambda_t \geq 1, \quad \forall t \in \mathcal{T} \tag{30}$$

$$\alpha_u > 0, \quad \forall u \in \mathcal{U}_t, t \in \mathcal{T} \tag{31}$$

The objective function (23) is equivalent to the objective function (22) when the auxiliary relaxation variable λ_t reaches 1, for all $t \in \mathcal{T}$, which now satisfies the standard GP condition on the objective function. To meet the GP requirements on constraints, Constraints (10) and (16) are equivalently transformed to Constraints (24) and (25) respectively based on Proposition 2 in Appendix D of the supplementary material. The constraint $f = A_{|\mathcal{N}|,|S_{|\mathcal{N}|}|} + 1$ is approximated via Constraints (26) and (27), and Constraints (1) are approximated via Constraints (28) and (29) according to the arithmetic–geometric mean approximation method in [59]. Constraints (30)–(31) define the domains of variables. (The detailed explanations of $GP^{(I)}$ can be found in Appendix D of the supplementary material.)

After solving the $GP^{(I)}$, $I \geq 1$, by MOSEK solver, an optimal solution $(\widetilde{\boldsymbol{A}}^{(I)}, \widetilde{\boldsymbol{G}}^{(I)}, \widetilde{f}^{(I)}, \widetilde{\lambda}^{(I)}, \widetilde{\boldsymbol{\alpha}}^{(I)})$ of $GP^{(I)}$ can be obtained, where the solution $(\widetilde{\boldsymbol{A}}^{(I)}, \widetilde{\boldsymbol{G}}^{(I)})$ will be further repaired to be feasible for SGP model by calling the repair method in Appendix C of the supplementary material, $\widetilde{f}^{(I)}$ denotes the value of auxiliary variable f, $\widetilde{\lambda}^{(I)}$ denotes the values of all auxiliary relaxation variables λ_t for $t \in \mathcal{T}$, and $\widetilde{\boldsymbol{\alpha}}^{(I)}$ represents the values of all variables α_u for $u \in \mathcal{U}_t$ and $t \in \mathcal{T}$. Then, with the repaired solution $(\widehat{\boldsymbol{A}}^{(I)}, \widehat{\boldsymbol{G}}^{(I)})$, the objective value of SGP model is updated as $\widehat{A}^{(I)}_{|\mathcal{N}|,|S_{|\mathcal{N}|}|}$ via Eq. (1). If the difference between $\widehat{A}^{(I)}_{|\mathcal{N}|,|S_{|\mathcal{N}|}|}$ and $\widehat{A}^{(I-1)}_{|\mathcal{N}|,|S_{|\mathcal{N}|}|}$ does not meet the predefined error criterion ϵ (a prefixed small enough positive value), then we enter into the $(I+1)$th iteration, and parameters $\beta_u^{(I+1)}$ and $w_t^{(I+1)}$ can be updated by the following formulae:

$$\beta_u^{(I+1)} = \frac{\alpha_u^{(I)}}{\sum_{u=1}^{|\mathcal{U}_t|} \alpha_u^{(I)}}, \quad \forall u \in \mathcal{U}_t, t \in \mathcal{T} \tag{32}$$

$$w_t^{(I+1)} = \theta \cdot w_t^{(I)}, \quad \forall t \in \mathcal{T} \tag{33}$$

where $\theta > 1$ is a given parameter.

With updated parameters $\beta_u^{(I+1)}$ and $w_t^{(I+1)}$, the $GP^{(I+1)}$ can be formulated, where $u \in \mathcal{U}_t$, $t \in \mathcal{T}$. The framework of the iterative-approximation-and-repair (IAR) algorithm is shown in Algorithm 1. Then, the lower bound of a non-leaf vertex in the PS-BAB tree is guaranteed by Proposition 3.

Algorithm 1: The Iterative-Approximation-and-Repair Algorithm

Input: Parameters $\underline{a}_{js}$, $\overline{a}_{js}$, $\underline{g}_{sm}^j$, $\overline{g}_{sm}^j$, Z_{js}, $\mathcal{T}$, $\mathcal{U}_t$; Iteration counter $I = 0$; Error criterion $\epsilon > 0$; Initial weight coefficient $w_t^{(0)} > 0$, $t \in \mathcal{T}$; Parameter $\theta > 1$; Set $\widehat{A}^{(-1)}_{|\mathcal{N}|,|S_{|\mathcal{N}|}|} = 0$.

Generate an initial solution $(\widetilde{\boldsymbol{A}}^{(0)}, \widetilde{\boldsymbol{G}}^{(0)})$, where values of variables in Constraints (5')–(7') and (11')–(13') are fixed as 0 or 1, other values are generated within given probability intervals of corresponding variables randomly;
Repair $(\widetilde{\boldsymbol{A}}^{(0)}, \widetilde{\boldsymbol{G}}^{(0)})$ to obtain $(\widehat{\boldsymbol{A}}^{(0)}, \widehat{\boldsymbol{G}}^{(0)})$ by calling the repair method (in Appendix C of the supplementary material);
With $(\widehat{\boldsymbol{A}}^{(0)}, \widehat{\boldsymbol{G}}^{(0)})$, obtain updated $\widehat{A}^{(0)}_{|\mathcal{N}|,|S_{|\mathcal{N}|}|}$ via Eq. (1);
while $|\widehat{A}^{(I)}_{|\mathcal{N}|,|S_{|\mathcal{N}|}|} - \widehat{A}^{(I-1)}_{|\mathcal{N}|,|S_{|\mathcal{N}|}|}| > \epsilon$ **do**
    $I = I + 1$;
    Update the parameter $\beta_u^{(I)}$ via Eq. (32), $\forall u \in \mathcal{U}_t, t \in \mathcal{T}$;
    Update Constraints (27) and (29) in $GP^{(I)}$ with parameter $\beta_u^{(I)}$, $\forall u \in \mathcal{U}_t, t \in \mathcal{T}$;
    Update the weight coefficient $w_t^{(I)}$ in $GP^{(I)}$ via Eq. (33), $\forall t \in \mathcal{T}$;
    Solve $GP^{(I)}$ via MOSEK solver, and obtain the solution $(\widetilde{\boldsymbol{A}}^{(I)}, \widetilde{\boldsymbol{G}}^{(I)}, \widetilde{f}^{(I)}, \widetilde{\lambda}^{(I)}, \widetilde{\boldsymbol{\alpha}}^{(I)})$;
    Repair $(\widetilde{\boldsymbol{A}}^{(I)}, \widetilde{\boldsymbol{G}}^{(I)})$ to obtain $(\widehat{\boldsymbol{A}}^{(I)}, \widehat{\boldsymbol{G}}^{(I)})$ by calling the repair method (in Appendix C of the supplementary material);
    With $(\widehat{\boldsymbol{A}}^{(I)}, \widehat{\boldsymbol{G}}^{(I)})$, obtain updated $\widehat{A}^{(I)}_{|\mathcal{N}|,|S_{|\mathcal{N}|}|}$ via Eq. (1);
end

Output: The feasible solution and the corresponding objective value of SGP model.

Proposition 3. *For the SGP model constructed at vertex v_l^s, the objective value calculated from the solution obtained via IAR algorithm is always not larger than its optimal objective value of SGP model, and it is a lower bound on the objective value of the subproblem at vertex v_l^s.*

Proof. See Appendix E of the supplementary material. □

To summarize, the proposed PS-BAB algorithm can find the optimal government intervention solution according to Theorem 3.

Theorem 3. *The PS-BAB algorithm guarantees the optimal solution for the problem.*

Proof. If the budget is not smaller than the upper limit proposed in Theorem 1, the optimal government intervention solution can be obtained by Theorem 1. If the condition of Theorem 1 is not met, the PS-BAB algorithm utilizes the depth-first search strategy to ensure

Table 2
Three combinations of intervention costs for suppliers.

Combination		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
I	C_{j1}	21460	11052	8538	16923	22318	9046	14484	22313	19710	8785
	C_{j2}	–	4240	–	–	–	–	–	–	–	–
II	C_{j1}	19949	21586	11460	8538	16923	8049	11052	15505	22318	22441
	C_{j2}	–	3407	–	–	–	–	–	–	–	–
III	C_{j1}	9122	15200	19610	11594	17284	16419	10794	9179	17867	18845
	C_{j2}	–	1980	–	–	–	–	–	–	–	–

S1 – S10: Suppliers 1 to 10.
C_{j1}: The cost of intervening supplier $j \in \{1, 2, \ldots, 10\}$ to be the fully-operational state.
C_{j2}: The cost of intervening supplier $j \in \{1, 2, \ldots, 10\}$ to be the semi-disrupted state.
-: The supplier does not has the semi-disrupted state.

that all possible regions of the solution space are explored. Besides, based on the proposition in [21], the validity of the dominance rule can be ensured. In addition, Theorem 2 and Proposition 3 guarantee the validity of lower bounds. Consequently, the non-leaf vertices in the PS-BAB tree can be correctly discarded under pruning rules. Therefore, the theorem holds. □

5. Computational experiments

In this section, computational experiments on 486 randomly generated instances are conducted to evaluate the performance of the proposed PS-BAB algorithm. In Section 5.1, the analysis on the case in Section 3 is performed and managerial insights are drawn. In Section 5.2, the efficiencies of the proposed dominance rule (DR) and IAR algorithm to obtain lower bounds of non-leaf vertices in the PS-BAB tree are evaluated. All computational experiments are implemented in Matlab2017b on a PC with Core I7 2.8 GHz processor and 8 GB RAM under Windows 10 Operating System. The computational time of the PS-BAB algorithm is limited to 10 h.

5.1. Case study

In the subsection, the case delineated in Section 3 is resolved utilizing the PS-BAB algorithm proposed in Section 4, which yields the most appropriate government intervention solution. Subsequently, two additional disruption scenarios and an adjusted SC structure are considered to investigate their influence on intervention solutions. Managerial insights are drawn from the analysis results.

5.1.1. Analysis on the case in Section 3

Recall that the SC network in Section 3 involves ten suppliers and one manufacturer, where suppliers 1 and 10 are attacked by disruptive events (regarded as disruption scenario 1). The probability intervals are given in Figs. 2 and 3. The intervention costs are randomly generated based on Assumption 6 in Section 3.4 and the data in [48]. In the real example provided by Zhou et al. [48], the action cost can vary from \$0 to \$23023. In line with [21], we assume that the intervention cost to achieve a fully-operational state is more expensive than that to the semi-disrupted state. Thus, the intervention costs to achieve a semi-disrupted and a fully-operational states in the experiments are randomly generated within the intervals [0, 6431) and [6431, 23023], respectively. To explore the impact of intervention costs on government interventions, 3 cost combinations for intervening suppliers are randomly generated, which are presented in Table 2. According to [48], the budgets allocated by the manufacturer to suppliers are capped at \$160000. In real applications, the government proposes a global budget to the manufacturer, such as General Motors company. To mitigate disruption risks, the manufacturer often redistributes the budget to their suppliers [28]. Thus, it is reasonable to set the budgets based on [48]. In this paper, to illustrate the impacts of different budgets, a sensitivity analysis is conducted, in which the range of budgets varies from \$0 to \$160000, with a step size of \$5000. Thus, there are 33 different budget values. In total, complicated with 3 cost combinations, there are $33 \cdot 3 = 99$ instances generated in Section 5.1.1.

The government intervention solutions for the case are illustrated in Fig. 7, where the horizontal and vertical axes represent the disruption risk of the manufacturer and the given budget, respectively. Detailed information of the solutions is presented in Table 3. As the budget increases from \$0 to \$160000, the manufacturer's disruption risk decreases from 41.68% to 10.00%. The manufacturer's disruption risk cannot be reduced below 10.00% no matter how large the budget is. This may be because the external government intervention cannot eliminate the operational risks inherent in the SC. In addition, the total intervention costs \$8785, \$3407, and \$1980 (resp. \$28495, \$44759, and \$36712) under the three cost combinations can be regarded as the lower limit (resp. upper limit) of the budget. If the budget is less than the lower limit, the manufacturer's disruption risk cannot be reduced. If the budget is greater than the upper limit, the risk cannot be further reduced. Thus, our proposed approach can determine appropriate lower and upper limits (denoted by Bl and Bu respectively) of the budget. Moreover, from Table 3, there are 4, 9, and 8 government intervention solutions under the three cost combinations, respectively. We can observe that supplier 10 is intervened the most times (i.e., 11 times), followed by supplier 4 (i.e., 7 times). Thus, in this case, supplier 10 can be considered the most critical supplier, and supplier 4 can be regarded as the second critical supplier.

Based on the above observations, the following managerial insights can be drawn.

Managerial Insight 1. *According to the SC structure and disruptive events on a SC, the budget allocated to the SC by the government should be controlled within a budget interval [Bl, Bu] to effectively reduce the manufacturer's disruption risk.*

Managerial Insight 2. *In the budget interval proposed by our approach, each budget value can achieve an objective of risk reduction. The manufacturer's disruption risk decreases with an increase in the budget. Thus, according to a desired objective, the government (resp. the SC decision-maker) can allocate (resp. demand) a corresponding budget.*

According to Theorem 1, if the allocated budget attains the upper limit of budget (i.e., Bu), intervening all tier-one suppliers of the manufacturer (except those that are already completely in fully-operational state) can achieve the maximum risk reduction for the manufacturer. Thus, we present the third insight for the SC.

Managerial Insight 3. *If the allocated budget is equal to or greater than Bu, the most effective way to reduce the manufacturer's disruption risk is to intervene all tier-one suppliers of the manufacturer to be the fully-operational state (except those that are already completely in full-operational state).*

In the case where the allocated budget is less than Bu, our approach provides an optimal decision that determines when and how to intervene the suppliers to effectively reduce the manufacturer risk.

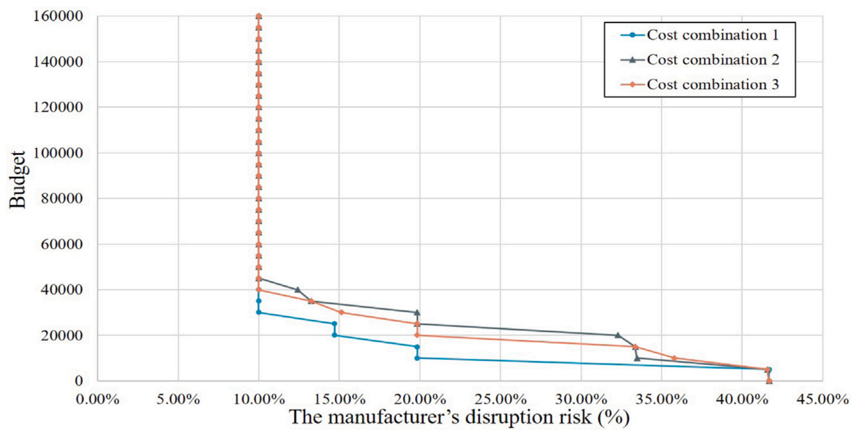

Fig. 7. Government intervention solutions under different budgets.

Table 3
The explanations of government intervention solutions in Fig. 7.

Cost combination	Budget ($)	Government intervention solution		Total intervention cost ($)	Risk (%)
		To state 1	To state 2		
I	0, 5000	–	–	0	41.68
	10000, 15000	Supplier 10	–	8785	19.83
	20000, 25000	Suppliers 3 and 10	–	17323	14.70
	≥ 30000	Suppliers 9 and 10	–	28495	10.00
II	0	–	–	0	41.68
	5000	–	Supplier 2	3407	41.57
	10000	Supplier 4	–	8538	33.48
	15000	Supplier 4	Supplier 2	11945	33.37
	20000	Suppliers 4 and 6	Supplier 2	19994	32.30
	25000, 30000	Supplier 10	–	22441	19.83
	35000	Suppliers 4 and 10	–	30979	13.26
	40000	Suppliers 4, 6 and 10	–	39028	12.41
	≥ 45000	Suppliers 9 and 10	–	44759	10.00
III	0	–	–	0	41.68
	5000	–	Supplier 2	1980	41.57
	10000	Supplier 1	–	9122	35.81
	15000	Supplier 4	Supplier 2	13574	33.37
	20000, 25000	Supplier 10	–	18845	19.83
	30000	Suppliers 1 and 10	–	27967	15.13
	35000	Suppliers 4 and 10	–	30439	13.26
	≥ 40000	Suppliers 9 and 10	–	36712	10.00

To state 1: Intervene a supplier to be the fully-operational state.
To state 2: Intervene a supplier to be the semi-disrupted state.

Managerial Insight 4. *Our approach provides an optimal decision support to SCs and indicates how intervening suppliers to effectively reduce the manufacturer's risk when the budget is less than the upper limit of budget.*

5.1.2. Government intervention under different disruption scenarios

Recall that the SC disruption illustrated in Section 3 is recorded as disruption scenario 1. Since the disruptions may hit any suppliers in the SC, in this subsection, two additional disruption scenarios are considered: only the first-echelon suppliers are attacked (disruption scenario 2) and only the fifth-echelon suppliers are hit (disruption scenario 3) by disruptive events, where the SC structure is the same as in Section 3. The rules of setting the state and conditional probabilities for disrupted suppliers are presented as follows [40]. The lower bound (resp. upper bound) of the probability of node $j \in \mathcal{N}^1$ in the sth state is set as $\underline{a}_{js} = \max\{a_{js} - \frac{\varphi}{2}, 0\}$ (resp. $\overline{a}_{js} = \min\{a_{js} + \frac{\varphi}{2}, 1\}$), where the width of probability interval φ is set as 0.01, and the nominal probability a_{js} is generated according to the axiom of probability, i.e., $\sum_{s=1}^{|S_j|} a_{js} = 1$, $s \in \mathcal{S}_j$. The lower bound (resp. upper bound) of the conditional probability of SC partner $j \in \mathcal{N} \backslash \mathcal{N}^1$ in the sth state is set as $\underline{g}^j_{sm} = \max\{g^j_{sm} - \frac{\phi}{2}, 0\}$ (resp. $\overline{g}^j_{sm} = \min\{g^j_{sm} + \frac{\phi}{2}, 1\}$), where the width of probability interval ϕ is set as 0.01, and the nominal conditional probability g^j_{sm} is created according to $\sum_{s=1}^{|S_j|} g^j_{sm} = 1$, $m \in \mathcal{M}_j$, $s \in \mathcal{S}_j$. In the two disruption scenarios, the nominal probabilities and nominal conditional probabilities of suppliers in the fully-disrupted state are randomly generated within the interval [0.7, 0.99]. The state and conditional probabilities of undisrupted suppliers are identical to those in Fig. 2. The budget and intervention cost settings are consistent with those in Section 5.1.1. In total, there are $33 \cdot 6 = 198$ instances generated in Section 5.1.2.

The government intervention solutions under disruption scenarios 2 and 3 are illustrated in Tables 4 and 5, respectively. From Table 4, we can observe that instead of intervening a disrupted supplier (i.e., supplier 1), intervening its downstream suppliers such as suppliers 3, 4, 6, and 9 can mitigate the manufacturer's disruption risk effectively. From Table 5, we can observe that when all first-tier suppliers (i.e., suppliers 9 and 10) of the manufacturer are disrupted, intervening supplier 9 can be less risky than intervening supplier 10 (i.e., 29.39% < 35.34%). Thus, if the costs of intervening suppliers 9 and 10 are the same, supplier 9 should be a priority for intervention.

5.1.3. Government intervention for different SC structure

Since different SC structures may impact the government intervention solutions, we adjust the SC structure in Section 3 to a new one (see

Table 4
Government intervention solutions under disruption scenario 2.

Cost combination	Budget ($)	Government intervention solution		Total intervention cost ($)	Risk (%)
		To state 1	To state 2		
I	0, 5000	–	–	0	30.09
	10000, 15000	Supplier 10	–	8785	20.50
	20000, 25000	Suppliers 3 and 10	–	17323	14.70
	≥ 30000	Suppliers 9 and 10	–	28495	10.00
II	0, 5000	–	–	0	30.09
	10000	Supplier 4	–	8438	22.15
	15000	Supplier 4	Supplier 2	11945	21.74
	20000	Suppliers 4 and 6	Supplier 2	19994	20.80
	25000, 30000	Suppliers 4 and 8	–	24043	14.83
	35000	Suppliers 4 and 10	–	30979	13.26
	40000	Suppliers 8 and 9	–	37823	11.50
	≥ 45000	Suppliers 9 and 10	–	44759	10.00
III	0, 5000	–	–	0	30.09
	10000	Supplier 8	–	9179	22.55
	15000	Supplier 4	Supplier 2	13574	21.74
	20000	Suppliers 1 and 8	–	18301	16.73
	25000	Suppliers 4 and 8	–	20773	14.83
	30000, 35000	Suppliers 8 and 9	–	27046	11.50
	≥ 40000	Suppliers 9 and 10	–	36712	10.00

To state 1: Intervene a supplier to be the fully-operational state.
To state 2: Intervene a supplier to be the semi-disrupted state.

Table 5
Government intervention solutions under disruption scenario 3.

Cost combination	Budget ($)	Government intervention solution		Total intervention cost ($)	Risk (%)
		To state 1	To state 2		
I	0, 5000	–	–	0	60.76
	10000, 15000	Supplier 10	–	8785	35.34
	20000	Supplier 9	–	19710	29.39
	25000	Supplier 9	Supplier 2	24950	29.28
	≥ 30000	Suppliers 9 and 10	–	28495	10.00
II	0, 5000	–	–	0	60.76
	10000	Supplier 4	–	8538	57.60
	15000	Supplier 4	Supplier 2	11945	57.47
	20000	Suppliers 4 and 6	Supplier 2	19994	56.37
	25000	Supplier 9	–	22318	29.39
	30000, 35000	Supplier 9	Supplier 2	25725	29.28
	40000	Suppliers 8 and 9	–	37823	27.50
	≥ 45000	Suppliers 9 and 10	–	44759	10.00
III	0, 5000	–	–	0	60.76
	10000	Supplier 8	–	9179	58.60
	15000	Supplier 4	Supplier 2	13574	57.47
	20000, 25000	Supplier 9	Supplier 2	19847	29.28
	30000, 35000	Suppliers 8 and 9	–	27046	27.50
	≥ 40000	Suppliers 9 and 10	–	36712	10.00

To state 1: Intervene a supplier to be the fully-operational state.
To state 2: Intervene a supplier to be the semi-disrupted state.

Fig. 8). It is assumed that the disruptive events attack suppliers 2, 3, and 5 in multiple echelons simultaneously (recorded as disruption scenario 4). The state and conditional probabilities are generated randomly as the same way in Section 5.1.2. The budget and intervention cost settings are consistent with those in Section 5.1.1. In total, there are $33 \cdot 3 = 99$ instances tested in Section 5.1.3. The experimental results are shown in Table 6.

From Table 6, we can observe that although suppliers 2 and 5 are directly attacked by disruptive events, they are not intervened in all intervention solutions. Specifically, the top two most frequently intervened SC partners are suppliers 8 and 10, where supplier 8 (resp. supplier 10) is the descendant node of suppliers 2 and 5 (resp. suppliers 2 and 3). This observation implies that intervening the downstream suppliers of disrupted suppliers can effectively reduce the manufacturer's disruption risk, which corresponds to the findings in Sections 5.1.1 and 5.1.2.

Thus, by summarizing the findings from Tables 3 to 6, we can draw the following managerial insight.

Managerial Insight 5. *Under various disruption scenarios, the critical supplier can be identified from the experimental results and prioritized for intervention if the budget is sufficient. In some cases, when suppliers in different echelons are attacked, it would be effective for the SC decision-maker to intervene their downstream suppliers to mitigate the disruption propagation.*

5.2. Numerical experiments

In this subsection, 90 randomly generated instances are conducted to evaluate the efficiencies of the dominance rule (DR) and IAR algorithm. Let $BAB1$ and $BAB2$ correspond to the PS-BAB algorithm without and with DR respectively, and lower bounds (LBs) of non-leaf vertices are calculated by BMIBNB solver. The experiments are conducted on 3-echelon (resp. 6-echelon) SCs with number of partners from 4 to 10 (resp. from 6 to 16), respectively. For each SC combination, five instances are randomly generated. In total, $5 \cdot (7 + 11) = 90$

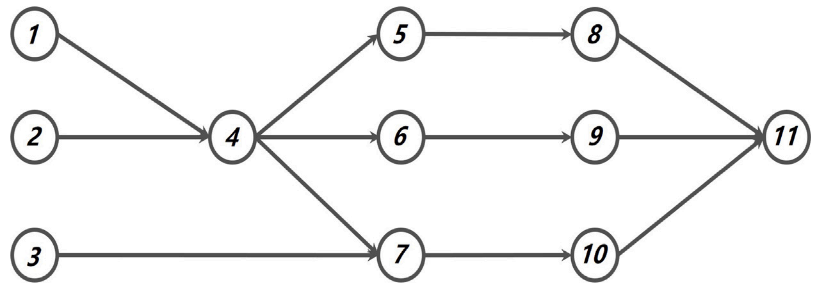

Fig. 8. A 5-echelon SC with 10 suppliers and 1 manufacturer.

Table 6
Government intervention solutions under disruption scenario 4.

Cost combination	Budget ($)	Government intervention solution		Total intervention cost ($)	Risk (%)
		To state 1	To state 2		
I	0, 5000	–	–	0	46.68
	10000, 15000	Supplier 10	–	8785	21.18
	20000, 25000	Suppliers 6 and 10	–	17831	14.44
	30000	Suppliers 9 and 10	–	28495	12.23
	35000	Suppliers 8 and 10	–	31098	9.07
	40000	Suppliers 8 and 9	–	39636	7.44
	45000, 50000	Suppliers 6, 8 and 10	–	49402	4.50
	≥ 55000	Suppliers 8, 9 and 10	–	50808	3.00
II	0	–	–	0	46.68
	5000	–	Supplier 3	3407	46.15
	10000	Supplier 6	–	8049	35.35
	15000	Supplier 6	Supplier 3	11456	34.92
	20000	Supplier 8	Supplier 3	18912	20.76
	25000	Suppliers 6 and 8	–	23554	13.11
	30000	Suppliers 6 and 8	Supplier 3	26961	12.94
	35000	Suppliers 6, 7, and 8	–	34606	11.71
	40000	Suppliers 8 and 10	–	37946	9.07
	45000, 50000 55000, 60000	Suppliers 6, 8 and 10	-	49402	4.50
	≥ 65000	Suppliers 8, 9 and 10	–	60264	3.00
III	0	–	–	0	46.68
	5000	–	Supplier 3	1980	46.15
	10000	Supplier 8	–	9179	21.00
	15000	Supplier 8	Supplier 3	11159	20.76
	20000	Suppliers 1 and 8	–	18301	18.54
	25000	Suppliers 4 and 8	Supplier 3	22753	14.53
	30000, 35000	Suppliers 8 and 10	–	28024	9.07
	40000	Suppliers 4, 8 and 10	–	39618	5.74
	45000	Suppliers 6, 8 and 10	–	44443	4.50
	≥ 50000	Suppliers 8, 9 and 10	–	47871	3.00

To state 1: Intervene a supplier to be the fully-operational state.
To state 2: Intervene a supplier to be the semi-disrupted state.

instances are tested, and the average computational results for each SC combination are recorded. All SC partners are assumed to have three states, and state (conditional) probability intervals for them are generated via the same method in Section 5.1. The intervention costs of suppliers are generated between the interval [0, 60], which are in correspondence with Assumption 6 in Section 3.4. The budget for interventions on all SC combinations is set as 150.

The average computational results for 3-echelon SC combinations are shown in Table 7. The first column represents the number of SC partners, i.e., $|\mathcal{N}|$. The second column reports the objective values, i.e., the average fully-disrupted probability of the manufacturer under five instances for each SC combination. The third to the fifth columns give the results of CT_{BAB1}, CT_{BAB2} and CT_{PS-BAB}, representing the average computational time of $BAB1$, $BAB2$ and PS-BAB, respectively. From Table 7, we can observe that $BAB1$ needs the most time to optimally solve all instances except when $|\mathcal{N}| = 4$. Compared with $BAB1$, $BAB2$ can reduce the computational time, and the improvement of $BAB2$ based on $BAB1$ is calculated via the formula: $(CT_{BAB1} - CT_{BAB2})/CT_{BAB1} \cdot 100\%$. The average improvement of $BAB2$ based on $BAB1$ for all instances is $10.87\% = (5209.26 - 4643.26)/5209.26 \cdot 100\%$, and the result demonstrates the efficiency of DR. Compared with the three algorithms, the PS-BAB is the most efficient, except small instances (i.e., SC combinations with $|\mathcal{N}| = 4$ and $|\mathcal{N}| = 5$). The improvement of PS-BAB based on $BAB1$ can be calculated as $(CT_{BAB1} - CT_{PS-BAB})/CT_{BAB1} \cdot 100\%$, and the average improvement for all instances is $83.63\% = (5209.26 - 852.95)/5209.26 \cdot 100\%$. Overall, the experimental results demonstrate the advantages of DR and the IAR procedure as crucial components in the PS-BAB algorithm.

Table 8 depicts the average computational results for 6-echelon SC combinations. It can be seen that when the number of SC partners increases from 6 to 16, $BAB1$ always takes the longest computational time to find optimal interventions, and the PS-BAB is most efficient except when $|\mathcal{N}| = 6$ and $|\mathcal{N}| = 7$. The average improvement of $BAB2$ based on $BAB1$ for all instances is $6.35\% = (7169.87 - 6714.43)/7169.87 \cdot 100\%$, and the average improvement of PS-BAB based on $BAB1$ for all instances is $75.17\% = (7169.87 - 1780.39)/7169.87 \cdot 100\%$. Comparing the results in Tables 7 and 8, it seems that with the same number of SC partners, the more "smooth" the SC structure is (i.e., the SC has more echelons), the more efficient our algorithm is. For example, when the number of SC partners is 10, the computational time of the PS-BAB for

Table 7
Comparison of CT_{BAB1}, CT_{BAB2} and CT_{PS-BAB} for 3-echelon SCs.

$\|\mathcal{N}\|$	Obj (%)	CT_{BAB1} (s)	CT_{BAB2} (s)	CT_{PS-BAB} (s)
4	5.48	14.49	12.98	18.27
5	13.45	35.51	24.34	29.06
6	10.61	198.06	108.39	56.19
7	8.81	419.13	382.03	184.76
8	4.75	3472.70	2972.66	697.11
9	13.08	9237.41	8083.44	1964.88
10	15.36	23 087.50	20 963.95	3290.35
Average		5209.26	4643.26	852.95

Table 8
Comparison of CT_{BAB1}, CT_{BAB2} and CT_{PS-BAB} for 6-echelon SCs.

$\|\mathcal{N}\|$	Obj (%)	CT_{BAB1} (s)	CT_{BAB2} (s)	CT_{PS-BAB} (s)
6	25.75	53.43	38.06	52.29
7	19.52	190.53	146.11	184.05
8	8.69	286.77	191.58	159.34
9	19.01	367.73	357.87	339.42
10	21.25	752.34	583.52	485.83
11	12.48	1348.95	1156.79	879.36
12	14.93	4101.18	3896.26	1424.87
13	10.84	5743.17	4922.74	1722.50
14	3.83	12 153.29	10 896.34	2370.92
15	12.72	17 871.14	15 669.49	3595.73
16	20.19	36000.00[a]	36000.00[a]	8369.99
Average		7169.87	6714.43	1780.39

[a] The optimal solution cannot be obtained in 36000 s.

3-echelon and 6-echelon SC combinations are 3290.35s and 485.83s, respectively. The reasons may be that (1) the dominance rule in our PS-BAB algorithm has more power when handling a "smooth" SC structure; and (2) the SC with a less "smooth" structure has more variables for the problem than other SCs, thus causing longer computational time.

In summary, the computational results show that (1) the dominance rule helps to improve the efficiency of the PS-BAB algorithm. (2) The IAR algorithm performs better than the BMIBNB solver when the number of SC partners is large. (3) According to the results of average improvements, the IAR algorithm is more effective than the dominance rule in improving the efficiency of PS-BAB algorithm.

6. Conclusion

In this paper, we investigate a SC resilience and viability improving problem, which is to minimize the worst-case probability of the manufacturer in the fully-disrupted state via implementing interventions under a limited budget. The CBN and Do-calculus are applied to quantify ripple effects and evaluate the government intervention effects. Considering that the probability information may be incomplete, probability intervals are utilized to represent the partial probability distribution information. To select an optimal intervention plan respecting the given budget, the hard combinatorial optimization problem is formulated by a new robust optimization model. To find the optimal intervention solution, an exact PS-BAB algorithm is developed. Computational results demonstrate the efficiency of the PS-BAB. Based on experimental analysis, managerial insights for managing SC risks are drawn.

The proposed robust optimization model is non-convex, thus the problem is extremely hard to be optimally solved for large scale instances. One of future research direction is to develop efficient matheuristics based on the in-depth problem analysis. In addition, three aspects can be extended: (1) the temporal aspect of disruption risk propagation should be considered to achieve optimal intervention solutions [60]. (2) The combination of economical and societal factors should be both considered into the decision of government intervention [9]. (3) Instead of focusing only on individual SCs, optimizing government interventions in SC networks with cycles and feedbacks, such as intertwined supply networks, can be further studied [61,62]. Finally, it is necessary to analyze the marginal increase of the total intervention cost with the marginal reduction of the fully-disrupted probability of the manufacturer, and investigating the multi-objective version of the problem is another promising area of future research.

CRediT authorship contribution statement

Ming Liu: Conceptualization, Methodology. **Yueyu Ding:** Writing – original draft, Methodology, Software. **Feng Chu:** Supervision, Validation, Writing – review & editing. **Alexandre Dolgui:** Supervision. **Feifeng Zheng:** Writing – review & editing.

Declaration of competing interest

The authors have no conflicts of interest to declare. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.omega.2023.102972.

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