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Flexible supply chain planning based on variable transportation modes

Yingjie Fan [a,b,*], Frank Schwartz [a], Stefan Voß [a,c]

[a] Institute of Information Systems (IWI), University of Hamburg, 20146 Hamburg, Germany
[b] School of Management, Xuzhou Institute of Technology, 221008 Xuzhou, China
[c] Escuela de Ingenieriá Industrial, Pontificia Universidad Católica de Valparaíso, 2340000 Valparaíso, Chile

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ABSTRACT

This paper investigates the application of diverse transportation modes for a global supply chain (SC) in stochastic environments. The motivation of our paper is to investigate the idea of enabling a global flexible SC with disruptive risks in making it less vulnerable by applying diverse transportation modes which is also our first contribution. The flexibility stems from the fact that transportation modes with a low-speed transportation contain latent time buffers that can be used by accelerating transport activities. This represents a promising approach to make supply chains (SCs) more flexible and to establish an additional degree of freedom in order to manage stochastic events like minor disruptions or serious catastrophes. In this paper, a stochastic programming model for a multi-stage multi-product SC is developed. SC partners, including multiple suppliers, a processing center, two assembling centers, multiple distribution centers and retailers, are incorporated into the model. The second contribution of this paper is that different types of possible future catastrophic disruptions are quantified and included in the model. SC catastrophic disruptions like transportation delays or the fact that a SC node is disrupted by a serious catastrophe are stochastic factors of our model. The model is solved by using *PySP*, a specific modeling and stochastic programming framework. In order to show the quality of solutions of the stochastic programming model (SP solutions), a large amount of scenarios is generated to simulate the real case for each instance. The expected SC costs for these scenarios will be evaluated based on SP solutions and wait-and-see solutions, which are benchmarks. In addition, decision makers with neutral, optimistic and pessimistic attitudes regarding the occurrence of disruptions are also simulated and evaluated in the computational experiments. Managerial insights are concluded from computational results. The most important conclusion is that proper transportation mode planning enables a flexible global supply chain. Further conclusions like the quality of stochastic solutions and solutions of simulating decision makers with neutral, optimistic and pessimistic attitudes, as well as the most beneficial transportation modes in SCs with uncertain environments are proposed based on the computational results.

1. Introduction

For a long time, SC risk typically has been ignored by managers in practice since most SC risks are hard to forecast. There still exists no general strategy which is inexpensive and effective to handle SCs in stochastic catastrophic environments. Without rapid responses and right decisions, complete SCs may break down if particular SC nodes or transportation links suffer a catastrophe. Nokia's huge success compared with Ericsson's great loss after a fire in a fabrication line of Philips on 17 March 2000 is a typical example (Chopra and Sodhi, 2004). From then on, researchers pay more attention on both risk management and SC risks.

There are some qualitative and quantitative models about SC risk management such as Guericke et al. (2012). They present the application of postponement strategies, which refers to transferring manufacturing steps of a product towards the end of a SC as an effective strategy for dealing with demand uncertainty. However, most quantitative models for managing SC risks focus on operational risks. In contrast, disruption risks such as earthquakes, tsunamis, floods, storms etc. are normally disregarded (Tang, 2006a; Wilding et al., 2012; Heckmann et al., 2015; Ho et al., 2015). In order to close this research gap, our motivation is to provide SC executives decision support by quantifying SC disruption risks and modeling SCs in stochastic environments.

Flexible transportation is introduced as a SC disruption mitigation strategy by Tang (2006b). But this strategy has not been

* Corresponding author at: University of Hamburg, Institute of Information Systems (IWI), Von-Melle-Park 5, 20146 Hamburg, Germany
E-mail addresses: fan.yingjie@uni-hamburg.de, faninj@gmail.com (Y. Fan), frank.schwartz@uni-hamburg.de (F. Schwartz), stefan.voss@uni-hamburg.de (S. Voß).

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investigated in detail. A diversification of transportation modes provides an opportunity to generate latent time buffers which can be activated in case of disruption events. The time buffers are generated by a transport mode which is characterized by a low-speed transportation. In this case, the buffers come into operation by switching from a low-speed transport mode to a high-speed transport mode. If the buffer time is sufficiently long, this approach makes SCs more flexible to avoid huge losses after catastrophic events. In reality, the approach can be found in the concept of slow steaming, too, where in the normal case the speed of transport is less than the original operating speed.

Flexible SCs are able to adapt effectively to disruptions in supply and changes in demand whilst maintaining customer service levels (Stevenson and Spring, 2007). In this paper, flexible SCs can be achieved by using variable transportation modes in two steps: The first step is to determine the transportation mode for each product on each transportation link. Buffer time should be preserved by using low-speed transportation modes. The second step is to eventually switch to a faster transportation mode after a disruption event happens in order to save transport time for adopting alternative plans. The decision of the second step depends on the location and severity of the disruption event. Furthermore, it also depends on the decision of the first step. The focus of this paper is on the question of how to determine the best transportation mode for each product on each transportation link in uncertain environments. A two stage multi-scenario SC model is built based on this problem. Progressive Hedging (PH; see the Appendix), which is proposed and theoretically proved as a method to be convergent by Rockafellar and Wets (1991) for multi-scenario problems, is used to solve the problem instances for this model. PySP (Watson et al., 2012), which provides a framework of using PH for multi-stage multi-scenario problems, is used to get solutions. In order to evaluate the most powerful solution technique, we apply PySP with different values of a specific parameter ρ, which is an inherent parameter of the PH approach. Solutions of diverse groups of instances are analyzed in order to determine a beneficial first stage decision. This decision tends to support the identification of a common transportation mode for different types of products as well as for different transportation links. The results of our numerical analyses reveal basic ideas about the best solution technique and the most advantageous SC transportation modes which provides decision support to SC executives.

Our paper is organized as follows. In the next section, a literature review is given and the theoretical background is explained. The investigated problem is illustrated in detail in Section 3. Section 4 contains a presentation of the developed model. Computational results are presented and analyzed in Section 5. The application of our model is provided in Section 6. The paper finishes with the conclusions in Section 7.

2. Literature review

SC risks are classified into operational risks and disruption risks (Tang, 2006a). Operational risks refer to inherent uncertainties such as uncertain customer demand, uncertain supply, and uncertain costs. Disruption risks refer to major disruptions caused by natural and man-made disasters. A typology of risk sources, consisting of environmental factors, industrial factors, organizational factors, problem-specific factors and decision-maker related factors is presented in Rao and Goldsby (2009). Relevant literature about *SC risk management* (SCRM) is collected and classified in, e.g., Tang (2006a), Kouvelis et al. (2006) and Dadfar et al. (2012). Although many qualitative analyses and quantitative models of SCRM exist, most quantitative models for managing SC risk focus on operational risks. In contrast, disruption risks are usually disregarded (Tang, 2006a). Whereas a good portion of the corresponding literature only focuses on demand fluctuations, rather few papers point out how to cope with catastrophic events. Woodruff and Voß (2006) present a first attempt to deploy PH on a SC production planning problem with big bang scenarios.

Postponement strategies provide an additional degree of freedom as well as mitigation options for decision making in stochastic SC environments. Combined with an integration of additional time buffers which may be established by longer standard shipping times, Fan et al. (2014) identify postponement as an effective way to cope with SC disruptions. In that paper, an enumeration is used to get the optimal expected annual SC costs, but the enumeration is only effective for pure binary small scale problems with a limited number of scenarios. Furthermore, the relationships between optimal SC transportation modes and probabilities of catastrophic scenarios have not yet been explored.

Apart from some small problem instances, stochastic optimization problems are notoriously hard to solve. A common approach to deal with stochastic problems in practice is scenario analysis. This approach decomposes a stochastic problem into a number of solvable sub-problems. PH has been applied in solving a number of stochastic programming problems (Voß and Woodruff, 2006), such as network problems (Mulvey and Vladimirou, 1991, 1992; Crainic et al., 2011), fishery problems (Helgason and Wallace, 1991; Wallace and Helgason, 1991), power system optimization (Takriti et al., 1996; Santos et al., 2009), resource allocation problems (Watson and Woodruff, 2011), and lot-sizing problems (Haugen et al., 2001). PH represents a solution technique that determines a solution which performs well for all scenarios of the multi-scenario problem. The algorithm is proved to be convergent for convex problems (Rockafellar and Wets, 1991). It utilizes the variable split form of the multi-scenario program. The non-anticipativity constraints of a stochastic model are integrated into the objective function as penalty and multiplier terms, and are progressively enforced by an iterative procedure (Mulvey and Vladimirou, 1991). In our research, PH is used for solving our stochastic programming model.

Helgason and Wallace (1991) show how to implement a scenario aggregation procedure in a simplified version of PH by solving the individual scenario problems only approximately, using an integrated application of a Lagrangian approach. They propose that solving the subproblems exactly amplifies oscillations of the individual scenarios, which then has to be dampened with stronger penalties. A drawback of this approach is that increasing the penalty slows down the speed of the algorithm. Therefore, exact solutions of the scenario problems are rarely used. Lokketangen and Woodruff (1996) provide a first implementation of general-purpose methods for finding good solutions to multistage, stochastic mixed-integer (0,1) programming problems. Tabu search is used for subproblems and PH is used to coordinate blending the subproblem solutions. The method is verified to be effective by computational experiments. They mention that without a good, integer-feasible solution during the initial iteration of PH, the solution will be hardly integer feasible.

In the existing research, PH as a scenario-based decomposition technique is applied in diverse research areas. One controversial issue has been the selection criterion of the penalty parameter of PH. Empirical tests are employed to examine the effect of various internal tactics on the algorithm's performance. Mulvey and Vladimirou (1991) report that the proper choice of a value for the penalty parameter depends on the problem structure. The effects of dynamic penalty adjustments and inexact subproblem solutions are evaluated in this paper. Fan and Liu (2010) propose similar conclusions in their paper. They postulate that on the contrary values of penalty parameters result in a slow convergence towards the optimal solution, and high values of penalty parameters produce faster initial convergence, but may arrive at a suboptimal solution. Until then, no explicit criteria have been identified in order to set adequate values of the penalty parameters. Watson and Woodruff (2011) develop novel and simple methods for determining element-specific penalty parameter values based on problem-specific data. Computational results show that in order to get a good performance the values of the penalty parameter ρ should be proportional to the unit costs of the items in the supply chain. The paper provides explicit methods of fixing the value of the penalty parameter ρ for the first time.

In order to generalize the application of PH as an effective heuristic that generates approximate solutions for multi-stage stochastic programs, PySP is introduced by Watson et al. (2012). PySP is a means to rapidly prototype and solve multi-stage multi-scenario programming problems. By leveraging the combination of a high-level programming language (Python) and the embedding of the primary deterministic model in that language (Pyomo), PySP provides completely generic and highly configurable solver implementations for stochastic programming (Watson et al., 2012).

3. Problem statement

SCs are increasingly prone to complexity and uncertainty, especially for global supply chains. According to an investigation report of 196 organizations from more than 22 industries by Partida (2013), 83 percent of the survey respondents had experienced at least one unexpected SC disruption in the last 24 months. Of those who had experienced a disruption, 78 percent believed that they should draw the sustained attention to possible disruptions. However, quantification and modeling of SC risk is still a challenge in the field of SCRM (Heckmann et al., 2015; Ho et al., 2015). It motivated us to provide SC executives decision support by quantifying SC disruption risks and modeling SCs in stochastic environments.

The papers Heckmann et al. (2015) and Fahimnia et al. (2015) address the same points that environmental factors and sustainability should be considered in SCRM. Sustainability risk is pointed out to be an emerging stream in the SCRM area in Fahimnia et al. (2015). In this background, slow steaming, as an eco-friendly and cheaper transportation mode, has attracted more ocean carriers' attention (Meyer et al., 2012). However, many shippers oppose the practice due to increased pipeline inventory associated with longer transportation time (Maloni et al., 2013).

Another motivation for our research is to investigate the application of slow steaming from the perspective of a global supply chain. From our initial computational results in Fan et al. (2014), slow steaming is applied for global SCs in stochastic environments. This important finding stimulated our interests of investigating the application of different transportation modes in global SCs in stochastic environments. The most convenient way is to simulate a SC with a stochastic programming model. In our simulation results, the best transportation plan of a SC has slow steaming for certain products on certain transportation links. It means that applying slow steaming in a proper way enables an eco-friendly flexible supply chain, especially for long distance transportation.

In order to quantify and model SC disruption risks, impacts after a SC catastrophe have to be analyzed in detail. The worst impact from SC catastrophes is possibly not from direct economic losses, but the underlying harm from the delay in meeting the demand of final products, and the impaired reputation induced from unmet demand. Hence, satisfying the demand of final products – in particular if a crucial node or an important transportation link is destroyed – is a key factor of a flexible and successful supply chain.

One of the most common strategies for getting rid of high negative impacts of low frequency catastrophic disruptions is to keep buffer stocks of products (Gupta et al., 2000). The buffer stocks keep the SC working during the time for adopting a contingency plan, such as asking for internal or external help, if a node or a transportation link is destroyed by a catastrophe. Two crucial issues of keeping inventory are where to locate it, i.e., where to build warehouses (or just stocks), and how to manage it. Without considering SC costs at first, the safest way might be to set up warehouses at each crucial node in the supply chain. But this strategy comes along with another problem: What happens if one of the warehouses and its nearest SC node are both destroyed at the same time?

For instance, 173 people died and about 22,000 new cars from Toyota, Volkswagen, Renault and others were largely destroyed in the Tianjin port explosions on 12 August 2015 (The Guardian, 2015). Negative impacts of this catastrophe for Volkswagen and Renault are limited because both of them have enough inventory in China. Whereas for Toyota, not only nearly 5000 new cars of Toyota's local joint venture were damaged; three of its factory lines shut down after explosions due to the stockout of parts (Automotive Purchasing, 2015). According to an industry analytics firm, the plant shutdown costs Toyota 2200 vehicles a day in lost productivity (IHS Automotive, 2015). In this case, inventory of cars at the local joint venture of Toyota won't reduce negative impacts from the Tianjin port explosions. Although the direct economic loss at the incident was refunded by insurance companies at last, indirect loss caused by stockout of cars for Toyota is huge. According to the record of Toyota's sales volume in the mainland of China (Sohu, 2015), Toyota had a gross sales loss of at least 35,000 cars in August and September 2015 (Fig. 1). From this point of view, even SCs with well-defined inventory strategies are still vulnerable in catastrophic environments.

An additional and more flexible strategy for coping with SC catastrophes is to use different transportation modes. This strategy utilizes the savings of transportation time if a low-speed transportation mode is replaced by a faster transportation mode. Therefore, this strategy generates time buffers which may assure even in case of a destroyed node in a SC that supplies of the final products suffer less or even no negative impacts, which depends on the time savings obtained from accelerated transport of products.

The capacity of time buffers generated from varying transportation modes depends on the distance of a transportation link as well as the difference of speed (or transportation time) between the low-speed and the faster transportation mode. When slow steaming is used as a transportation mode for a long-distance transportation, a SC has a bigger capacity of time buffers. For instance, according to the sea route database at “Ports.com”, transportation times from Shanghai to Hamburg are 28.4 days with a slow steaming speed (18 knots), 18.9 days with a fast steaming speed (27 knots), and two or three days by air. In this case, the capacity of time buffers ranges from 9.5 days to as many as 25 days.

Variable transportation modes provide an additional degree of freedom in SC disruption risk management. Products in transit appear as a type of inventory which helps providing buffer time once a catastrophe happens.

A comparison between low-speed transportation and high-speed transportation is presented as follows. For each product on a long distance transportation link (for example, from a node A, say Shanghai, China, to a node B, say Hamburg, Germany), we have two strategies to cope with SC disruption risks (Fig. 2): either Strategy 1 – keeping a high level of stock in the warehouse at the downstream node B and transport products with a high-speed transportation mode, or Strategy 2 – keeping a lower level of stock

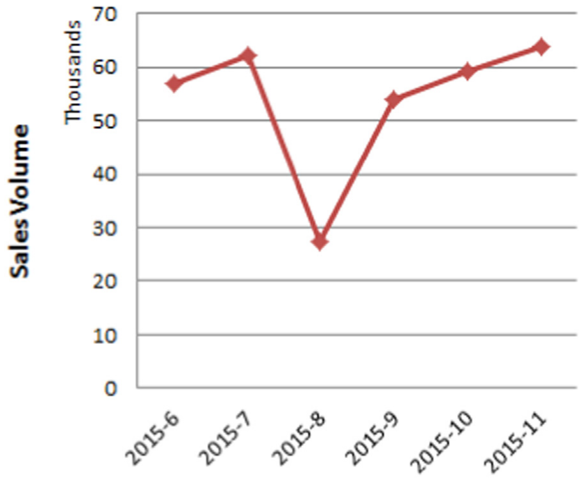


Fig. 1. Toyota's sales volume in the mainland of China from June 2015 to November 2015.

in the warehouse at node B and transport products with a low-speed transportation mode. Suppose that the quantities of products in transit plus stock in the warehouse for both strategies are the same, and transportation batch sizes are also supposed to be the same.

Assume, for instance, a disruption where a warehouse at node B is destroyed by a catastrophe, compared to Strategy 1, Strategy 2 has longer buffer time before stockout due to more products in transit. If the production capacity at the upstream node is limited, stockout is more easily to happen for products with Strategy 1. Furthermore, Strategy 2 has more advantages: lower transportation costs, less Greenhouse Gases (GHGs) emissions and lower storage costs. Although it may be more likely for Strategy 2 to experience transportation delays, buffer stock in the warehouse at node B will help to reduce the negative impacts from transportation delays effectively. In this sense, reducing the inventory level at a warehouse and using a low-speed transportation mode may enable a more flexible SC without increasing SC costs. This will also make the SC more eco-friendly.

The explanations above suggest the conclusion that variable transportation modes represent an appropriate approach to make SCs more flexible. In the following, this is to be investigated in more detail.

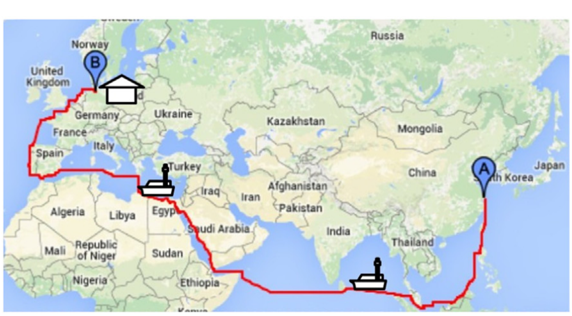
In order to make use of the flexibility of variable transportation modes, an initial transportation mode for each transportation link in the SC should be fixed at a proper level. A SC with predominantly low-speed transportation modes has more available buffer time to manage a catastrophic event than a SC with predominantly high-speed transportation modes, but it also suffers higher capital holding costs due to more products in transit. SCs with tight lead time constraints are to be obliged to implement only few transport links with a low-speed transportation mode. In this case, low-speed transportation modes should be only used for crucial products on crucial links. We note in passing that there is quite some literature on load-dependent lead times; see, e.g., Pahl et al. (2007).

In our investigations, SC catastrophes refer to SC nodes or transportation links. If a catastrophe happens in a node of a supply chain, this node becomes dysfunctional for a certain period of time, ranging from a couple of days or weeks up to a couple of months - depending on the severity of the catastrophe. If a catastrophe happens on a transportation link of the supply chain, this effects that products in transit through this destroyed transportation link are delayed for some time, e.g., a couple of days. Various SC catastrophes constitute the investigated scenarios. They are represented by a moderate number of discrete realizations of the stochastic quantities. A decomposition of a stochastic program across scenarios partitions the investigated problem into manageable subproblems. This enables an efficient use of parallel processors (Mulvey and Vladimirou, 1991). According to this characteristic, the process of calculating SC costs is decomposed into two stages: SC costs without considering any catastrophe are assumed to be the first stage costs. The corresponding first stage decisions include decisions regarding the initial transportation modes of transportation links, which are scenario invariant. Extra SC costs during the reconstruction time after catastrophic events are regarded as second stage costs. Transportation modes on the transportation links are adjusted by the second stage decision in order to gain available time for implementing alternative plans after catastrophes. The second stage transportation mode adjustment depends on the realization of the catastrophe and the first stage transportation modes since buffer times of the SC have been fixed when the first stage decisions are made.

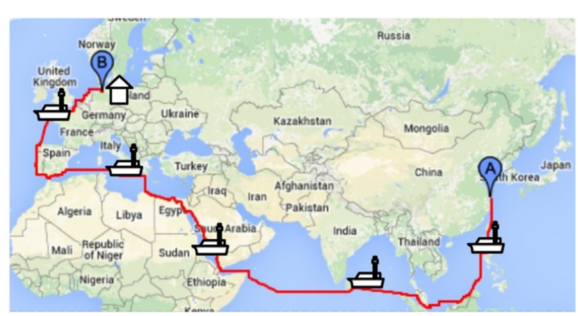
PH is used for solving the two-stage multi-scenario SC model. Solutions for a multi-scenario problem become convergent by adding penalty and multiplier terms to the objective function in each iteration. PySP provides a convenient platform based on PH to solve this type of problems. However, PySP has not been used widely, and the selection criterion of the penalty parameter, as mentioned above, has been a controversial issue. In order to find solutions with a good quality, we also test the performance of PySP with different selection criteria of the penalty parameter ρ.

4. Model description

The model will be described in detail in this section. The assumptions and the scenario tree will be explained at first, then the model formulations will be presented.



(a) Strategy 1



(b) Strategy 2

Fig. 2. High-speed and higher inventory vs. low-speed and lower inventory.

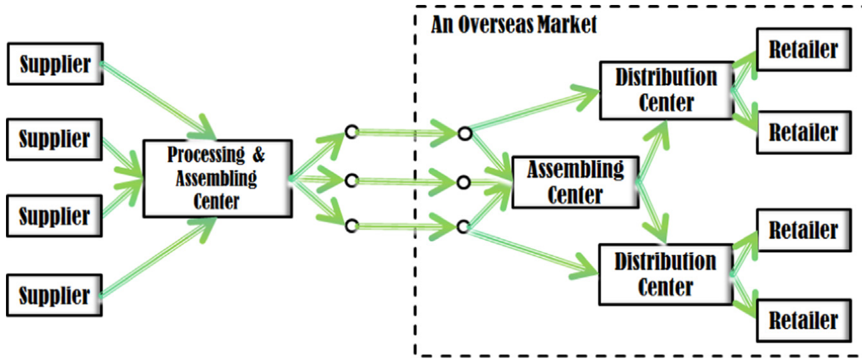


Fig. 3. An example of a supply chain.

4.1. Assumptions

Fig. 3 shows an example of a supply chain, which motivates our model. Raw materials and parts are provided by suppliers, and semi-finished products are fabricated in processing centers. Final products which are made from semi-finished products are finalized in the assembling centers. Afterwards, they are shipped to distribution centers. Final products are transported from distribution centers to retailers who sell them to local customers.

Referring to the frequency of assessment of SC resiliency and exposure to disruption risk in the investigation report of Partida (2013), about half of the investigated organizations conduct these assessments every 12 months or less, about 40 percent conduct these assessments sporadically or only after a major disruption incident. In our research, we assume that a SC assesses catastrophic risks on a longer time basis such as a year. Except of natural disasters, other factors, such as driver strikes, delays at customs, port congestion, or containers not being returned, also result in transportation delays. Thus, severe SC transportation delay risk is assessed on a shorter time basis such as a season or a month. The parameter time horizon is defined according to the frequency of a possible disruption.

Catastrophic events require extra time to adapt SCs to such an incident. The length of extra time depends on the complexity of appropriate emergency plans. Extra time for catastrophic events referring to transportation links is a couple of days; in case of a catastrophic event referring to crucial SC nodes a couple of weeks or more may be required. Additionally, a catastrophe induces extra costs due to, e.g., overtime working costs. These costs are variable because the recovery time ranges from a couple of days up to a couple of weeks, depending on the severity of a catastrophe and the importance of the destroyed node.

In our model, three transportation modes for each transportation link are considered. They represent a high-, a medium- and a low-speed transportation mode and come along with different transportation costs and transportation times. Furthermore, capital holding costs, which depend on the holding time and the capital holding quantity, are also included in the SC costs. The model is a two-stage decision model. Each transportation mode of each product on each transportation link of a SC is specified by a decision variable. The transportation modes of transportation links are determined on the first stage. On the second stage, after the occurrence of a catastrophe the transportation modes of transportation links may be changed. All transportation mode decisions are represented by binary variables.

In the context of the first stage decision, let us assume that we produce according to a make to order policy. Then no storage is taken into account. Stockout costs arise if stockouts of products happen due to catastrophic events. However, the second stage decision takes into account storage costs if inventories are built up after the selection of a faster transportation mode. Furthermore, SCs with lead time constraints and also SCs without lead time constraints are explored in our experiments.

Two different SC structures, one with implemented and another one without implemented postponement strategies, are investigated in our computational experiments in order to determine features of flexible transportation mode planning. One out of three transportation modes is chosen for each product for each transportation link with the first stage decision. Transportation modes can be changed after the occurrence of a catastrophe. All activities in the SC can be performed in an alternative location by an associated external partner, except for the assembling center. The alternative assembling activity is provided by an internal partner. The alternative partners provide the same or similar products or services as the original one. The alternative location is assumed to be far away from the original one which means it is unlikely that both the original node and also its alternative node are destroyed simultaneously after a catastrophe. Two assembling centers, one located close to the processing center and another one located close to the foreign market, are the internal alternative partners of each other. For assembling centers with shorter distances to a foreign market we assume that they have higher labor costs than assembling centers with longer distances to the foreign market. If the assembling center in a foreign area is destroyed, the products can be finalized by the internal partner who provides a combined processing and assembling center which may provide reduced assembling costs. Regarding the considered time horizon, to ease exposition, it is assumed that no more than one catastrophic event occurs.

Transportation plans are made with the consideration of the assessment of catastrophic risk. Once a catastrophic event happens in a real case, the SC will need to assess catastrophic risks again, transportation plans will also be adjusted according to the latest assessment of catastrophic risks. The focus of this paper is on SC disruption risks. This includes the investigation that a SC node, for example a port which is used for transferring crucial products, may be destroyed, or the transportation of products is delayed on a transportation link. Demand fluctuation which belongs to operational risk is not taken into our consideration. Hence, customer demand is assumed to be constant in the model. Note that the two stages in our model are not defined according to a chronological order. In lieu thereof, the first stage represents decisions considering any catastrophic scenarios, and the second stage incorporates decisions in order to manage the negative effects a SC is suffering with after the event of a catastrophic scenario.

4.2. Scenario tree

A two-stage scenario tree is shown in Fig. 4. An innovative idea of our stochastic programming model is that stages are not

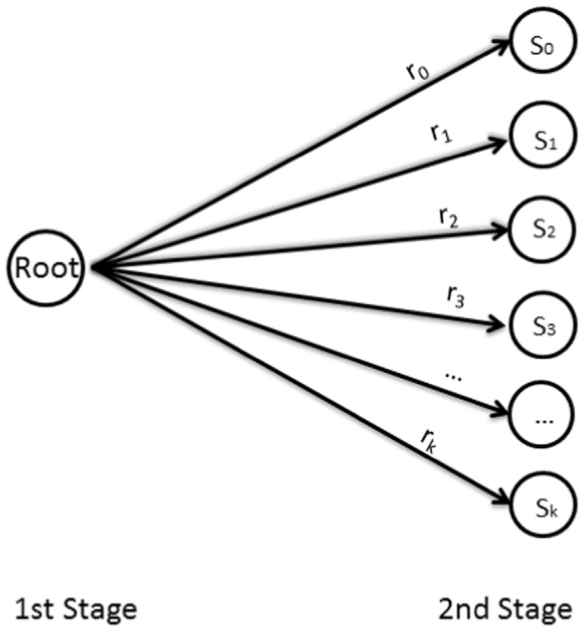


Fig. 4. A two-stage scenario tree.

referring to time stages. The root node which belongs to the 1st stage represents SC costs during a time period without considering any disruptions. Each leaf node represents a possibility of extra costs due to a disruption during this time period which belongs to the 2nd stage. The advantage of setting time independent stages is that the solution of the model will not be impacted by the moment a disruptive event occurs. We assume that the risk for every day is the same in the considered time horizon. In most of the cases, we may have the knowledge about the severity of a disruption such as the length of the period that a factory cannot work after a fire or an explosion, but it would be hard to predict when the disruptive event will happen. This kind of low probability event is normally out of the consideration of SC executives, but the negative impacts are huge.

According to the parameters in our model, a risk evaluation of a global SC in a time interval should be made at the first step. The length of the time interval depends on a supply chain's environment. A scenario tree is generated based on risk evaluation (Fan et al., 2015). For each scenario, these parameters are required: the involved node or transportation link, the recovering time of the involved node, the probability of this scenario. Except of all disruption scenarios, a further scenario is without any catastrophe for the global supply chain. The summation of the probabilities of all scenarios should be equal to one. With all required parameters, PySP will eventually provide a good solution for a problem. The solution will maintain good levels of time buffers with consideration of all scenarios in the scenario tree.

4.3. Model formulation

We consider a SC network Net=(N, $Conn$) where N is the set of nodes and $Conn$ is the set of arcs between the nodes.

Set

N	Set of nodes
S	Set of suppliers, $S \subset N$
RW	Set of retailers/wholesalers, $RW \subset N$
P	Set of products
P_i	Set of products $P_i \subset P$ at node $i \in N$
$Conn$	Set of transportation links $N \times N$ between the nodes in the supply chain
K	Set of scenarios

Parameters

T	Time horizon
$C^{O}_{p_i i}$	Operational cost per unit of product $p_i \in P_i$ at node $i \in N$
$C^{O}_{p_i ik}$	Operational cost per unit of product $p_i \in P_i$ at node $i \in N$ for scenario $k \in K$
$C^{P}_{p_i i}$	Purchasing cost per unit of product $p_i \in P_i$ at node $i \in N$
$C^{P}_{p_i ik}$	Purchasing cost per unit of product $p_i \in P_i$ at node $i \in N$ for scenario $k \in K$
$C^{Th}_{p_i ij}$	Costs of high-speed transport per unit of product $p_i \in P_i$ from node i to node j, $(i, j) \in Conn$
$C^{Tm}_{p_i ij}$	Costs of medium-speed transport per unit of product $p_i \in P_i$ from node i to node j, $(i, j) \in Conn$
$C^{Tl}_{p_i ij}$	Costs of low-speed transport per unit of product $p_i \in P_i$ from node i to node j, $(i, j) \in Conn$
$C^{TP}_{p_i ij}$	Transportation cost of product $p_i \in P_i$ between nodes i and j, $(i, j) \in Conn$
$C^{TP}_{p_i ijk}$	Transportation cost of product $p_i \in P_i$ between nodes i and j, $(i, j) \in Conn$ during catastrophe $k \in K$
$T^{h}_{p_i ij}$	Time for high-speed transport of product $p_i \in P_i$ between nodes i and j, $(i, j) \in Conn$
$T^{m}_{p_i ij}$	Time for medium-speed transport of product $p_i \in P_i$ between nodes i and j, $(i, j) \in Conn$
$T^{l}_{p_i ij}$	Time for low-speed transport of product $p_i \in P_i$ between nodes i and j, $(i, j) \in Conn$
$T_{p_i ij}$	Transportation time for product $p_i \in P_i$ between nodes i and j, $(i, j) \in Conn$
$T_{p_i ijk}$	Transportation time for product $p_i \in P_i$ between nodes i and j, $(i, j) \in Conn$ during catastrophe $k \in K$
$T^{n2r}_{p_i p_j ij}$	Time interval of product $p_i \in P_i$ being finished and sent out from node $i \in N$ until it is transformed into the final product p_j and sold at retailer $j \in RW$
$T^{n2r}_{p_i p_j ijk}$	Time interval of product $p_i \in P_i$ being finished and sent out from node $i \in N$ until it is transformed into the final product p_j and sold at retailer $j \in RW$ after catastrophe $k \in K$
LT_{p_i}	The longest SC lead time of $p_i \in P_i$
$Q_{p_i p_j ij}$	Number of products $p_i \in P_i$ needed to make one unit of product $p_j \in P_j$, $(i, j) \in Conn$
C^{h}	Per period holding cost coefficient of capital lockup
$D_{p_i i}$	Demand per period of product $p_i \in P_i$ at retailer $i \in RW$
$C^{Stockout}_{p_i}$	Per unit penalty cost coefficient for unmet demand of the final product $p_i \in P_i$
$T^{Stockout}_{p_i i}$	Time period of stockout of product $p_i \in P_i$ at retailer $i \in RW$
$C^{I}_{p_i}$	Per unit storage cost coefficient of the final product $p_i \in P_i$
$T^{I}_{p_i i}$	Storage time of product $p_i \in P_i$ at retailer $i \in RW$
T^{R}_{k}	Reconstruction time of the destroyed node after a catastrophe in scenario $k \in K$
r_k	Probability of scenario $k \in K$ within the time horizon T
$C^{Cum}_{p_i i}$	Cumulated costs per unit of product $p_i \in P_i$ after being finished at node $i \in N$, including purchasing costs, transportation costs of related materials from its upstream nodes, holding costs of these materials during transportation and operational costs of $p_i \in P_i$ at node $i \in N$
$C^{Cum}_{p_i ik}$	Cumulated costs per unit of product $p_i \in P_i$ after being finished at node $i \in N$ during the reconstruction period of a catastrophe in scenario $k \in K$
T^{ex}_{k}	Extra time when using the alternative node after the catastrophe in scenario $k \in K$

C_k^{SCtot} Total SC costs in scenario $k \in K$
C^{SC1} First stage SC costs – SC costs without considering impacts of catastrophes
C_k^{SC2} Second stage SC costs – extra SC costs during the reconstruction time of scenario $k \in K$

First stage decision variables

$y_{p_i ij}^h$ Selection of a high-speed transportation mode for product $p_i \in P_i$ between nodes i and j if $y_{p_i ij}^h = 1$, otherwise $y_{p_i ij}^h = 0$, $(i, j) \in Conn$
$y_{p_i ij}^m$ Selection of a medium-speed transportation mode for product $p_i \in P_i$ between nodes i and j if $y_{p_i ij}^m = 1$, otherwise $y_{p_i ij}^m = 0$, $(i, j) \in Conn$
$y_{p_i ij}^l$ Selection of a low-speed transportation mode for product $p_i \in P_i$ between nodes i and j if $y_{p_i ij}^l = 1$, otherwise $y_{p_i ij}^l = 0$, $(i, j) \in Conn$

Second stage decision variables (after the realization of catastrophic scenarios):

$y_{p_i ijk}^h$ Modification variable for a high-speed transportation mode for product $p_i \in P_i$ in scenario $k \in K$ between nodes i and j, $\left(y_{p_i ijk}^h + y_{p_i ij}^h\right) \in \{0, 1\}$, $(i, j) \in Conn$
$y_{p_i ijk}^m$ Modification variable for a medium-speed transportation mode for product $p_i \in P_i$ in scenario $k \in K$ between nodes i and j, $\left(y_{p_i ijk}^m + y_{p_i ij}^m\right) \in \{0, 1\}$, $(i, j) \in Conn$
$y_{p_i ijk}^l$ Modification variable for a low-speed transportation mode for product $p_i \in P_i$ in scenario $k \in K$ between nodes i and j, $\left(y_{p_i ijk}^l + y_{p_i ij}^l\right) \in \{0, 1\}$, $(i, j) \in Conn$

Objective function:

$$\text{minimize} \quad \sum_{k \in K} r_k * C_k^{SCtot}$$
$$\text{subject to} \tag{1}$$

SC costs for scenario $k \in K$:

$$C_k^{SCtot} := C^{SC1} + C_k^{SC2} \tag{2}$$

Stage one:

Total costs at retailers $i \in RW$:

$$C^{SC1} := \sum_{p_i \in P_i | i \in RW} C_{p_i i}^{Cum} * D_{p_i i} * T \tag{3}$$

Purchasing costs of product $p_i \in P_i$ from suppliers:

$$C_{p_i i}^{Cum} := C_{p_i i}^{P} \quad \forall\, i \in S,\ p_i \in P_i \tag{4}$$

Costs per unit of product $p_j \in P_j$:

$$C_{p_j j}^{Cum} := \sum_{(i,j) \in Conn} \sum_{p_i \in P_i} \left(C_{p_i i}^{Cum} * Q_{p_i p_j ij} + C^{h} * C_{p_i i}^{P} * Q_{p_i p_j ij} * T_{p_i ij} + C_{p_i ij}^{TP} * Q_{p_i p_j ij} \right) + C_{p_j j}^{O}\ \forall\, p_j \in P_j, j \in N \tag{5}$$

Time interval between product $p_i \in P_i$ being finished until it is transformed into the final product p_r and sold at retailer $r \in RW$:

$$T_{p_i p_r ir}^{n2r} := T_{p_i ir} \quad \forall\, r \in RW,\ (i, r) \in Conn,\ Q_{p_i p_r ir} > 0,\ p_r \in P_r,\ p_i \in P_i \tag{6a}$$

$$T_{p_i p_r ir}^{n2r} := T_{p_i ij} + T_{p_j p_r jr}^{n2r} \quad \forall\, r \in RW \wedge i \in N | (i, r) \notin Conn,\ (i, j) \in Conn,\ Q_{p_i p_j ij} > 0,\ j \notin RW,\ p_r \in P_r,\ p_i \in P_i,\ p_j \in P_j \tag{6b}$$

Lead time constraints:

$$T_{p_i p_j ij}^{n2r} \le LT_{p_j} \quad \forall\, i \in S, j \in RW, p_i \in P_i, p_j \in P_j \tag{7}$$

In order to ensure that only one transportation mode is selected for a product on the transportation link from node $i \in N$ to node $j \in N$, we set the transportation mode constraints as follows:

$$y_{p_i ij}^h + y_{p_i ij}^m + y_{p_i ij}^l = 1 \quad \forall\, p_i \in P_i, (i, j) \in Conn \tag{8}$$

$$y_{p_i ij}^h, y_{p_i ij}^m, y_{p_i ij}^l \in \{0, 1\} \quad \forall\, p_i \in P_i, (i, j) \in Conn \tag{9}$$

Transportation time of product $p_i \in P_i$ from node i to node j while $(i, j) \in Conn$:

$$T_{p_i ij} := y_{p_i ij}^h * T_{p_i ij}^h + y_{p_i ij}^m * T_{p_i ij}^m + y_{p_i ij}^l * T_{p_i ij}^l \quad \forall\, (i, j) \in Conn, p_i \in P_i \tag{10}$$

Transportation costs of product $p_i \in P_i$ from node i to node j while $(i, j) \in Conn$:

$$C_{p_i ij}^{TP} := y_{p_i ij}^h * C_{p_i ij}^{Th} + y_{p_i ij}^m * C_{p_i ij}^{Tm} + y_{p_i ij}^l * C_{p_i ij}^{Tl} \quad \forall\, (i, j) \in Conn,\ p_i \in P_i \tag{11}$$

Stage two:

Per period SC extra costs during the reconstruction time of scenario $k \in K$:

$$C_k^{SC2} := \sum_{i \in RW} \sum_{p_i \in P_i} \left[\left(C_{p_i ik}^{Cum} - C_{p_i i}^{Cum} \right) * D_{p_i i} * T_k^R + T_{p_i i}^{Stockout} * C_{p_i}^{Stockout} + T_{p_i i}^{I} * C_{p_i}^{I} \right] \quad \forall\, k \in K \tag{12}$$

Notice that the finalizing of products may be moved to an area with lower labor costs, if an overseas assembling center is destroyed. It is possible that C_k^{SC2} is negative in this case which means that SC costs decrease in case of a destroyed overseas assembling center (though this may be over-compensated by other cost values).

The modification factors of an appropriate transportation mode after a catastrophe are indicated by $y_{p_i ijk}^h$, $y_{p_i ijk}^m$ and $y_{p_i ijk}^l$.

$$y_{p_i ijk}^h, y_{p_i ijk}^m, y_{p_i ijk}^l \in \{-1, 0, 1\} \quad \forall\, p_i \in P_i,\ (i, j) \in Conn,\ k \in K \tag{13}$$

$$y_{p_i ijk}^h + y_{p_i ijk}^m + y_{p_i ijk}^l = 0 \quad \forall\, p_i \in P_i,\ (i, j) \in Conn,\ k \in K \tag{14}$$

$$y_{p_i ij}^h + y_{p_i ijk}^h \ge 0 \quad \forall\, p_i \in P_i,\ (i, j) \in Conn,\ k \in K \tag{15a}$$

$$y_{p_i ij}^m + y_{p_i ijk}^m \ge 0 \quad \forall\, p_i \in P_i,\ (i, j) \in Conn,\ k \in K \tag{15b}$$

$$y_{p_i ij}^l + y_{p_i ijk}^l \ge 0 \quad \forall\, p_i \in P_i,\ (i, j) \in Conn,\ k \in K \tag{15c}$$

The desirable transportation mode is selected by adding a transportation mode modification variable $y^h_{p_iijk}$, $y^m_{p_iijk}$ or $y^l_{p_iijk}$ to corresponding transportation mode variables $y^h_{p_iij}$, $y^m_{p_iij}$ and $y^l_{p_iij}$, respectively. In case of changing a transportation mode after a catastrophe, the values of the modification variables referring to the current transportation modes become -1, the values of the modification variables referring to the desirable transportation modes become 1, and the remaining modification variables should be 0. For example, if the original transportation mode of $p_i \in P_i$ on the transportation link of $(i, j) \in Conn$ is a low-speed mode ($y^h_{p_iij}$:=0, $y^m_{p_iij}$:=0, $y^l_{p_iij}$:=1), in case of a catastrophic event $k \in K$ it needs to be switched to the high-speed mode ($y^h_{p_iijk}$:=1, $y^m_{p_iijk}$:=0, $y^l_{p_iijk}$:= $-$ 1). If the transportation mode variable and the transportation mode modification variable refer to the same transportation mode together, an acceleration of transportation takes place ($y^h_{p_iij}$:=1, $y^m_{p_iij}$:=0, $y^l_{p_iij}$:=0). The constraints in (15a)-(15c) ensure that transportation mode values remain valid after a modification:

$$T_{p_iijk} := \left(y^h_{p_iij} + y^h_{p_iijk}\right) * T^h_{p_iij} + \left(y^m_{p_iij} + y^m_{p_iijk}\right) * T^m_{p_iij} + \left(y^l_{p_iij} + y^l_{p_iijk}\right) * T^l_{p_iij} \quad \forall\ (i, j) \in Conn,\ \ p_i \in P_i,\ \ k \in K \tag{16}$$

$$C^{TP}_{p_iijk} := \left(y^h_{p_iij} + y^h_{p_iijk}\right) * C^{Th}_{p_iij} + \left(y^m_{p_iij} + y^m_{p_iijk}\right) * C^{Tm}_{p_iij} + \left(y^l_{p_iij} + y^l_{p_iijk}\right) * C^{Tl}_{p_iij} \quad \forall\ (i, j) \in Conn,\ \ p_i \in P_i,\ \ k \in K \tag{17}$$

Purchasing costs of product $p_i \in P_i$ from suppliers for scenario $k \in K$:

$$C^{Cum}_{p_iik} := C^P_{p_iik} \quad \forall\ i \in S,\ \ p_i \in P_i,\ \ k \in K \tag{18}$$

Costs of per unit product $p_j \in P_j$ for scenario $k \in K$:

$$C^{Cum}_{p_jjk} := \sum_{(i,j) \in Conn} \sum_{p_i \in P_i} \left(C^{Cum}_{p_iik} * Q_{p_ip_jij} + C^h * C^P_{p_iik} * Q_{p_ip_jij} * T_{p_iijk} + C^{TP}_{p_iijk} * Q_{p_ip_jij} \right) + C^O_{p_jjk} \quad \forall\ p_j \in P_j, j \in N,\ k \in K \tag{19}$$

Time interval of product $p_i \in P_i$ being finished and sent out from node $i \in N$ until it is transformed into the final product p_j and sold at retailer $j \in RW$ after a catastrophe:

$$T^{n2r}_{p_ip_rirk} := T_{p_iirk} \quad \forall\ r \in RW,\ (i, r) \in Conn,\ Q_{p_ip_rir} > 0,\ p_r \in P_r,\ p_i \in P_i \tag{20a}$$

$$T^{n2r}_{p_ip_rirk} := T_{p_iijk} + T^{n2r}_{p_jp_rjrk} \quad \forall\ r \in RW \wedge i \in N | (i, r) \notin Conn,\ (i, j) \in Conn,\ Q_{p_ip_jij} > 0,\ j \notin RW,\ p_r \in P_r,\ p_i \in P_i,\ p_j \in P_j \tag{20b}$$

Stockout time of the final product p_j:

$$T^{Stockout}_{p_jj} = \max\left\{0,\ T^{n2r}_{p_{i^*}p_ji^*jk} + T^{ex}_k - T^{n2r}_{p_{i^*}p_ji^*j}\right\} \quad \forall\ j \in RW,\ p_{i^*} \in P_{i^*},\ k \in K \tag{21}$$

Node i^* in Formula (21) indicates the location of a catastrophe in scenario $k \in K$, which means that node i^* is destroyed or a disruption happens on the transportation link $(i^*, j) \in Conn$. The stockout time in Formula (21) refers to unmet demand of final products at each retailer. The available time after a catastrophe in scenario k is $T^{n2r}_{p_{i^*}p_ji^*j}$, the latest batch of products on the upstream side of the destroyed site arrives at the retailers after time period $T^{n2r}_{p_{i^*}p_ji^*j} + T^{ex}_k$. If this batch of products is not able to arrive during the available time period, unmet demand of final products gets penalized.

Inventory holding time of the final product p_j after accelerating transportation:

$$T^I_{p_jj} := -\min\left\{0,\ T^{n2r}_{p_{i^*}p_ji^*jk} + T^{ex}_k - T^{n2r}_{p_{i^*}p_ji^*j}\right\} \quad \forall\ j \in RW,\ p_{i^*} \in P_{i^*},\ k \in K \tag{22}$$

According to our assumptions for the proposed model, there are no inventories if catastrophes are assumed to be absent. However, short time intervals with inventory may exist if the transportation of items is accelerated after a disruption. In this case, inventory costs are charged. Furthermore, inventory costs also ensure that the slack time obtained from changing transportation modes is only used as much as needed after emergencies.

In order to show the feasibility of the model and the quality of SP solutions, computational experiments with different SC structures and parameters will be conducted in the next section. According to our computational experiments, a few general managerial insights will be presented, too. Furthermore, it will provide additional managerial insights for a SC executive by using parameters of a SC from the real world.

5. Computational results

In order to evaluate the quality of solutions of our stochastic programming model (SP solutions) and deduce some general implications, 276 instances of SC parameters are randomly designed in our computational experiments. Wait-and-see solutions are the benchmarks for all our computational results. Wait-and-see solutions can be achieved only when there is no uncertainty. For each instance, a SP solution is solved based on a set of representative scenarios. To evaluate the expected SC costs of SP solutions in practical applications, one thousand scenarios, which are independent from the representative scenarios, are generated based on the prediction of disruptions to simulate real cases. The expected SC costs for these scenarios will be calculated based on SP solutions. The quality of SP solutions can be identified through the comparison between SP solutions and wait-and-see solutions. The respective gaps of expected SC costs between SP solutions and wait-and-see solutions are calculated and presented in this section. For each SP solution, a gap is obtained from dividing the expected SC costs for one thousand scenarios based on the SP solution by the expected SC costs for these scenarios based on wait-and-see solutions. The gap indicates the quality of the SP solution. A small gap indicates a better quality than a large gap. In Figs. 5–8, it is a gap between the line inside a box and the dash line. In addition, the expected SC costs of solutions of decision makers with neutral, optimistic and pessimistic attitudes regarding the occurrence of disruptions will be analyzed and compared with the results of SP solutions.

The results are classified into four groups. In order to figure out the number of representative scenarios for generating SP solutions, the quality of SP solutions with respect to a different number of representative scenarios is analyzed in the first investigation (Section 5.1). A second investigation deals with SCs with a very low risk (around 10% in the considered time horizon), a medium risk (around 50% in the considered time horizon) and a very high risk (around 90% in the considered time horizon) of catastrophic events (Section 5.2). Our third investigation is concerned with impacts from postponement strategies in stochastic catastrophic environments (Section 5.3). Furthermore, the impacts from different types of SC disruptions will be analyzed in Section 5.4. In this section, the results are classified into four groups with respect to four different types of disruptions: (1) disruptions at a crucial supplier, (2) disruptions at a distribution center, (3) disruptions at a processing center, (4) disruptions during long-distance international transportation of products. Finally, transportation modes for SP solutions are analyzed in order to give guidelines for SC executives (Section 5.5).

In our computational experiments, scenarios for instances are generated with Python 3.5 (installed with scipy and numpy). The extra time for an alternative strategy T_k^{ex} is assumed to be exponentially distributed which ranges from 5 to 15 days. The reconstruction time after a catastrophe T_k^R is assumed to be normally distributed which ranges from 10 to 40 days. The time horizon for a severe catastrophe is 360 days, and 90 or 30 days for a medium or minor catastrophe. All these parameters are defined according to the frequency and the severity of a potential disruption. In our model, the disruption should not happen more than once during the considered time horizon. In order to satisfy this condition, the time horizon should be defined based on the historical frequency of a type of catastrophic events.

All SP solutions are generated with PySP (Pyomo 4.2, Gurobi 6.5) on a Linux server with 2 CPUs (Intel® Xeon® Processor E5-2630 v3, 20M Cache, 2.40 GHz). The computing time for an instance with 200 scenarios is around 200 s for each PH iteration. The number of iterations are different for our instances and ranges from 2 to 200, as a user-defined maximum iteration number.

5.1. Analysis of the number of representative scenarios

In order to determine the number of representative scenarios for our computational experiments, the quality of SP solutions with respect to a different number of representative scenarios will be analyzed.

Four groups of SP solutions are generated with 50, 100, 150 and 200 representative scenarios, respectively. Gaps of these SP solutions are shown in Fig. 5. SP solutions with 50 representative scenarios are unstable, although the median of gaps is around 1%. SP solutions with 150 and 200 scenarios show better quality and stability. In order to make sure that we obtain high quality SP solutions, 100, 150 or 200 scenarios are used for the subsequent computational experiments.

5.2. Analysis of disruptions with different probabilities

In our computational experiments, the quality of SP solutions are different for catastrophic events with different probabilities. Gaps of SP solutions for catastrophic events with low, medium and high probabilities are shown in Fig. 6.

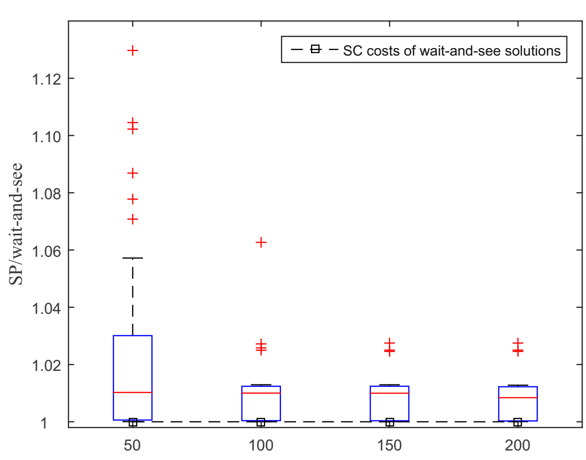


Fig. 5. Gaps of SP solutions with different number of respective scenarios. The line inside a box is the median. The box encloses 50% of the values within the box. A plus sign shows a value outside the corresponding box.

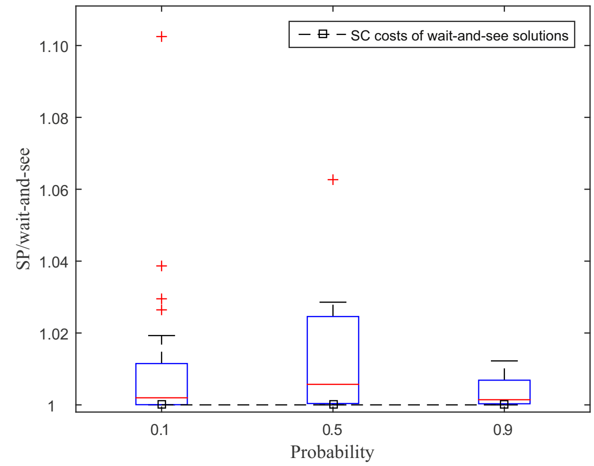


Fig. 6. Gaps of SP solutions for catastrophic events with different probabilities.

Compared with medium and low probability catastrophic events, SP solutions for high probability catastrophic events show smaller gaps (mostly less than 1%). The expected SC costs of SP solutions in high probability catastrophic environments are usually less than 1% higher than the expected SC costs of wait-and-see solutions. Most of SP solutions for low probability catastrophic events also show good quality, but not as stable as SP solutions for high probability catastrophic events. For medium probability catastrophic events, SP solutions have the biggest gaps, although they are mostly less than 3%. This finding points out a topic for the next step – to improve the quality of SP solutions for SCs with medium probability catastrophic events.

5.3. Analysis of different SC structures

The impacts from SC postponement strategies will be analyzed in this section. Results for two different SC structures, with and without implemented postponement strategies, are classified into two groups (PP and NPP). Gaps of SP solutions as well as solutions of decision makers with neutral, optimistic, and pessimistic attitudes regarding the occurrence of breakdowns are presented in Fig. 7. In stochastic catastrophic environments, decision makers with optimistic attitudes always ignore possible catastrophic events. They make decisions based on the assumption that catastrophic events will never happen. On the opposite side, decision makers with pessimistic attitudes always prepare for the worst case. Pessimistic managers make decisions based on the assumption that the catastrophic event will happen at the worst situation. Unlike the former two decision makers, once identifying a possible catastrophic event, decision makers with neutral attitudes will prepare for the catastrophic events according to the assumption that the catastrophic event will happen at an average level of severity.

In Group PP, all solutions perform better than solutions in Group NPP. SP solutions show the best quality and stability, while solutions of the optimistic decision makers show the worst quality and stability. In particular, gaps of solutions of the neutral and pessimistic decision makers in Group PP are very close to the benchmarks. From the comparison of SP solutions and the solutions generated by the experiments with different decision makers (optimistic, pessimistic, and neutral) in Group PP, we find out: In low risk environments, most SP solutions are similar to or even the same as solutions of decision makers with optimistic attitudes. In high risk environments, most SP solutions are similar or even the same as solutions of experiments for decision makers with pessimistic attitudes. Similar rules do not work for SCs without implemented postponement strategies (Group NPP).

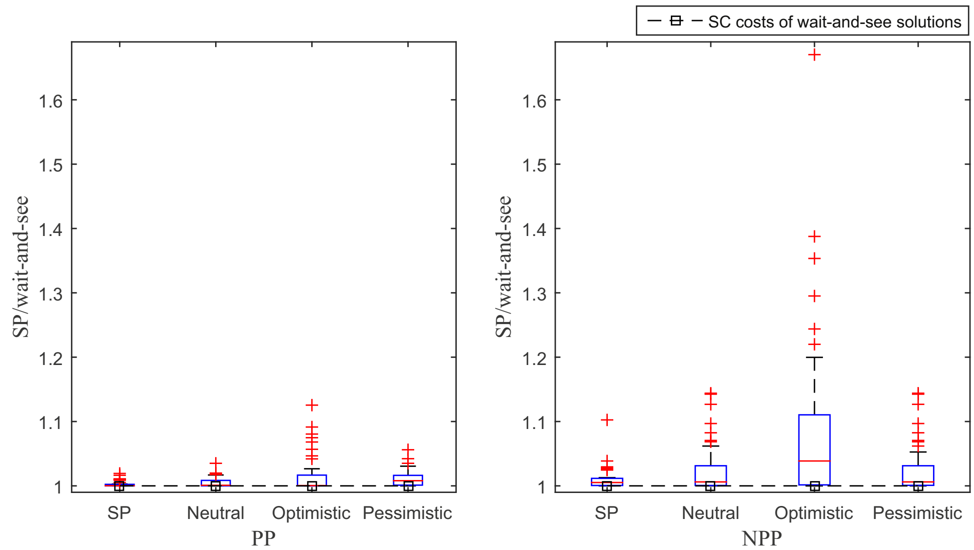


Fig. 7. Gaps of solutions for SCs with different structures.

From this point of view, we conclude: Compared with SCs without implemented postponement strategies, SC structures with implemented postponement strategies are more flexible in stochastic catastrophic environments. This conclusion brings us to conduct more experiments to explore further differences between SC structures of PP and NPP in Section 5.4.

5.4. Analysis of different types of disruptions

Except of the probability of catastrophic events and the SC structures, the types of catastrophic events impact the quality of SP solutions, too. But the impacts of disruption types to different SC structures are different. Thus, in Fig. 8, results are presented in eight sub-graphs with respect to two SC structures (PP and NPP) and four types of disruptions, i.e., supplier disruptions, distribution center disruptions, processing center disruptions and transportation delays.

In Fig. 8, most of the solutions in PP sub-graphs have smaller gaps than the corresponding solutions in NPP sub-graphs. For SCs with PP structure, gaps of SP solutions and solutions of the optimistic decision makers are zero for three types of disruptions, i.e., supplier disruptions (PP), processing center disruptions (PP) and transportation delays (PP). In the sub-graph of transportation delays (PP), SP solutions and solutions of the neutral, optimistic and pessimistic decision makers are as good as wait-and-see solutions. Solutions of the optimistic decision makers have the biggest gaps in all NPP sub-graphs.

In order to find out general rules for transportation mode selection from these computational experiments, we investigated transportation modes for each solution in detail. We found that the transportation modes for the final products significantly impact SC costs. In low risk environments, high-speed transportation modes are applied for most of the final products, medium- and low-speed transportation modes are applied for most of materials and semi-finished products. Meanwhile, the transportation modes for products' long-distance transportation significantly impact the flexibility of SCs. Adopting medium- or low-speed modes for the products' long-distance transportation enables more flexible SCs.

For SCs with PP structure, semi-finished products are transported for long-distance links with medium- or low-speed transportation modes for SP solutions and solutions of the optimistic decision makers in low risk environments. In this case, SCs with a PP structure are flexible to cope with stochastic catastrophic disruptions.

For SCs with NPP structure, the final products are transported for long-distance links with high-speed transportation modes for SP solutions in low risk environments. In this case, in order to keep latent time buffers for coping with stochastic catastrophic disruptions, the final products' long-distance transportation have to be medium- or low-speed which will significantly increase SC costs. Otherwise, SCs will experience huge economic losses once a catastrophic event occurs. This is consistent with solutions of the optimistic decision makers.

In this section, computational results and transportation modes analysis reveal the same insight as Section 5.3 that in stochastic catastrophic environments, the SC structure of PP is more flexible than the SC structure of NPP.

5.5. Analysis of transportation modes

In addition to the findings discussed above, further managerial insights are found by analyzing transportation modes of SP solutions which also provide guidelines for SC planners:

1. Low-speed transportation modes are only used for inexpensive items if transportation distances are moderate and lead time constraints are not too tight.
2. For long distance transportation, high- and medium-speed transportation modes are usually selected for valuable products, such as final products. Low-speed transportation is only used for these product types in case of very tight lead time constraints.
3. In low risk environments, low- or medium-speed transportation is applied for the majority of unprocessed raw material or parts, while high-speed transportation modes are used for the transportation of most final products.
4. In high risk environments, especially for distribution center disruptions, the most favorable transportation modes for transports of final products to retailers with a high demand as well as to retailers nearby distribution centers are always low- or medium-speed transportation modes.

6. Application of the stochastic programming model

According to the investigations of Partida (2013), global SCs mostly operate in stochastic environments. Our stochastic

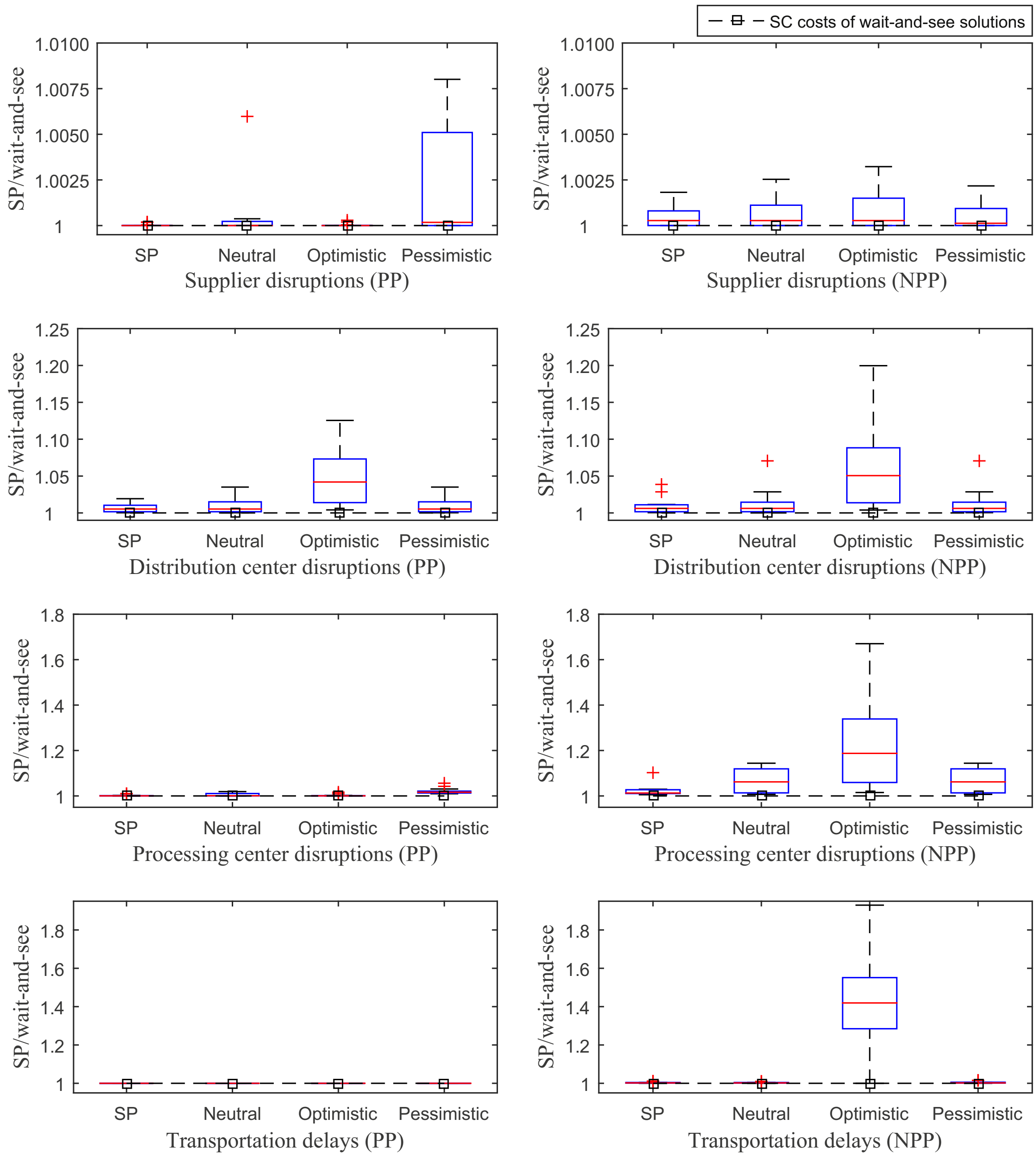


Fig. 8. Gaps of solutions for different types of catastrophic events.

programming model copes with potential future catastrophic disruptions involving a flexible SC with latent time buffers during transportation of products. Variable transportation modes are used as a strategy for enabling a flexible supply chain. Rather than an ex post strategy (or a rescue plan), our strategy is an ex ante strategy.

A framework of applying our stochastic programming model in practice is presented in Fig. 9. With the prediction of a potential catastrophic event's severity, a scenario generator is developed based on the probability distributions of parameters associated with the severity. A number of scenarios will be generated by the scenario generator as inputs of our stochastic programming model (Section 4). Incorporating with these scenarios and parameters of a SC, the stochastic programming model can be solved by PySP. Each SP solution represents a transportation mode plan. Notice that prediction methods are not the focus of this paper.

With an adequate SC structure and an appropriate transportation mode planning, the SC will have flexibility for coping with catastrophes. Our model is able to provide decision support for global SC executives in order to plan the transportation modes for different products, especially for the long distance transportation. Due to the fact that the structure of a global SC and the global SC environment are dynamic, the transportation mode decision should be adjusted in fixed time intervals such as a month or a few months, or after a catastrophe. It indicates that in stochastic catastrophic environments, transportation mode planning for global SCs should be adjusted in fixed time intervals.

Our stochastic programming model is especially applicable for SCs in the environments with potential catastrophic events. For these catastrophic events, the severity and frequency/probability can be forecasted based on the historical data, but the time of their occurrence cannot be predicted in advance. In order to deal with

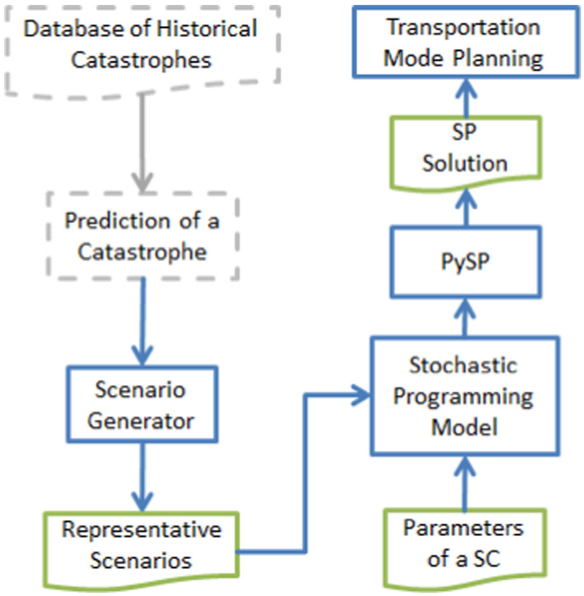


Fig. 9. A framework of applying the stochastic programming model.

this type of catastrophic events, SC planning based on variable transportation modes represents a promising approach. By using the stochastic programming model that we developed in this paper, high quality solutions will be generated with PySP.

7. Conclusion

In this paper, an adjustment of the transportation speed of products was considered as an innovative way to obtain buffer time to manage catastrophic risks in a supply chain. This paper made several contributions to the field of SC disruption management. First, SC disruption risk was quantified and a two-stage multi-scenario stochastic programming model was developed in order to analyze SCs with stochastic events like catastrophes. From a research perspective, our paper fills the research gap of modeling and quantifying flexibility with a set of given parameters. Solutions of our stochastic programming model provide decision support for SC executives in order to select proper transportation modes and enable a flexible supply chain. Second, the application of flexible transportation modes has been investigated in detail as an additional strategy to manage SC disruption risks. By using slower transportation speed for certain products on certain transportation links, a SC can become more flexible with reduced storage levels at warehouses. With this background, slow steaming, as a typical slow speed and eco-friendly transportation mode, will be adopted more extensively to enable a flexible and sustainable supply chain.

Furthermore, in order to find out general rules for transportation mode selection for products, results from 276 instances were collected and analyzed. The calculation in order to identify the most appropriate transportation modes for raw materials, semi-finished products as well as final products (SP solutions) takes place with PySP. Each SP solution was compared with wait-and-see solutions as benchmarks to evaluate the quality of the SP solution. Our simulation results manifest that SP solutions were always superior to solutions of decision makers with neutral, optimistic and pessimistic attitudes regarding the occurrence of disruptions.

The results were the basis for diverse managerial insights: SCs with implemented postponement strategies were more flexible in stochastic catastrophic environments. The transportation modes for the final products significantly impact SC costs. The transportation modes for products' long-distance transportation significantly impact the flexibility of SCs. SCs with a predominant number of products using a low-speed transportation mode were highly flexible in high risk environments, but in case of tight lead time constraints, only a very limited number of products, namely the most valuable products were able to use low-speed transportation modes.

The best strategy to cope with short-term SC disruptions and disruptions at distribution centers is to save slack time during the transport of final products. In case of long-term SC catastrophes, the best strategy to cope with these disturbances is to save slack time during the transport of raw material as well as during the international transport of final products. Further results show that SCs with implemented postponement strategies are more flexible than SCs without implemented postponement strategies, because the best transportation modes of products in case of implemented postponement strategies are identical both in high-risk and low-risk environments.

Most importantly, these findings were based on a somewhat limited number of computational experiments. Nevertheless, with data of the real world, our model provides decision support in detail for a specific SC of a real case.

Regarding the solution technique, we investigate different selection criteria for the penalty parameter of the applied PH-algorithm. We are able to point out for almost all of our instances that the best performing solutions are obtained with an element-specific penalty parameter criterion proposed by Watson et al. (2012).

To conclude the paper, utilizing/implementing variable transportation modes is an additional strategy to cope with SC disruption risks. By quantifying SC disruption risks and considering transportation modes as variables, the two-stage multi-scenario stochastic programming model proposed in our paper will provide decision support to enable flexible and sustainable supply chains.

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Appendix

The progressive hedging algorithm proposed by Rockafellar and Wets (1991) is a well-known approach within the area of stochastic optimization. It is supposed to converge to a global optimum in the convex case. In the non-convex case, if sub-problems are solved to local optimality, it is supposed to converge to a local optimal solution. Here we describe our application of PH to let the reader know the details of our related implementation. For a more general description see the original reference; some general context is provided by Römisch and Schultz (2001). According to Watson et al. (2007), the probability of each scenario $s \in S$ is denoted by $Pr(s)$. The goal is to minimize expected cost, which can be written

$$\text{minimize} \sum_{s \in S} Pr(s)(c \times x)$$

$$\text{s. t. : } x \in Q_s$$

where the use of the decision vector $x(x_s = x, \forall\, s \in S)$ that does not depend on the scenario implicitly implements the non-anticipativity constraints that avoid allowing the decisions to depend on the scenario. For such an optimization problem, the basic PH algorithm can be stated as follows, taking a perturbation factor $\rho > 0$ as the sole input parameter:

1. k:=0
2. For all scenario indices $s \in S$

$$x_s^{(0)} := \text{argmin}_x (c \times x) \colon x \in Q_s$$

3. $\bar{x}^{(0)} := \sum_{s \in S} Pr(s) \times x_s^{(0)}$
4. $w_s^{(0)} := \rho(x_s^{(0)} - \bar{x}^{(0)})$
5. k:=$k + 1$
6. For all scenario indices $s \in S$

$$x_s^{(k)} := \text{argmin}_x (c \times x) + w_s^{(k-1)} \times x + \rho/2 \left\| x - \bar{x}^{(k-1)} \right\|^2 \colon x \in Q_s$$

$$w_s^{(k)} := w_s^{(k-1)} + \rho\left(x_s^{(k-1)} - \bar{x}^{(k-1)} \right)$$

and

$$\bar{x}^{(k)} := \sum_{s \in S} Pr(s) x_s^{(k)}$$

7. If the termination criteria are not met, then go to step 5.

The termination criteria are based mainly on the convergence of the $x_s^{(k)}$ to a common $\bar{x}$.

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