A Proposal of Resilient Supply Chain Network Planning Method with Supplier Selection and Inventory Levels Determination Using Two-Stage Stochastic Programming

Kobayashi, Hibiki ; Kaihara, Toshiya ; Kokuryo, Daisuke ; Tanaka, Rina ; Hara, Masashi ; Miyachi, Yuto ; Sariddichainunta, Puchit

(Citation)
Advances in Production Management Systems. Production Management Systems for Responsible Manufacturing, Service, and Logistics Futures:714-729

(Issue Date)
2023-09-14

(Resource Type)
conference paper

(Version)
Accepted Manuscript

A proposal of resilient supply chain network planning method with supplier selection and inventory levels determination using two-stage stochastic programming

Hibiki Kobayashi[1], Toshiya Kaihara[1], Daisuke Kokuryo[1],

Rina Tanaka[2], Masashi Hara[2], Yuto Miyachi[2] and Puchit Sariddichainunta[2]

[1] Graduate School of System Informatics, Kobe University,
1-1 Rokkodai-cho, Nada, Kobe, Hyogo 657-8501, Japan
hkobayashi@kaede.cs.kobe-u.ac.jp, kaihara@kobe-u.ac.jp, kokuryo@port.kobe-u.ac.jp
[2] Lion Corporation
1-3-28 Kuramae, Taito, Tokyo 111-8644, Japan
r-tanaka@lion.co.jp, h-masashi@lion.co.jp, y-miya00@lion.co.jp, puchit@lion.co.jp

Abstract. The importance of risk management has been pointed out in supply chain management which stably supplies products with considering economic efficiency. Supply chain network plan usually consists of two-stage decision process in business environment. Two-stage stochastic programming is appropriate for decision making under uncertainly in business environment where two steps of decision processes are involved. Therefore, we propose a planning method of resilient supply chain networks using two-stage stochastic programming. To improve computational efficiency while taking uncertain future events into account, we also propose a risk optimization method to design a resilient supply chain with reducing the number of scenarios by scenario sampling. In this paper, we attempt to plan a supply chain network consisting of suppliers, manufacturers, and wholesalers by selecting material suppliers and determining appropriate inventory levels in consideration of risk. Its optimality and resilience are evaluated by computer experiments. Furthermore, we evaluate the effectiveness of the proposed method in terms of computational efficiency as well as the optimality of the solution with scenario sampling by computer experiments.

Keywords: Supply Chain Network, Stochastic programming, Resilience, Inventory control, Scenario reduction

1 Introduction

Recently, the influence of supply chain risks has increased in many manufacturing industries [1]. There are two types of supply chain risks: operational risks and disruption risks. The former is a risk that can occur in normal production activities such as fluctuations in demand and production timing. The latter refers to the risks caused by unexpected events with irregular timing and scale such as earthquakes, tsunamis, and pandemics. The latter is called supply chain disruption because the supply chain network is temporarily disrupted by various influences. Even large companies may be eliminated by unexpected risks and risk management that takes into account the entire supply chain management is necessary for survival [2]. For example, the 2011 Japan earthquake and tsunami reduced Toyota's production by 40,000 vehicles, costing $72 million in lost profits per day [3]. The COVID-19 pandemic has disrupted all parts of supply chains due to unprecedented world responses to control the virus, ranging from border closure, statewide lockdown, and workforce limitation [2]. In risk management against supply chain disruption, our group has started research on constructing a supply chain network that can deal appropriately with supply chain disruptions. Aiming for a resilient supply chain that can withstand disruptions of varying length, impact, and probability is essential to ensure the functioning and success of the supply chain [4]. A resilient supply chain should be able to prepare, respond and recover from disturbances and afterwards maintain a positive steady state operation in an acceptable cost and time [5]. Emphasizing supply chain efficiency exacerbates disruption propagation, while emphasizing supply chain stability undermines efficiency. It is important to design, operate, and manage supply chains based on the tradeoff between economic optimality and stability, while taking future events into account [4]. Supply chain network planning usually consider two stage of decision process in a business environment [6]. The first stage considers the design of the supply chain, such as to determine facility locations and their capacity, and the second stage considers supply chain operations, such as production quantity and delivery routing. Decisions in each stage may affect the other stages and cannot be determined independently. In other words, the design and operational decisions of the supply chain must be considered to consider the optimality of operations in a disruption risk environment simultaneously. Reference [6] proposes two-stage stochastic program to determine facility placement for supply chain network design under facility disruptions. However, the model assumes that risk mitigation is only by opening and closing facilities, and do not take into account inventory, which is important as a lubricant in the supply chain. Reference [7] optimizes supply chain design considering disruptions by holding inventories, replicating bases, and reinforcing bases. However, the operation of the supply chain is verified by simulation, and the optimality of decision making after disruptions is not guaranteed.

In this paper, a method for planning resilient supply chain networks with material supplier selection and inventory level determination is proposed for a supply chain consisting of suppliers, manufacturers and wholesalers. In order to determine appropriate supplier selection and inventory levels considering future disruption risks, a two-stage stochastic programming [6] is applied. Furthermore, in order to obtain a solution with appropriate computational time and accuracy even if the problem scale is increased, we also propose a computational method that introduces Latin hypercube sampling [8], which extracts scenarios uniformly from the entire scenario space, to the proposed method. In computational experiments, the proposed method is compared with the conventional exact solution method in terms of solution accuracy and computation time for selecting material suppliers and appropriate inventory levels.

2 Target Model and Risks

This chapter provides an overview of the targeted supply chain and disruption risks.

2.1 Target Supply Chain

This paper focuses on a supply chain network consisting of multiple suppliers, one manufacturer including multiple factories and distribution centers, and wholesalers, respectively from the perspective of a manufacturing company. Figure 1 shows an overview of target supply chain network. The target is determined through discussions with the collaborating company.

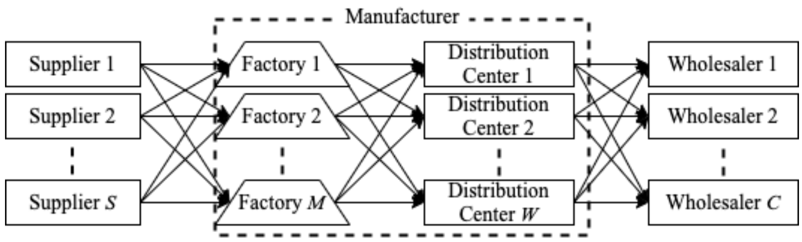

Fig. 1 Targeted Supply Chain Network

The target supply chain network has the following characteristics.

- Stock replenishment at each location follows fixed order period system.
- When wholesalers place orders to the distribution center, the quantity that does not meet demand is considered out-of-stock.
- The manufacturer selects material suppliers and determines appropriate inventory levels, taking into account of economic feasibility in response to disruptions.

2.2 Disruption Risks

In this paper, we consider a multi-period scenario of future events, assuming disruptions that occur at suppliers, factories, and distribution centers. The disruptions and scenarios are established based on reference [7]. The disruptions and scenarios are as follows:

- The facility where the disruption occurs will be deactivated.
- The disruption scale is expressed by the length of the stoppage period.
- The probability of occurrence of disruption is smaller for longer stoppage periods.
- Disruptions of any scale will be completed within the planning period.
- There are two scenarios: a normal scenario in which the disruption does not occur, and a scenario in which the disruption occurs only once during the planning period, with the length of the stoppage period varying according to the probability of occurrence set by the disruption.

3 A proposal of material supplier selection and appropriate inventory level determination method with risk resilience

This chapter describes a method for selecting material suppliers and determining appropriate inventory levels using two-stage stochastic programming for planning a resilient supply chain network.

3.1 Notation

The definition of the characters used in the formulation is as follows:
Sets

- $\boldsymbol{S}$: set of suppliers ($s = 1,2, \dots, S$)
- $\boldsymbol{M}$: set of factories ($m = 1,2, \dots, M$)
- $\boldsymbol{W}$: set of distribution centers ($w = 1,2, \dots, W$)
- $\boldsymbol{C}$: set of Wholesalers ($c = 1,2, \dots, C$)
- $\boldsymbol{K}$: set of scenarios ($k = 1,2, \dots, K$)
- $\boldsymbol{T}$: set of planning periods ($t = 1,2, \dots, T$)

Parameters

- $Caps_s$: capacity at supplier s
- $Capm_m$: material inventory capacity at factory m
- $Capp_m$: products inventory capacity at factory m
- $Capw_w$: inventory capacity at distribution center w
- PM_m : production capacity at factory m
- D_{ktc} : demand for products at wholesaler c in scenario k, period t
- CS_{sm} : contract costs between supplier s and factory m
- CB_{sm} : purchasing cost per unit of material from supplier s by factory m
- CTS_{sm} : transportation cost per unit from supplier s by factory m
- CTM_{mw} : transportation cost per unit from factory m by distribution center w
- CTW_{wc} : transportation cost per unit from distribution center w by wholesaler c
- CP_m : production cost per unit of product at factory m
- CL_c : stockout loss cost at wholesaler c
- HM_m : storage cost per unit of material at factory m
- HP_m : storage cost per unit of product at factory m
- HW_w : storage cost per unit of product at distribution center w
- LSM_{sm} : transportation period from supplier s by factory m
- LMW_{mw} : transportation period from factory m by distribution center w
- p_k : probability of scenario k
- α_{kts} : $\begin{cases} 1 : \text{if supplier } s \text{ operates in scenario } k, \text{period } t \\ 0 : \text{if a disruption occurs at supplier } s \text{ in scenario } k, \text{period } t \end{cases}$
- β_{ktm} : $\begin{cases} 1 : \text{if factory } m \text{ operates in scenario } k, \text{period } t \\ 0 : \text{if a disruption occurs at facory } m \text{ in scenario } k, \text{period } t \end{cases}$

- γ_{ktw} : $\begin{cases} 1 : \text{if distribution center } w \text{ operates in scenario } k, \text{period } t \\ 0 : \text{if a disruption occurs at distribution center } w \text{ in scenario } k, \text{period } t \end{cases}$

Decision Variables

- x_{sm} : $\begin{cases} 1 : \text{if supplier } s \text{ is contracted by factory } m \\ 0 : \text{otherwise} \end{cases}$
- lm_m : inventory level of materials at factory m
- lp_m : inventory level of products at factory m
- lw_w : inventory level of products at distribution center w
- pp_{ktm} : production quantity of factory m in scenario k at period t
- b_{ktsm} : quantity of materials purchased from supplier s by factory m in scenario k at period t
- qw_{ktmw} : quantity of products ordered from distribution center w to factory m in scenario k at period t
- qc_{ktwc} : quantity of products ordered from wholesaler c to distribution center w in scenario k at period t

Dependent Variables

- am_{ktm} : quantity of materials arrived of factory m in scenario k at period t
- aw_{ktw} : quantity of products arrived at distribution center w in scenario k at period t
- ac_{ktc} : quantity of products arrived at wholesaler c in scenario k at period t
- im_{ktm} : inventory quantity of materials of factory m in scenario k at period t
- ip_{ktm} : inventory quantity of products of factory m in scenario k at period t
- iw_{ktw} : inventory quantity of products of distribution center w in scenario k at period t
- ld_{ktc} : stockout quantity of wholesaler c in scenario k at period t

3.2 Method of selection of material suppliers and determination of appropriate inventory levels with risk resilience

This section outlines the proposed method for planning resilient supply chain networks with material supplier selection and inventory level determination for a supply chain consisting of suppliers, manufacturers and wholesalers. In order to determine appropriate supplier selection and inventory levels considering future disruption risks, two-stage stochastic programming is applied [6]. Furthermore, in order to obtain a solution with appropriate computational time and accuracy even if the problem scale is increased, we also propose a computational method that introduces Latin hypercube sampling [8], which extracts scenarios uniformly from the entire scenario space, to the proposed method.

This study proposes a method for selecting material suppliers and determining appropriate inventory levels with the aim of planning a resilient supply chain network. As discussed in Chapter 1, optimizing operations in a disruption risk environment requires simultaneous consideration of supply chain design and operational decision making.

Compared to other methods such as deterministic model or Mixed Integer Program (MIP), two-stage stochastic programming is more appropriate for decision making under uncertainty in business environment where two steps of decision processes are involved. Two-stage stochastic programming allows decisions in each stage to occur simultaneously and fits to business decision process. Two-stage stochastic programming also allows to consider the disruption risks environments by using scenarios. Therefore, the proposed method uses a two-stage stochastic programming method.

Figure 2 shows a conceptual diagram of the proposed method. The disruption risks described in section 2.2 are assumed in Figure 2. A disruption scenario is assumed in the form of a branch from the no disruption scenario to another scenario in the period when the disruption occurs. Under these possible future scenarios, two stage of decision process will be considered to plan a supply chain network that minimizes the total expected future costs. First, the first stage of the decision process involves selecting material suppliers and determining appropriate inventory levels, taking into account of all possible scenarios as shown in Figure 2. Therefore, the existence of a contract between supplier s and factory m (x_{sm}) and the inventory levels at each facility (lm_m, lp_m and lw_w) are established as first-stage decision variables, which are common variables for all scenarios. Next, the second stage of the decision process, the production, purchase, and order quantities are determined for each scenario. We define the production quantity of factory m in scenario k at period t (pp_{ktm}) and the quantity of materials purchased from supplier s (b_{ktsm}), the quantity of products ordered from distribution center w to factory m (qw_{ktmw}), and the quantity of products ordered from wholesaler c to distribution center w (qc_{ktwc}) as second-stage decision variables, variables that are determined for each scenario in the two-stage stochastic programming method. Decision variables at each of these stages are considered simultaneously to plan a resilient supply chain network, aiming to minimize costs in all possible future scenarios.

The evaluation of resilience focuses on the total cost and one of them, the stockout loss cost. The proposed method is compared with a deterministic method that does not consider risk. The total cost under normal conditions and the total cost and stockout loss cost when the disruption risk occurs are evaluated. This will allow us to evaluate the feasibility of designing a resilient supply chain that can provide a stable supply of products while taking economic feasibility into consideration.

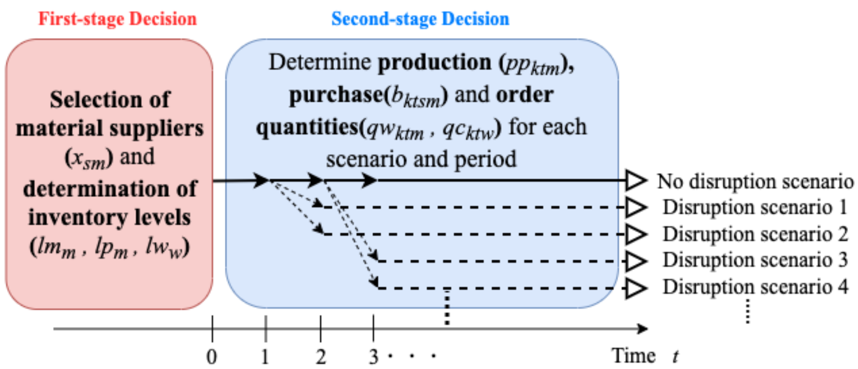

Fig. 2 Conceptual diagram of the proposed method

The proposed method uses all possible scenarios to select material suppliers and determine appropriate inventory levels. This allows the optimal selection of material suppliers and determination of appropriate inventory levels for all scenarios, while optimizing the second-stage decision, including production quantity, for each scenario assumed. However, with this method, the number of scenarios that has to be assumed becomes enormous as the types of risks and the number of facilities increase, so it is not realistic to derive an exact solution in practical time. In order to solve this problem, we propose a method to reduce the computation time by narrowing down the number of scenarios while maintaining the solution accuracy.

This paper proposes a computational method that uses Latin hypercube sampling, which allows samples to be extracted evenly from the entire sampling space, and allows the selection of multiple appropriate scenarios to improve the efficiency of the computation. Latin hypercube sampling is a technique that samples evenly from the entire sampling space and avoids forming clusters [8]. The Latin hypercube sampling requires one extract from each row and column. So, the samples are spread over the entire sampling space, which consists of multiple elements as shown in Figure 3.

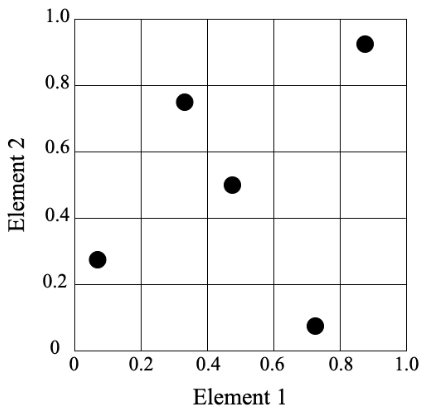

Fig. 3 Example of Latin hypercube sampling

By repeatedly sampling scenarios using Latin hypercube sampling and solving problems, all scenarios are considered. This creates a supply chain network that is resilient to all possible scenarios.

3.3 Algorithm of proposed method

The algorithm for the proposed method is described below.

STEP1. Select the scenarios with variations in the occurrence times and facilities using Latin hypercube sampling for each disruption scale. The existence of this process is a major difference between the proposed method and the exact solution method. This sampling reduces the number of scenarios and improves computational efficiency. First, for each disruption scale, a space is generated where the vertical axis is the period

of occurrence of the disruption and the horizontal axis is the facility where the disruption occurs, and then the space is divided by the number of facilities. Next, one scenario from each facility (column) and each time range (row) is selected. In this way, it is possible to sample scenarios with variations in the period of occurrence and facilities for each disruption scale.
STEP2. Solve the problems of selecting material suppliers and determining appropriate inventory levels using the scenarios selected in **STEP1**.
STEP3. Evaluate the solution obtained at **STEP2**. To evaluate the solution, we fix the first stage decisions of the original problem and then solve the obtained problem for other scenarios [7]. The objective function value obtained is evaluated whether the solution obtained from **STEP2** is optimal in the original problem.
STEP4. If the evaluation value of the solution obtained in **STEP3** is better than that of the tentative solution, the solution is accepted and then go to **STEP5**. If not, go to **STEP6**.
STEP5. Update the tentative solution with the solution received in **STEP4**.
STEP6. Repeat **STEP1** through **STEP5** until the number of iterations N for the entire flow is reached.

3.4 Formulation

In this section, the formulation for making the resilient supply chain network by considering this two-stage decision process is explained as follows:

min. $$COST = CA + CR \tag{1}$$

where $$CA = \sum_{s \in \boldsymbol{S}} \sum_{m \in \boldsymbol{M}} CS_{sm} \cdot x_{sm} \tag{2}$$

$$\begin{aligned} CR = \sum_{k \in \boldsymbol{K}} p_k \sum_{t \in \boldsymbol{T}} \Bigg\{ & \sum_{m \in \boldsymbol{M}} CP_m \cdot pp_{ktm} + \sum_{s \in \boldsymbol{S}} \sum_{m \in \boldsymbol{M}} CB_{sm} \cdot b_{ktsm} \\ & + \sum_{m \in \boldsymbol{M}} (HM_m \cdot im_{ktm} + HP_m \cdot ip_{ktm}) \\ & + \sum_{w \in \boldsymbol{W}} HW_w \cdot iw_{ktw} + \sum_{s \in \boldsymbol{S}} \sum_{m \in \boldsymbol{M}} CTS_{sm} \cdot b_{ktsm} \\ & + \sum_{m \in \boldsymbol{M}} \sum_{w \in \boldsymbol{W}} CTM_{mw} \cdot qw_{ktmw} \\ & + \sum_{w \in \boldsymbol{W}} \sum_{c \in \boldsymbol{C}} CTW_{wc} \cdot qc_{ktwc} + \sum_{c \in \boldsymbol{C}} CL_c \cdot ld_{ktc} \Bigg\} \end{aligned} \tag{3}$$

$$am_{ktm} = \sum_{s \in \boldsymbol{S}} b_{k(t - LSM_{sm})sm}, \forall m, \forall k, \forall t \tag{4}$$

$$aw_{ktw} = \sum_{m \in \boldsymbol{M}} qw_{k(t - LMW_{mw})mw}, \forall w, \forall k, \forall t \tag{5}$$

$$ac_{ktc} = \sum_{w \in \boldsymbol{W}} qc_{ktwc}, \forall c, \forall k, \forall t \tag{6}$$

$$D_{ktc} = ac_{ktc} + ld_{ktc}, \forall c, \forall k, \forall t \tag{7}$$

sub. to

$$0 \le pp_{ktm} \le \min\{im_{k(t-1)m}, \left(lp_m - ip_{k(t-1)m}\right) \cdot \beta_{ktm}\}, \forall m, \forall k, \forall t \tag{8}$$

$$im_{ktm} = im_{k(t-1)m} + am_{ktm} - pp_{ktm} \ge 0, \forall m, \forall k, \forall t \tag{9}$$

$$ip_{ktm} = ip_{k(t-1)m} + pp_{ktm} - \sum_{w \in \boldsymbol{W}} qw_{ktmw} \ge 0, \forall m, \forall k, \forall t \tag{10}$$

$$iw_{ktw} = iw_{k(t-1)w} + aw_{ktw} - \sum_{c \in \boldsymbol{C}} qc_{ktwc} \ge 0, \forall w, \forall k, \forall t \tag{11}$$

$$0 \le qc_{ktwc} \le \min\left\{\left(D_{ktc} - \sum_{w' \in \boldsymbol{W}'} qc_{ktw'c}\right), \left(iw_{k(t-1)w} - \sum_{c' \in \boldsymbol{C}'} qc_{ktwc'}\right) \cdot \gamma_{ktw}\right\}, \forall w, \forall c, \forall k, \forall t \tag{12}$$

$$0 \le qw_{ktmw} \le \min\left\{\left(lw_w - iw_{k(t-1)w} - \sum_{m \in \boldsymbol{M}} \sum_{\tau = t - LMW_{mw}+1}^{t-1} qw_{k\tau mw} - \sum_{m' \in \boldsymbol{M}'} qw_{ktm'w}\right), \left(ip_{k(t-1)m} - \sum_{w'' \in \boldsymbol{W}''} qw_{ktmw'} \cdot \beta_{ktm}\right)\right\}, \forall m, \forall w, \forall k, \forall t \tag{13}$$

$$0 \le b_{ktsm} \le \min\left\{\left(lm_m - im_{k(t-1)m} - \sum_{s \in \boldsymbol{S}} \sum_{\tau = t - LSM_{sm}+1}^{t-1} b_{k\tau sm} - \sum_{s' \in \boldsymbol{S}'} b_{kts'm}\right), \left(Caps_s - \sum_{m'' \in \boldsymbol{M}''} b_{ktsm'}\right) \cdot \alpha_{kts} \cdot x_{sm}\right\}, \forall s, \forall m, \forall k, \forall t \tag{14}$$

$$x_{sm} \in \{0,1\}, \forall s, \forall m, \forall k, \forall t \tag{15}$$

$$0 \le lm_m \le Capm_m, \forall m \tag{16}$$

$$0 \le lp_m \le Capp_m, \forall m \tag{17}$$

$$0 \le lw_w \le Capw_w, \forall w \tag{18}$$

$$pp_{kt'm} = pp_{k't'm}, \forall m, \forall k \quad (20)$$

$$b_{kt'sm} = b_{k't'sm}, \forall s, \forall m, \forall k \quad (21)$$

$$qw_{kt'mw} = qw_{k't'mw}, \forall m, \forall w, \forall k \quad (22)$$

$$qc_{kt'wc} = qc_{k't'wc}, \forall w, \forall c, \forall k \quad (23)$$

The objective function (1) minimizes the sum of the cost of the first stage (CA) and the expected cost of the second stage (CR).

Equations (2) - (7) are relational expressions. First, the first stage cost shown in equation (2) is the contractual costs with suppliers at each factory. The second stage cost shown in equation (3) is the sum of the expected values of production costs (term 1), purchase costs (term 2), inventory storage costs (terms 3 and 4), transportation costs (terms 5, 6 and 7), and stockout loss costs (term 8). Equations (4) - (6) show the quantity of materials and products arrived at each facility in scenario k at period t. Equation (7) is a conservation of demand equation that states that the sum of the quantity arrived and the stockout quantity of wholesaler c in scenario k, period t equals the quantity demanded.

Next, equations (8) - (23) are constraints. Equation (8) is a constraint on the production capacity of factory m in scenario k, period t. The upper bound is the amount of material inventory or inventory level minus the starting inventory of the product. If a disruption occurs at factory m, production will not be possible. Equations (9) - (11) are constraints on the amount of inventory at the end of the period at each facility in scenario k and period t. Inventory replenishment follows fixed order period system to purchase materials and produce and ship products each period. The initial inventory quantity at each facility is set to the inventory level set for each facility. Equations (12) - (14) are constraints on the order quantity and purchase quantity, and downstream facilities order or purchase in order from the upstream facilities with the lowest transportation cost. The upper bound in equations (12) is the upstream supply availability or demand minus the remaining to be ordered. The upper bound in equations (13) and (14) is the upstream supply availability or inventory level minus the starting inventory and the remaining to be ordered. In other words, after one downstream facility places an order with a group of facilities ($\boldsymbol{W'}$, $\boldsymbol{M'}$, $\boldsymbol{S'}$) whose transportation costs are lower than those from one upstream facility, it places an additional order with that upstream facility if the required quantity is not met. On the other hand, after one upstream location responds to orders from a group of facilities ($\boldsymbol{C'}$, $\boldsymbol{W''}$, $\boldsymbol{M''}$) whose transportation costs are lower than those from one downstream facility, it responds to an order from that downstream facility with the remaining inventory. If a disruption occurs at one upstream facility, downstream facilities cannot place orders with that facility. Equation (15) indicates that x_{sm} is a binary variable. Equations (16) - (18) show the range of possible inventory levels for each location. Equations (19) - (23) are constraints for nonanticipativity [9]. It is shown that the second-stage decision variable in period t' $(1,2,\dots,t)$ is the same as in the no disruption scenario (k') when a certain disruption in scenario k arises from period $t+1$.

4 Computational Experiments

We evaluate the optimality and resilience of the supply chain network planned by computer experiments against the risk-aware methods for selecting material suppliers and determining appropriate inventory levels described in Chapter 3. Furthermore, we compare the solution accuracy and computation time of the proposed scenario sampling-based method with those of the conventional exact solution. In order to compare with the exact solution method, this paper focuses on problems of a scale that can obtain a solution with appropriate computational time. IBM ILOG CPLEX 12.10 [10] is used to solve each problem.

4.1 Experimental Conditions

The experimental conditions are set as follows, after discussions with the collaborating company:

- Number of suppliers ($\boldsymbol{S}$): 5
- Number of factories ($\boldsymbol{M}$): 2
- Number of distribution centers ($\boldsymbol{W}$): 10
- Number of wholesalers ($\boldsymbol{C}$): 10
- Number of planning periods ($\boldsymbol{T}$): 15
- Contract costs between supplier s and factory m (CS_{sm}): 100
- Stockout loss cost at wholesaler c (CL_c): 100

The conditions for the proposed method with scenario sampling are as follows:

- Number of sampling problems generated (N): 30
- Number of trials of the proposed method: 5

In this experiment, it is assumed that the disruption occurs at the supplier or the factory, and the stoppage periods of the location where the disruption occurs are 1, 3, 5, and 7 periods. Table 1 shows the probability of disruption occurrence at each facility assumed in the proposed method. To ensure that the weights of economic efficiency and stability are equal, the experiment assumes that the probability of occurrence of the no disruption scenario is 0.50 and the sum of the probabilities of occurrence of the scenarios in which some disruption occurs is 0.50. In this experiment, demand is assumed to be given.

Table 1 Probability of occurrence of each disruption

Stoppage period	No	1	3	5	7
Probability	0.50	0.25	0.15	0.075	0.025

We evaluate the resilience of the supply chain network and the risk-aware strategic decisions made using the proposed method by conducting computer experiments. In addition, we compare the solution accuracy and computation time of the proposed scenario sampling-based method with those of the conventional exact solution.

4.2 Experimental Result

Table 2 shows the objective function values ($COST$) and computational time when the proposed method aims at cost minimization with consideration of disruption risk, and when it aims at cost minimization only. Note that the objective function values for the proposed computational method in Table 2 are the recalculated expected values for all scenarios, not just the sampled scenarios. The results of the proposed computational method show the average (Avg.) and the standard deviation (S.D.). Figure 5 compares the selection of material suppliers for each factory in both cases. Figure 6 compares the inventory levels at each facility. In Figure 6 the inventory level at factories was higher than at distribution centers because demand from 10 distribution centers is met at two factories. The reason for the difference in inventory levels of materials and products at the factories is that the supply capacity of suppliers is set lower than the production capacity of factories. The reason for the difference in inventory levels among distribution centers is that the network structure is such that factory 1 has a longer transportation distance from distribution center 1 to 10, and factory 2, conversely, has a longer transportation distance from distribution center 10 to 1. As a result, the decision was made to increase inventory levels at distribution centers 4, 5, 6, and 7, which are located far from any of the factories, in consideration of transportation time and cost.

As shown in Table 2, the obtained expected the objective function value by the exact solution method increases by 4.8% when disruption risk is taken into account. The computation time for only cost minimization is very short because the solution is obtained only in the no disruption scenario. This increase in the expected value is due to the increase in contract costs due to contracts with multiple material suppliers and the associated increase in transportation costs due to longer transportation distances. Other reasons for the increase are higher inventory costs from raising the steady-state inventory levels, as well as the expected stockout loss costs.

Table 2 Results of objective function value and computation time

	Cost minimization without risk	Cost minimization with risk		
		Exact method	Computational method	
			Avg.	S.D.
Objective function value	32580	34142	34158.20	8.58
Computational time (sec.)	0.96	90564.32	33981.80	3875.50

As shown in Figure 5, each factory contracted multiple material suppliers. The selection of suppliers was the same as the exact solution for each trial of the proposed computational method.

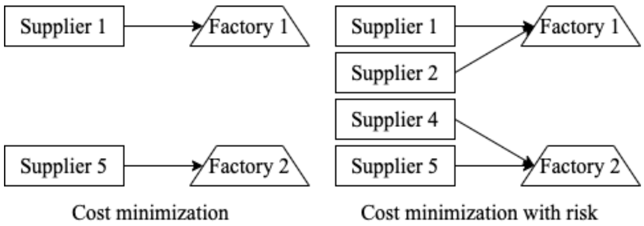

Fig. 5 Results of selection of material suppliers

As shown in Figure 6, each factory has increased its inventory level of products. When a factory stops production, all downstream facilities are affected, so they increased their inventories of products. Inventory levels varied in each trial of proposed computational method, but were close to this exact solution.

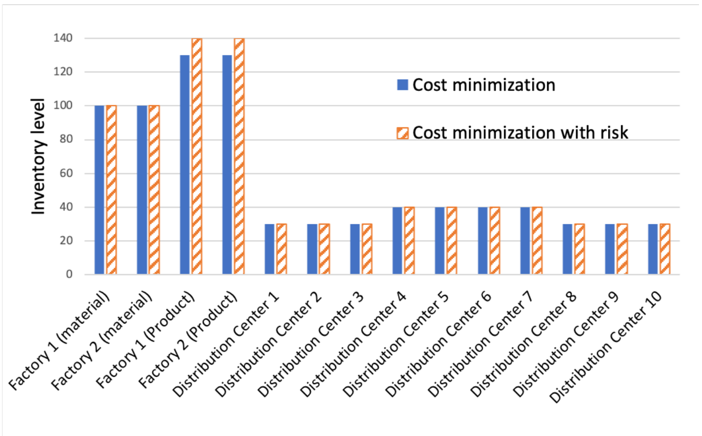

Fig. 6 Results of inventory levels

As for the proposed computational method, Table 2 shows that the average objective function value of the original problem when using the solution of the proposed method reached 99.9% of the exact solution. Therefore, the proposed computational method can extract appropriate scenarios from the sampling space and plan a resilient supply chain network. The reason why the objective function values of the proposed computational method were different for each trial is that the inventory levels differ slightly from one trial to another as described. The computational time of the proposed computational method was reduced by 62.5% from the exact solution method. In other words, the proposed computational method with Latin hypercube sampling contributes to a significant reduction in calculation time through scenario sampling. From the above, it can be said that the proposed method reduces computation time and improves computational efficiency while maintaining the optimality of the solution by appropriately reducing scenarios.

Next, we evaluate the supply chain network resiliency with contracting multiple material suppliers and increasing inventory levels, taking into account of disruption risks. The proposed method is compared with the deterministic method, which only aims at cost minimization. Since the results of the proposed calculation method and the exact solution are very close, the exact solution was used for the resilience evaluation. We investigate the extent to which the proposed method reduces total expected cost and stockout loss cost compared to the deterministic method.

A comparison of the average of total cost and stockout loss cost for each disruption magnitude is shown in Figure 7 for the target model set at the obtained selection of material suppliers and inventory levels. The expected total cost for cost minimization with disruption risk under normal circumstances was higher by 1.0% than for cost minimization only. On the other hand, in the situation where disruption risk occurred, the total costs of cost minimization considering the disruption risk were 1.1% for 1-period, 4.5% for 3-period, 8.1% for 5-period and 11.6% for 7-period suspensions lower than the those of cost minimization only, respectively. In addition, by considering the disruption risks, it has been confirmed that the cost of stockout loss was greatly suppressed compared to the case where it is not considered. These results indicate that the proposed method can construct a resilient supply chain network to respond to and recover from disruption risk and maintain a positive steady state operation in an acceptable cost and time.

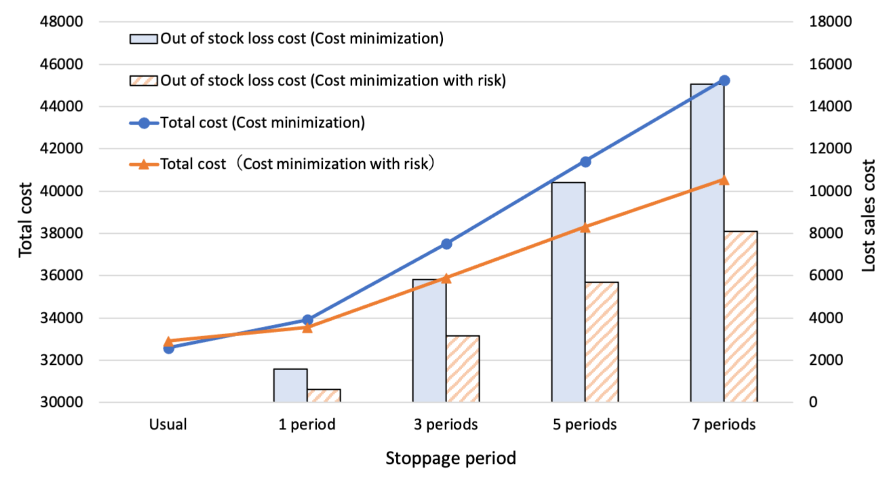

Fig. 7 Simulation results for each risk (evaluation of resilience)

5 Conclusion

This paper proposed a method for selecting material suppliers and determining appropriate inventory levels using two-stage stochastic programming, with the aim of planning a resilient supply chain network. Computational experiments suggested that the proposed method is capable of planning a supply chain network that is resilient to disruption risk. The total cost under normal conditions and the total cost and stockout loss cost when the disruption risk occurs were evaluated. This demonstrated the feasibility of designing a resilient supply chain that can provide a stable supply of products while taking into account economics. In order to reduce the number of scenarios and shorten the computation time with maintaining resilience to disruption risks, a computation method using scenario sampling was also proposed. Comparing the objective function values and the computation time with the exact solution method, it has been confirmed that the proposed method can reduce the computation time by 62.5% with maintaining solution accuracy of more than 99%. Thus, the validity of the applied Latin hypercube sampling method was also confirmed. This paper focused on a supply chain in which a single object is processed from raw material to finished product and then passed on to the customer. In future studies, in order to bring the problem closer to reality and apply it to real manufacturers, it is necessary to incorporate into the formulation the assembly of multiple parts into a single product, for example.

In the future, we plan to use the proposed computational method to further resiliency of the entire network by focusing on the downstream of the supply chain network, including the decision-making process regarding the placement and establishment of distribution centers and the multiple products to be distributed.

Acknowledgement

We would like to thank Prof. Nobutada Fujii (Kobe University) and Dr. Ruriko Watanabe (Waseda University) for providing appropriate advices.

References

1. Report on the International Economic Survey Project for the Integrated Domestic and International Economic Growth Strategy (Survey for Strengthening Supply Chains in Asia at Large). Ministry of Economy, https://www.meti.go.jp/meti_lib/report/2020FY/000173.pdf, last accessed 2023/04/14.
2. Wicaksana, A., Ho, W., Talluri, S. and Dolgui, A.: A decade of progress in supply chain risk management: risk typology, emerging topics, and research collaborators. International Journal of Production Research 60(24) 7155-7177 (2022).
3. Ho, W., Zheng, T., Yildiz, H. and Talluri, S.: Supply chain risk management: A literature review. International Journal of Production Research 53(16), 5031-5069 (2015).
4. Golan, M.S., Jernegan, L.H. and Linkov, I.: Trends and applications of resilience analytics in supply chain modeling: systematic literature review in the context of the COVD-19 pandemic. Environment Systems and Decisions 40, 222-243 (2020).
5. Ribeiro, J.P. and Barbosa-Povoa, A.: Supply chain resilience: Definitions and quantitative modeling approaches - a literature review. Computers and Industrial Engineering 115, 109-122 (2018).
6. Kungwalsong, K., Cheng, C.Y., Yuangyai, C. and Janjarassuk, U.: Two-Stage Stochastic Program for Supply Chain Network Design under Facility Disruptions. Sustainability 13(5) (2021).
7. Ohmori, S. and Yoshimoto, K.: Optimal Risk Mitigation Planning for Supply Chain Disruption. Journal of Japan Industrial Management Association 66, 12-22 (2015).
8. Olsson, A., Sandberg, G. and Dahlblom, O.: On Latin hypercube sampling for structural reliability analysis. Structural Safety 25, 47-68 (2003).
9. Shiina, T.: Stochastic programming. Asakurashoten Co., Ltd, Japan, Published in Japanese (2015).
10. ILOG CPLEX-IBM, https://www.ibm.com/jp-ja/products/ilog-cplex-optimization-studio, last accessed 2023/04/14.