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An integrated model of supply chain resilience considering supply and demand uncertainties

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Abstract

The complexity of the global supply chain has increased dramatically over the past few decades as a result of uncertainty caused by various factors. This paper studies the optimal strategy for supply chain resilience models considering supply disruptions and demand fluctuations. We present two-stage stochastic programming models based on different scenarios, including a risk-neutral model that considers the expected total cost, a risk-averse model that considers the *conditional value-at-risk* measure, and a responsiveness model that considers the service level. We also propose multiobjective mathematical programming that considers all three models simultaneously and suggests the solution approach. Finally, we present the results of computational experiments and demonstrate how to cope with uncertainty through flexibility and redundancy. We offer a set of nondominated solutions from the multiobjective model and derive managerial insights, which suggest a decision-making strategy between the disruption risk, expected total cost, and service level.

Keywords: supply chain risk management; supply chain resilience; risk-averse model; decision support system; multiobjective model

1. Introduction

Disruption typically occurs in a supply chain because of the complexity and uncertainty of global supply chains (Meena and Sarmah, 2016; Taleizadeh, 2017). Especially during and after the worst of the COVID-19 pandemic, there was a negative impact on supply chain operations due to the fluctuations in production and demand (Sarkis, 2020; Chowdhury et al., 2021; Yang et al., 2024). For this reason, the focus on supply chain risk management has expanded among researchers and practitioners because of worries about unforeseen catastrophic incidents (Sodhi et al., 2012; Ho et al., 2015; Li et al., 2022). Therefore, a risk-averse model considering uncertainties in the supply chain will be necessary and practical for decision-makers in a rapidly changing environment (Taghizadeh

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and Venkatachalam, 2023). In addition, restoring the supply chain through recovery after the disruption has become an important decision in practice (Ivanov et al., 2017; Khamseh et al., 2021).

While the probability of a supply chain disruption is low, its potential implications are severe and can produce undesirable consequences, making it a crucial attribute to consider (Snyder et al., 2016; Shen and Li, 2017). To deal with this disruption situation, estimating the expected supplier dependency ratio, and intensively managing items based on the ratio is necessary. In other words, the risk can be mitigated by sourcing items from various suppliers. Individual supplier disruption and disruption of all suppliers within the same region must be considered at the same time. We define regional disruption as a larger-scale disruption involving the disruption of many suppliers. As a result, regional factors reflect the disruption from all regional suppliers and the large-scale investment for trade with a specific region as a regional contract cost. We also propose a study that considers both supply risk and demand risk simultaneously. When supply disruptions occur, market demand fluctuations dramatically increase. In a chaotic situation, customers tend to hoard in preparation for an uncertain situation. Reflecting on this, we consider demand fluctuations for each scenario according to the level of disruptions.

Methodologies for supply chain resilience include flexibility and redundancy (Kamalahmadi et al., 2022). Flexibility refers to the capability to increase the production of suppliers temporarily. Emergency procuring cost occurs because it temporarily increases the capacity of an undisrupted supplier. On the other hand, redundancy refers to a strategy in which a backup supplier is contracted in advance and supplied in a disruption situation. In this case, procuring cost is the same but the backup contract cost occurs. This paper explores recovery strategies to enhance supply chain resilience, effectively managing after disruptions.

Two-stage stochastic programming is a well-known mathematical model that can reflect our problem situation well (Torabi et al., 2015; Walker and Kwon, 2024). In the first stage, supplier selection and order allocation decision-making are made before a disruption occurs. In the second stage, decisions are made to recover through flexibility and redundancy after the disruption uncertainty is realized. This study also discusses the risk-averse supply chain resilience model. *Conditional value-at-risk* ($CVaR$) is a popular risk measure defined as the expectation of the α-tail scenarios (Gao et al., 2019; Filippi et al., 2020). By creating disruption scenarios, we minimize the $CVaR$ measure to evade the worst-case scenario. As a result, when a disruption has catastrophic consequences, the risk-averse model is more prone to make reasonable decisions.

Multiobjective mathematical programming (MOMP), which makes various decisions simultaneously, has recently received much attention (Yu and Goh, 2014; Margolis et al., 2018; Ozkan, 2023). Objective functions have a trade-off with each other, and it is essential to strike a good balance. MOMP seeks solutions that are as close to the Pareto frontier as possible. The Pareto frontier is the set of nondominated solutions in which improving one objective function does not improve at least one other objective function (Chiandussi et al., 2012; Petrelli et al., 2021). A traditional method for generating the Pareto frontier is the ϵ-constraint method. This method optimizes one objective, while the other objectives are constrained using a parameter ϵ. The major drawback of this method is that the solutions cannot be guaranteed to be efficient because the parameter vector must be contained in the domain of the objective functions. Mavrotas (2009) offered an enhanced form, the augmented ϵ-constraint method (AUGMECON), to address this problem. This method enables the generation of weakly Pareto optimal solutions while speeding up the overall process by avoiding redundant iterations. Afterward, an improved version of the augmented ϵ-constraint method (AUGMECON2 was developed to improve AUGMECON by introducing the concept of lexicographic optimization and bypass coefficient, which performed better for generating Pareto sets by Mavrotas and Florios (2013).

We aim to propose supply chain resilience models considering supply disruptions and demand fluctuations, and decision-making is performed to restore the supply chain through flexibility and redundancy for each disruption scenario. We introduce the risk-neutral model that focuses on the expected total cost, the risk-averse model that considers the $CVaR$ measure, and the responsiveness model that evaluates the service level. In addition, we develop a multiobjective model by utilizing the solution approach of AUGMECON2, considering the three models simultaneously. Finally, we present the supplier and regional dependency ratios, which can be used to build an appropriate portfolio, and we compare the performance of various models using numerical experiments. We provide a Pareto frontier and managerial insights as a result of the multiobjective model.

The subsequent sections of this paper are structured as follows. Section 2 reviews the relevant literature related to our study and highlights the research gaps where our research offers noteworthy contributions. The problem statement for the risk-neutral, risk-averse, and responsiveness models for supply chain resilience with stochastic measures is presented in Section 3. Section 4 combines the three models to create a problem statement for the multiobjective model and suggests the solution approach. Section 5 contains numerical experiments for both the single-objective and multiobjective models. We analyze the performance of each model from various perspectives. Section 6 brings the paper to a close.

2. Literature review

In this section, we provide an in-depth review of existing literature to pinpoint and highlight the research gaps that this paper tackles.

2.1. *Supply chain uncertainty*

Several previous studies have considered supply chain uncertainty, such as supply disruptions and demand fluctuations (Kamalahmadi and Mellat-Parast, 2016; Sawik, 2016; Esmaeili-Najafabadi et al., 2021; Bilir, 2023). Kamalahmadi et al. (2022) examined the impact on supply chain responsiveness of a semisuper event that causes regional disruption. Sawik (2014) suggested the concept of regional disruption separately from local disruption. There have also been previous studies in the supply chain that considered demand uncertainty. Liu et al. (2020) developed a newsvendor model that determines the optimal order quantity for retailers by considering demand uncertainty. Jin et al. (2024) presented a model in which retailers consider uncertain demand and defective products in a two-echelon supply chain via the Stackelberg game. Chen et al. (2023) examined how demand disruptions affect optimal pricing and product allocation strategies in a dual-channel system under varying capacity constraints. However, there has been no previous research that simultaneously considered supplier and regional disruption and demand fluctuations as types of uncertainty in the supply chain model.

2.2. Supply chain resilience model

Much of the current research on supply chain resilience is based on qualitative methods (Clement et al., 2021). A limited number of quantitative approaches specifically evaluate the performance of supply chain resilience or investigate how various mitigation strategies influence resilience in supply chains (Alikhani et al., 2023; Ghomi et al., 2023). Hosseini et al. (2019) proposed a model for resilient supplier selection and order allocation considering cost and distance, and the augmented ϵ-constraint method (AUGMECON) is applied to deal with the biobjective model. Haeri et al. (2020) designed a multiobjective integrated model to improve blood supply chain resilience using an interactive fuzzy approach. Sawik (2022) proposed supply chain resilience through prepositioning and backup suppliers through two-stage stochastic programming. Falsafi et al. (2022) presented a resilience model for transport modes considering disruptions in the automotive supply chain. This study proposes a supply chain resilience model considering a risk-averse strategy.

2.3. Multiobjective mathematical programming

Among various methodologies for solving MOMP, we apply the improved version of the augmented ϵ-constraint method (AUGMECON2) model to effectively and efficiently estimate the Pareto frontier, and the performance is compared and analyzed through numerical experiments. There exist several recent preceding studies utilizing AUGMECON and AUGMECON2 (Hosseini et al., 2019; Shafiee et al., 2022). Shekarian et al. (2020) presented a multiobjective model considering disruption in the supply chain and analyzed the effect of flexibility and agility through AUGMECON. Recently, Eskandari et al. (2023) utilized AUGMECON to optimize product assortments based on customer preferences, aiming to maximize expected revenue and customer satisfaction. It has been demonstrated that AUGMECON2 efficiently obtains the Pareto frontier. Aboytes-Ojeda et al. (2022) designed the biofuel supply chain with uncertainty and applied AUGMECON to solve the biobjective model considering the expected total cost and *CVaR*. Shafiee et al. (2022) applied AUGMECON2 to deal with the multiobjective model in the supply chain network. In this study, we compare AUGMECON2 with a convex combination model and analyze how effectively it estimates the Pareto frontier.

Table 1 outlines the recent studies related to the supply chain model considering uncertainty, highlighting the research gaps through an extensive literature review. Our paper addresses these gaps by presenting an integrated model of the supply chain resilience model that considers both supply disruptions and demand fluctuations. While most existing studies adopt a risk-neutral model, this paper introduces a risk-averse model considering *value-at-risk* (*VaR*) and *CVaR* as risk measures. Furthermore, we developed MOMP that integrates risk-neutral, risk-averse, and responsiveness models. The comprehensive literature review, as shown in Table 1, supports that our study on the integrated model of supply chain resilience is pioneering.

This paper makes several key contributions, which are outlined as follows:

- We define the supply chain resilience model by considering supply disruptions and demand fluctuations, offering a more accurate assumption of potential uncertainties in the supply chain. In addition, we propose a decision support system to restore a supply chain in a scenario where

Table 1
Recent supply chain models considering uncertainty

Source	Multiobjective	Resilience	Risk measure	Types of uncertainty	Solution approach
Torabi et al. (2015)	✓	✓	–	Supplier	AUGMECON
Sawik (2016)	–	–	VaR, CVaR	Supplier, region	Commercial software
Kamalahmadi and Mellat-Parast (2016)	–	✓	–	Supplier, region	Commercial software
Hosseini et al. (2019)	✓	✓	VaR	Supplier	AUGMECON
Esmaeili-Najafabadi et al. (2021)	–	–	VaR, CVaR	Supplier, region	Meta-heuristic algorithms
Shafiee et al. (2022)	✓	✓	–	Supplier	AUGMECON2
Sawik (2022)	–	✓	VaR, CVaR	Supplier, region	Commercial software
Ghomi et al. (2023)	✓	✓	–	Supplier, demand	AUGMECON
Alikhani et al. (2023)	–	✓	–	Supplier, demand	Heuristic algorithms
This study	✓	✓	VaR, CVaR	Supplier, region, demand	AUGMECON2

uncertainty occurs. This assists policymakers in building a robust supply chain in dealing with uncertainty.

- We introduce a risk-averse model, considering VaR and CVaR as risk measures alongside a risk-neutral model that calculates the total expected cost. The CVaR is evaluated using an equivalent equation, leading to the scenario-based risk-averse model that significantly accounts for worst-case scenarios. We also offer a responsiveness model, which considers the service level.
- We develop multiobjective models to integrate risk-neutral, risk-averse, and responsiveness models. These models allow decision-makers to evaluate how increased expected costs can offset disruption risks. In addition, we design a decision support system by suggesting various reference points between expected cost, risk cost, and service level.
- We apply AUGMECON2, a recently developed solution approach, to solve the multiobjective model effectively and efficiently. Through numerical experiments, we compare and analyze the performance of various models. Finally, we establish a Pareto frontier with the multiobjective model and derive managerial insights.

3. Supply chain resilience models

This section defines two-stage stochastic programming for supply chain resilience models. We design a supply chain network with the supply chain of appliances such as phones and refrigerators in mind. We consider various types of risks that may arise from appliance manufacturers. In this study, we categorize suppliers based on regional characteristics. We divide them into K regions and assume that the number of suppliers in the region k is I_k. Each supplier provides items to retailers, who then sell the items to customers. In the first stage, we select regions to contract and select suppliers existing in those regions as prime or backup suppliers. Decisions about order allocation are made under normal situations that do not consider the occurrence of disruption. In the second stage, a recovery strategy is established to cope with supply disruptions and demand fluctuations. For the recovery, the prime suppliers can temporarily increase the production quantity, and backup suppliers can provide emergency items immediately. Finally, penalties and refunding costs are imposed on unsatisfied items. The risk-neutral model that considers expected total cost would contract low-cost suppliers in reasonable regions. On the other hand, the risk-averse model that considers the impact of disruption risks and demand fluctuations would prefer a mix of expensive but reliable suppliers. The responsiveness model takes as many strategies as possible to recover the supply chain, regardless of cost.

We consider a finite set of disruption scenarios $\omega \in \Omega = \{\omega_1, \omega_2, \ldots, \omega_S\}$ and the probability of each scenario ω with P_ω. We consider normal, supplier disruption, and regional disruption situations for the scenarios. The disruption probability of a supplier i in the region k is defined as β_{ik}. When all suppliers in the same region are disrupted, this is referred to as regional disruption. The regional disruption probability for region k is defined as η_k. When a disruption occurs, demand fluctuates as customers stock up on items. We reflect on the situation in which demand increases for each disruption scenario. In particular, when regional disruption occurs, there is a surge in demand. Therefore, the realized market demand can finally be calculated by adding the demand fluctuation

Table 2
Indexes and parameters

i	Index of supplier's type $i \in I = \{1, 2, \ldots, I_k\}$
k	Index of region's type $k \in K = \{1, 2, \ldots, K\}$
ω	Index of disruption scenario $\omega \in \Omega = \{\omega_1, \omega_1, \ldots, \omega_S\}$
c_{ik}	Procuring cost purchased from supplier i located in region k
ec_{ik}	Emergency procuring cost purchased from supplier i located in region k
$pcap_{ik}$	Capacity of prime supplier i located in region k
$bcap_{ik}$	Capacity of backup supplier i located in region k
p_{ik}	Prime contract cost of supplier i located in region k
b_{ik}	Backup contract cost of supplier i located in region k
t_{ik}	Transportation cost of supplier i located in region k
sf_{ik}	Supplier flexibility of supplier i located in region k
r_k	Regional contract cost of region k
d	Expected market demand
θ	Demand fluctuation parameter
m	Unit shortage cost
P_ω	Probability of scenario ω
D_ω	Realized market demand of scenario ω
$status_{ik\omega}$	0 if supplier i located in region k is disrupted in scenario ω; otherwise 1
β_{ik}	The probability of disruption for supplier i located in region k
η_k	The probability of disruption for suppliers located in region k
α	Tolerance level

parameter θ according to the disruption scenario to the expected market demand as follows:

$$D_\omega = d + \frac{\theta}{P_\omega}, \tag{1}$$

c_{ik} and ec_{ik} are the procuring and emergency procuring costs purchased from supplier i located in region k, respectively. $pccp_{ik}$ and $bcap_{ik}$ are the capacities of prime and backup supplier i located in region k, respectively. p_{ik} and b_{ik} are the prime and backup contract costs of supplier i located in region k, respectively. t_{ik} is the transportation cost of supplier i located in region k. sf_{ik} is the supplier flexibility of supplier i located in region k that can temporarily increase the capacity of the supplier. We also define the regional contract cost of the region k as r_k and unit shortage cost as m. $status_{ik\omega}$ represents the status of the supplier i located in region k in scenario ω. In the risk-averse model, α represents the tolerance level for the risk measure. Definitions for all indexes and parameters are shown in Table 2.

Table 3 provides a summary of the decision variables at the first and second stages. In the first stage, regions and suppliers are contracted with order allocation. In the second stage, disruption scenarios are realized and deal with decision-making to recover through flexibility and redundancy. In addition, we consider penalties and refunding costs for the unfulfilled quantity due to supply disruptions and demand fluctuations. In the risk-averse model, which will be explained in Section 3.2, τ_ω and VaR are the decision variables.

Table 3
Decision variables

First-stage decision variables	
a_{ik}	Order allocation from supplier i located in region k
x_{ik}	1 if supplier i located in region k is contracted as a prime supplier; otherwise 0
y_{ik}	1 if supplier i located in region k is contracted as a backup supplier; otherwise 0
z_k	1 if region k is contracted; otherwise 0
Second-stage decision variables	
$q_{ik\omega}$	Quantity of items from prime supplier i located in region k of scenario ω
$eq_{ik\omega}$	Quantity of emergency items from prime supplier i located in region k of scenario ω
$bq_{ik\omega}$	Quantity of emergency items from backup supplier i located in region k of scenario ω
u_ω	Quantity of unsatisfied items in scenario ω
τ_ω	Tail cost of scenario ω
VaR_α	*value-at-risk* measure for a given tolerance level α

3.1. Risk-neutral model

We present scenario-based two-stage risk-neutral stochastic programming to minimize the expected total cost. The objective function F_1 consists of supplier selection and order allocation costs for the first stage and recovery costs through flexibility and redundancy with the transportation, penalty, and refunding costs considering each scenario with uncertainty for the second stage. Therefore, the risk-neutral model that minimizes expected total cost is defined as follows (risk-neutral model):

$$\begin{aligned} \min\ F_1 = &\sum_{i\in I}\sum_{k\in K} p_{ik}x_{ik} + \sum_{i\in I}\sum_{k\in K} b_{ik}y_{ik} + \sum_{k\in K} r_k z_k + \sum_{i\in I}\sum_{k\in K} c_{ik}a_{ik} \\ &+ \sum_{i\in I}\sum_{k\in K}\sum_{\omega\in\Omega} P_\omega\{c_{ik}bq_{ik\omega} + t_{ik}(q_{ik\omega} + bq_{ik\omega} + eq_{ik\omega}) + ec_{ik}eq_{ik\omega} + mu_\omega \\ &+ (status_{ik\omega} - 1)c_{ik}a_{ik}\}, \end{aligned} \tag{2}$$

$$\text{subject to } \sum_{i\in I}\sum_{k\in K} a_{ik} = d, \tag{3}$$

$$x_{ik} \le z_k \quad \forall i\in I,\ \forall k\in K, \tag{4}$$

$$y_{ik} \le z_k \quad \forall i\in I,\ \forall k\in K, \tag{5}$$

$$x_{ik} + y_{ik} \le 1 \quad \forall i\in I,\ \forall k\in K, \tag{6}$$

$$a_{ik} \le x_{ik}pcap_{ik} \quad \forall i\in I,\ \forall k\in K, \tag{7}$$

$$q_{ik\omega} = a_{ik}status_{ik\omega} \quad \forall i\in I,\ \forall k\in K,\ \forall\omega\in\Omega, \tag{8}$$

$$eq_{ik\omega} \le x_{ik}pcap_{ik}sf_{ik}status_{ik\omega} \quad \forall i\in I,\ \forall k\in K,\ \forall\omega\in\Omega, \tag{9}$$

$$bq_{ik\omega} \le y_{ik}bcap_{ik}status_{ik\omega} \quad \forall i\in I,\ \forall k\in K,\ \forall\omega\in\Omega, \tag{10}$$

$$\sum_{i\in I}\sum_{k\in K}(bq_{ik\omega} + eq_{ik\omega}) \le \sum_{i\in I}\sum_{k\in K} a_{ik}(1 - status_{ik\omega}) + D_\omega - d \quad \forall\omega\in\Omega, \tag{11}$$

$$u_\omega = D_\omega - \sum_{i\in I}\sum_{k\in K}(q_{ik\omega} + eq_{ik\omega} + bq_{ik\omega}) \quad \forall\omega \in \Omega, \tag{12}$$

$$x_{ik}, y_{ik}, z_k \in \{0, 1\} \quad \forall i \in I,\ \forall k \in K, \tag{13}$$

$$a_{ik}, q_{ik\omega}, bq_{ik\omega}, eq_{ik\omega}, u_\omega \in \mathbb{Z} \quad \forall i \in I,\ \forall k \in K,\ \forall\omega \in \Omega, \tag{14}$$

Constraints (3)–(7) are conditions related to decision-making in the first stage. Constraint (3) indicates that the total order allocation satisfies the expected market demand. Constraints (4) and (5) restrict that the prime and backup suppliers should be contracted only when the region is available. Constraint (6) is a condition for the contract as a prime or backup supplier. Constraint (7) ensures that order allocation does not exceed the capacity of the prime supplier. Constraints (8)–(12) are conditions related to decision-making in the second stage. Constraint (8) ensures that the order has been allocated according to the status of the supplier in each scenario. Constraint (9) is a condition for a prime supplier to produce an emergency item through flexibility in a disruption situation. Constraint (10) is a condition for receiving an emergency item from a backup supplier. Constraint (11) is a condition where the quantity of a recovery item is less than or equal to the sum of the unallocated quantity due to disruption and the quantity of demand fluctuations. Constraint (12) finally determines the unsatisfied quantity through allocation and recovery. For each decision variable, constraints (13) and (14) are binary and integer conditions, respectively.

3.2. Risk-averse model

In the risk-averse model, we present scenario-based two-stage stochastic programming considering the *CVaR* measure. In particular, we assume uncertainty about disruption and demand. *VaR* is the α-percentile of the random variable Z. We define VaR_α for a given tolerance level, $\alpha \in (0, 1]$, as follows:

$$VaR_\alpha(Z) = \inf\{\tau : \text{Prob}[\tau \leq Z] \geq \alpha,\ \tau \in \mathbb{R}\}. \tag{15}$$

Furthermore, *CVaR* means the expectation of Z from α-percentile cases. We consider *CVaR* as a risk measure for computational tractability, and *CVaR* is defined for a given tolerance level, $\alpha \in (0, 1]$, as follows:

$$CVaR_\alpha(Z) = \mathbb{E}[Z|Z \geq VaR_\alpha(Z)]. \tag{16}$$

To make *CVaR* more tractable, Rockafellar and Uryasev (2000) proposed the auxiliary function. As a result, the equivalent equation is presented to solve the optimization problem more tractable:

$$CVaR_\alpha(Z) = \tau + \frac{1}{\alpha}\mathbb{E}([Z - \tau]_+), \tag{17}$$

where $[Z - \tau]_+$ is defined as $\max(Z - \tau, 0)$ (Rockafellar and Uryasev, 2000). It is known that minimizing (16) and (17) is equivalent.

We suggest the optimization model with constraints to calculate expectations. As a result, the risk-averse model that minimizes the $CVaR$ measure for a given tolerance level $\alpha \in (0, 1]$ is defined as follows (risk-averse model):

$$\min\ F_2 = \sum_{i\in I}\sum_{k\in K} p_{ik}x_{ik} + \sum_{i\in I}\sum_{k\in K} b_{ik}y_{ik} + \sum_{k\in K} r_k z_k + \sum_{i\in I}\sum_{k\in K} c_{ik}a_{ik} + \left(\tau + \frac{1}{\alpha}\sum_{\omega\in\Omega} P_\omega \tau_\omega\right), \quad (18)$$

subject to (3)–(14)

$$\tau_\omega \geq \sum_{i\in I}\sum_{k\in K}\{c_{ik}bq_{ik\omega} + t_{ik}(q_{ik\omega} + bq_{ik\omega} + eq_{ik\omega}) + ec_{ik}eq_{ik\omega} + mu_\omega$$
$$+ (status_{ik\omega} - 1)c_{ik}a_{ik}\} - \tau, \quad (19)$$

$$\tau_\omega \geq 0 \ \ \forall \omega \in \Omega. \quad (20)$$

Constraints (3)–(14) are the same conditions in the risk-neutral model. The tail cost for scenario ω is τ_ω, and the tail cost τ corresponds to VaR_α when the tolerance level is α. Constraint (19) searches for cases where the cost of the second stage exceeds τ in the scenario ω. For each scenario, constraint (20) is a nonnegative condition.

3.3. Responsiveness model

We consider the service level β apart from cost in the responsiveness model. The service level β is a quantitative performance measure describing the proportion of total demand satisfied without delay from stock on hand. In particular, in large-scale disruption situations such as disasters, demand increases rapidly. In this situation, we calculate how much the total demand is being satisfied. We present the responsiveness model for analysis in a multiobjective model. Therefore, we maximize the expected service level β as an objective function as follows (responsiveness model):

$$\max\ F_3 = 1 - \frac{\sum_{\omega\in\Omega} u_\omega}{\sum_{\omega\in\Omega} D_\omega}, \quad (21)$$

subject to (3)–(14).

3.4. Stochastic measures

We concentrate on stochastic measures to determine whether our models using a stochastic programming approach are worthwhile. We now examine how uncertainty affects the model using two well-known measures, which are the expected value of perfect information (EVPI) and the value of the stochastic solution (VSS) (Birge and Louveaux, 2011). The measures indicate how valuable the two-stage stochastic programming is compared to the deterministic model. The EVPI quantifies how much a decision-maker would be willing to spend to obtain perfect information. Wait-and-see (WS) problems solve the deterministic models for each uncertainty scenario. As the random variables for each WS problem are fully known, the best strategic decision for the individual problem will be taken. The average value of all such WS problems is calculated by taking the probability of each scenario into account. As an opposite concept, the here-and-now value is derived from the recourse problem as the optimal stochastic programming (SP) solution. The EVPI is the difference between the average value with perfect information and the optimal stochastic programming solution. The VSS determines how bad a solution is if decisions are made based on the expected values of random parameters rather than values of different scenarios. To accomplish this, we solve a deterministic model in which all random parameters are replaced with expected values. The VSS is evaluated as the difference between the optimal stochastic programming solution and the expected solution using the expected value (EEV). EVPI and VSS can also be shown by the definition as follows:

$$EVPI = Z_{SP} - Z_{WS}, \tag{22}$$

$$VSS = Z_{EEV} - Z_{SP.} \tag{23}$$

These two measures are based on expected values and are used to evaluate a risk-neutral model. They cannot, however, be used to assess a risk-averse model directly. As a result, we modify these measures and calculate the Z_{RWS_α} and Z_{REV_α} using the $CVaR$ measure rather than the expected value. More specifically, we employ the measures for the risk-averse model (Noyan, 2012):

$$RVPI_\alpha = Z_{RSP_\alpha} - Z_{RWS_{\alpha,}} \tag{24}$$

$$RVSS_\alpha = Z_{REV_\alpha} - Z_{RSP_{\alpha.}} \tag{25}$$

In this case, Z_{RSP_α} is the value of solving the risk-averse model for a given tolerance level, α. Z_{RWS_α} is obtained as perfect information by solving the risk-averse model for each scenario as a WS problem and then taking the objective function value for a given tolerance level, α. Z_{REV_α} is obtained by solving the risk-averse model with deterministic expected values for a given tolerance level, α. Based on the $CVaR$ measure of the objective function value obtained from the WS solution and the objective function value of the risk-averse model solutions, $RVPI_\alpha$ calculates the gain of perfect information. $RVSS_\alpha$ quantifies the gain of solving the risk-averse model for a given tolerance level, α. The higher $RVSS_\alpha$ values, the greater the value added to considering a risk-averse model rather than a deterministic model.

4. Multiobjective mathematical programming

The multiobjective model simultaneously optimizes the risk-neutral, risk-averse, and responsiveness models discussed in Section 3. The goal is to minimize the expected total cost and the $CVaR$ measure while maximizing the service level. Due to the multiobjective nature of our models, it is impossible to find a unique optimal solution. Thus, our goal is to identify a set of nondominated solutions efficiently. The set of nondominated solutions is termed the Pareto frontier. This implies the trade-off relationship between cost, risk, and responsiveness. Depending on where the weights are assigned, the results provide a decision-making criterion. An integrated multiobjective model is expressed as follows (multiobjective model):

$$\begin{aligned}&\min\ F_1, F_2\\&\max\ F_3\\&\text{subject to } (3)\text{–}(14),\ (19),\ (20).\end{aligned} \tag{26}$$

4.1. Solution approach

Compared to the single-objective model, the process of solving the multiobjective model is quite difficult and challenging. There are various methodologies to solve the multiobjective model. In our study, we implement a recently developed method to derive the Pareto frontier efficiently. We optimize the multiobjective model through the improved version of the augmented ϵ-constraint method (AUGMECON2) for finding the set of optimal solutions (Mavrotas and Florios, 2013). We slightly modify the AUGMECON2 model to solve our integrated model as follows (AUGMECON2 model):

$$\min \quad F_1 - eps * (s_2/r_2 - 10^{-1} * s_3/r_3), \tag{27}$$

$$\text{subject to } (3) - (14),\ (19),\ (20)$$

$$F_2 + s_2 = e_2, \tag{28}$$

$$F_3 + s_3 = e_3, \tag{29}$$

$$s_2\ \ s_3 \geq 0, \tag{30}$$

where e_2 and e_3 represent the right-hand side for the particular iteration based on the grid points for the objective functions F_2 and F_3. The ranges of the respective objective functions are represented by the parameters r_2 and r_3. The nonnegative surplus decision variables of the respective constraints are s_2 and s_3. eps is a very small number with a value ranging from 10^{-3} to 10^{-6}.

When we perform lexicographic optimization on objective functions F_1, F_2, and F_3, we can create a payoff table and determine the ranges of objective functions. As a result, r_k and g_k represent the range and desired number of grid points of objective function F_k. The range of the kth objective function is then divided into g_k intervals, and the result indicates the step size of iterations. Therefore, $\Pi_{k=1}^{3}(g_k + 1)$ is the maximum number of iterations. The right-hand side value e_k is calculated as follows:

$$e_k = ub_k - (i_k * (r_k)/g_k)), \tag{31}$$

where ub_k and i_k denote the upper bound and the counter for objective function F_k, respectively. In iterations, we calculate the bypass coefficient as $int(s_k * g_k/r_k)$. When the surplus variable s_k is greater than $int(r_k/g_k)$, it determines that the equivalent solution will be acquired from the next

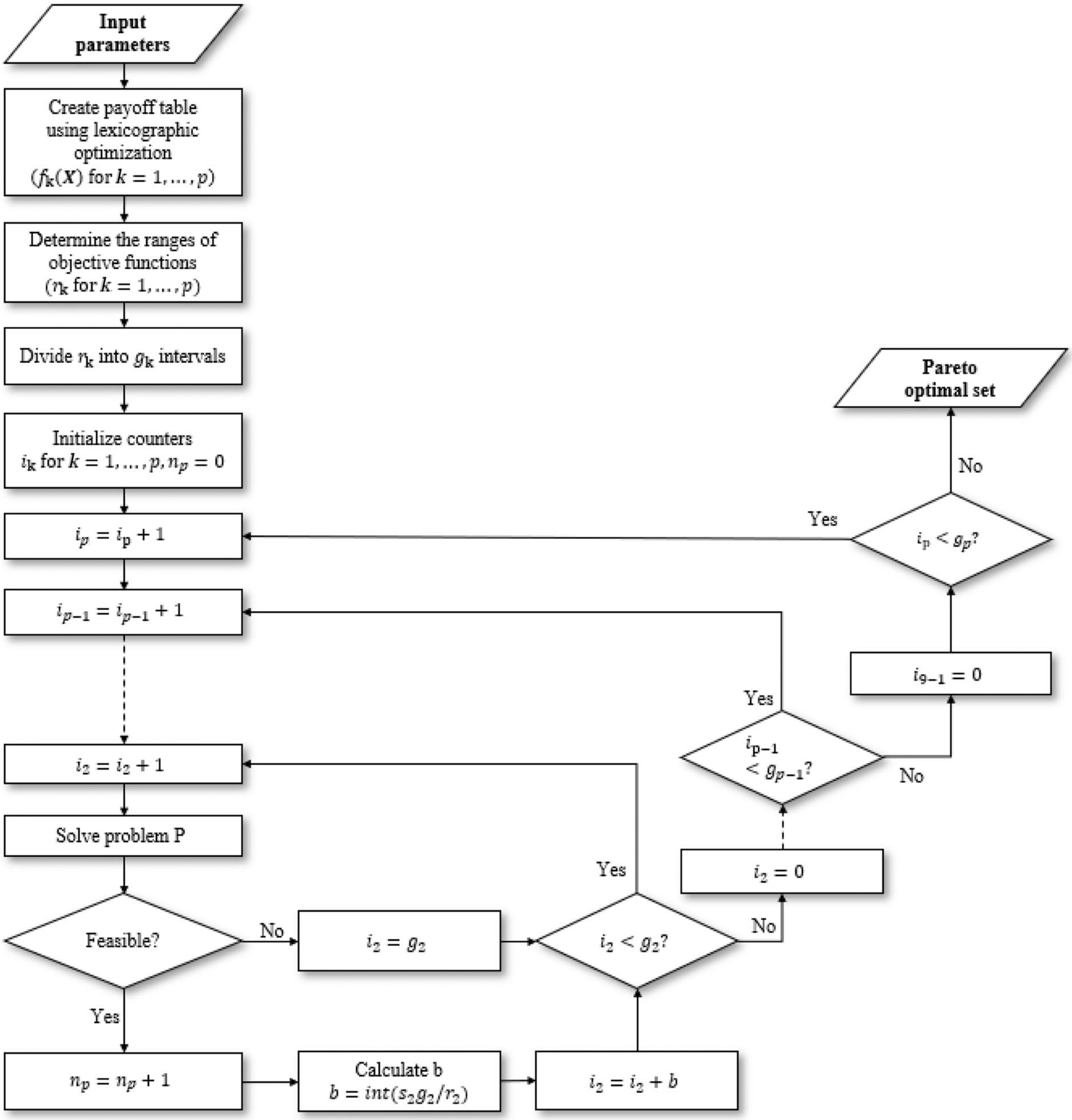

Fig. 1. Flowchart of the AUGMECON2 model.

iteration. This renders the iteration redundant, allowing us to skip it because a new nondominated solution is not generated. The bypass coefficient b indicates how many iterations we can skip in a row. Figure 1 shows the flowchart of the AUGMECON2 model.

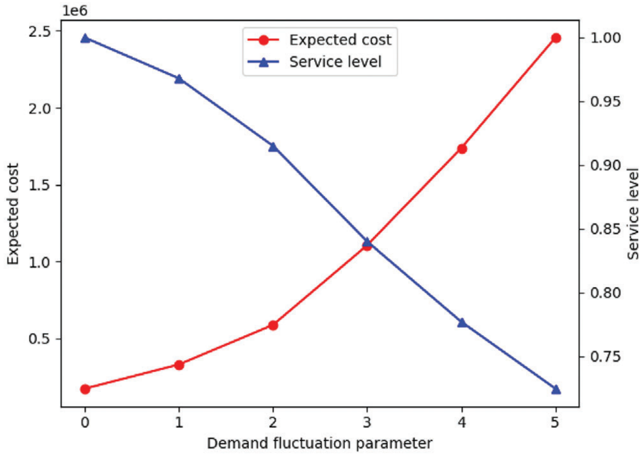

Fig. 2. The result of the expected total cost and service level according to the demand fluctuation parameter θ.

5. Computational experiments

In this section, we conduct computational experiments to demonstrate the efficacy of each model and offer managerial insights. All experiments were conducted on CPLEX version 21.1.2 with an AMD Ryzen 7 2700X eight-core processor with 3.70 GHz and 16GB RAM. We assume that there exist six regions with 10 suppliers in each region, and suppliers have different characteristics in each region. Suppliers from low-numbered regions have a high transportation cost with low reliability, but they supply at a low procuring cost and have high capacity. This represents overseas suppliers based on the standards of developing countries. On the other hand, for high-numbered regions, we assume domestic suppliers with high reliability, low transportation cost, high procuring cost, and low capacity. Because regional disruption is such an overwhelming event, the probability of occurrence is extremely low. Table 4 shows the parameter set that takes into account the characteristics of each region and supplier. We reprocessed the parameter set from a case study by Kamalahmadi et al. (2022), which was grounded in data observed from an appliance manufacturer.

5.1. Results from the single-objective model

First, we conducted computational experiments to find an appropriate demand fluctuation parameter θ. In detail, we performed a sensitivity analysis on six cases of the demand fluctuation parameter set through the risk-neutral model. As the demand fluctuation parameter θ increases, the surge in demand is emphasized. Therefore, the service level decreases, and the expected total cost increases exponentially. Figure 2 shows the tendencies according to the demand fluctuation parameter. Table 5 shows the results of six cases based on the demand fluctuation parameter settings. The number of suppliers and regions contracted also tends to increase. When the demand fluctuation parameter equals 1, four out of six regions and 39 out of 60 suppliers contracted, and the expected total cost is 330,479. In addition, the risk-neutral model with the demand fluctuation

Table 4
Characteristics of each region and supplier

Parameters	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6
c_{ik}	$Uniform(10, 12.25)$	$Uniform(12.5, 14.75)$	$Uniform(15, 17.25)$	$Uniform(17.5, 19.75)$	$Uniform(20, 22.25)$	$Uniform(22.5, 24.75)$
ec_{ik}	$Uniform(20, 22.25)$	$Uniform(22.25, 24.75)$	$Uniform(25, 27.25)$	$Uniform(27.5, 29.75)$	$Uniform(30, 32.25)$	$Uniform(32.5, 34.75)$
$pcap_{ik}$	$Uniform(190, 200)$	$Uniform(180, 190)$	$Uniform(170, 180)$	$Uniform(160, 170)$	$Uniform(150, 160)$	$Uniform(140, 150)$
$bcap_{ik}$	$Uniform(130, 140)$	$Uniform(120, 130)$	$Uniform(110, 120)$	$Uniform(100, 110)$	$Uniform(90, 100)$	$Uniform(80, 90)$
η_k	0.0006	0.0005	0.00004	0.0003	0.0002	0.0001
β_{ik}	$Uniform(0.005, 0.006)$	$Uniform(0.004, 0.005)$	$Uniform(0.003, 0.004)$	$Uniform(0.002, 0.003)$	$Uniform(0.001, 0.002)$	$Uniform(0, 0.001)$
sf_{ik}	$Uniform(0.5, 0.6)$	$Uniform(0.4, 0.5)$	$Uniform(0.3, 0.4)$	$Uniform(0.2, 0.3)$	$Uniform(0.1, 0.2)$	$Uniform(0, 0.1)$
p_{ik}	1000	1000	1000	1000	1000	1000
b_{ik}	2000	2000	2000	2000	2000	2000
r_k	50000	40000	30000	20000	10000	0
t_{ik}	$Uniform(11, 12)$	$Uniform(10, 11)$	$Uniform(9, 10)$	$Uniform(8, 9)$	$Uniform(7, 8)$	$Uniform(6, 7)$

Table 5
Results of the risk-neutral model according to the demand fluctuation parameter θ

θ	0	1	2	3	4	5
Number of regions contracted	3	4	6	6	6	6
Number of prime suppliers	28	30	41	35	34	32
Number of backup suppliers	0	9	19	25	26	28
Service level	1.00	0.97	0.91	0.84	0.78	0.72
Normal allocation ratio	0.97	0.77	0.63	0.54	0.47	0.42
Flexibility ratio	0.03	0.11	0.13	0.11	0.12	0.11
Redundancy ratio	0.00	0.09	0.15	0.19	0.19	0.20
Expected total cost	173,362	330,479	587,852	1,105,454	1,737,503	2,456,211

Table 6
Results for the risk-averse model according to the tolerance level α

Tolerance level	1	0.5	0.25	0.2	0.15	0.1	0.05	0.02	0.01
CVaR measure	330,479	395,840	497,754	543,105	613,890	752,556	1,164,289	2,391,155	4,428,858
Number of regions contracted	4	5	6	6	6	6	6	6	6
Number of prime suppliers	30	40	49	40	33	30	27	25	25
Number of backup suppliers	9	0	10	19	26	29	32	34	34
service level	0.97	0.97	0.98	0.98	0.98	0.98	0.98	0.98	0.98
Normal allocation ratio	0.77	0.77	0.77	0.77	0.77	0.77	0.77	0.77	0.77
Flexibility ratio	0.11	0.2	0.11	0.08	0.06	0.06	0.06	0.06	0.06
Redundancy ratio	0.09	0	0.11	0.13	0.15	0.16	0.16	0.16	0.15
expected total cost	330,479	335,061	359,135	366,164	371,881	374,545	377,439	379,401	379,443

parameter 1 can cope well in disruption situations through flexibility and redundancy. As a result, we concluded that the demand fluctuation parameter 1 is a representative parameter and used it in the following experiment.

We performed experiments for each of the nine specified tolerance thresholds in the risk-averse model. Table 6 summarizes the results for the risk-averse model based on tolerance level α. As the tolerance level α becomes smaller, there are cases ($\alpha = 0.25,\ 0.2,\ 0.15,\ 0.1,\ 0.05,\ 0.02,\ 0.01$) where all regions are contracted to mitigate the disruption risk. When the tolerance level α is extremely small ($\alpha = 0.05,\ 0.02,\ 0.01$), we confirm that backup suppliers are contracted more than prime suppliers. This strategy reduces risk by contracting many backup suppliers in extreme situations with high risk. As a result of the experiment, if the tolerance level α is 1, we confirm that it is the same as the risk-neutral model. As the tolerance level α decreases, the expected total cost increases monotonically while the *CVaR* measure increases exponentially, as shown in Fig. 3. Note that the considerable risk costs in a disruption situation can be offset by sacrificing some expected total costs.

Figures 4 and 5 show the expected supplier dependency ratios in the risk-neutral and risk-averse models, respectively. The red lines are the planned allocation ratios before a disruption occurs in the first stage. The blue lines are the allocation and recovery ratios to be recovered after a disruption occurs in the second stage. In the risk-neutral model, all suppliers in regions 4 and 5 are not contracted in any case, and order quantity is recovered from region 6 only in case of disruption. On the

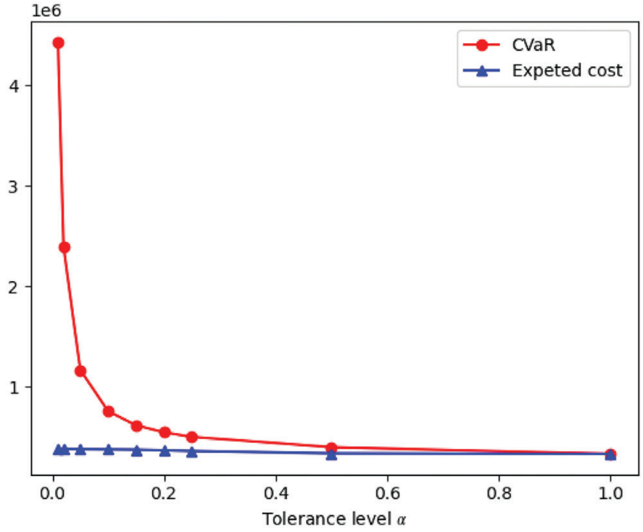

Fig. 3. Comparison of $CVaR$ and expected cost according to the tolerance level α.

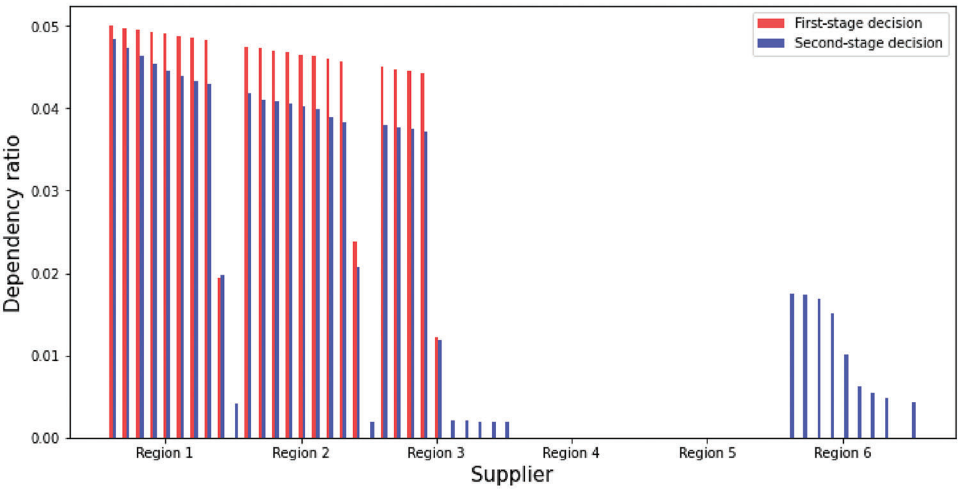

Fig. 4. Expected supplier dependency ratios in the risk-neutral model.

other hand, in the risk-averse model, contracts are made with 59 out of 60 suppliers in all regions in preparation for disruption situations. In particular, suppliers in regions 1–3 normally supply for the first stage, and when disruption occurs, items are provided by almost all suppliers and respond well. This indicates that when there is a disruption with an overseas supplier, the domestic supplier can resolve the disruption urgently. Figure 6 shows the results of the expected supplier dependency ratios for each supplier in the responsiveness model. All suppliers in all regions are contracted, and the expected total cost is 383,517, which is higher than when the tolerance level α is 0.01 in the risk-averse model. By contracting 24 as prime suppliers and 36 as backup suppliers, the final expected

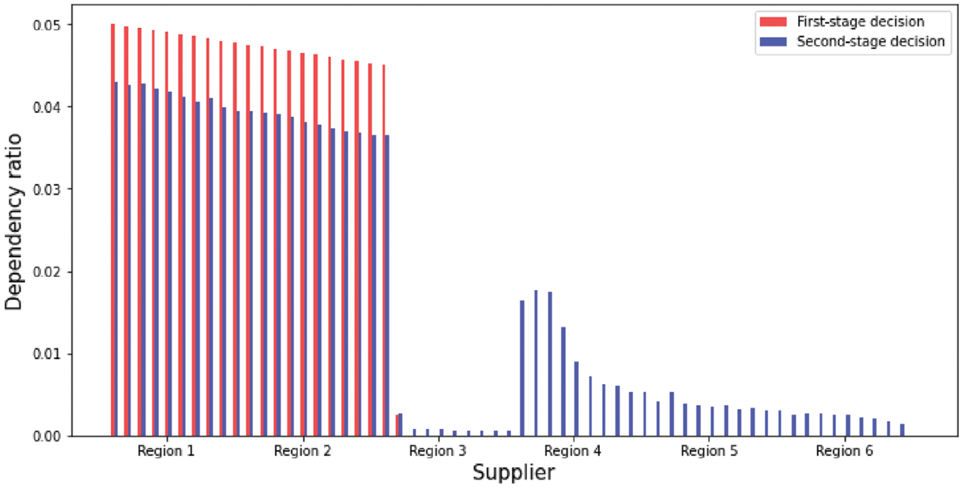

Fig. 5. Expected supplier dependency ratios in the risk-averse model ($\alpha = 0.1$).

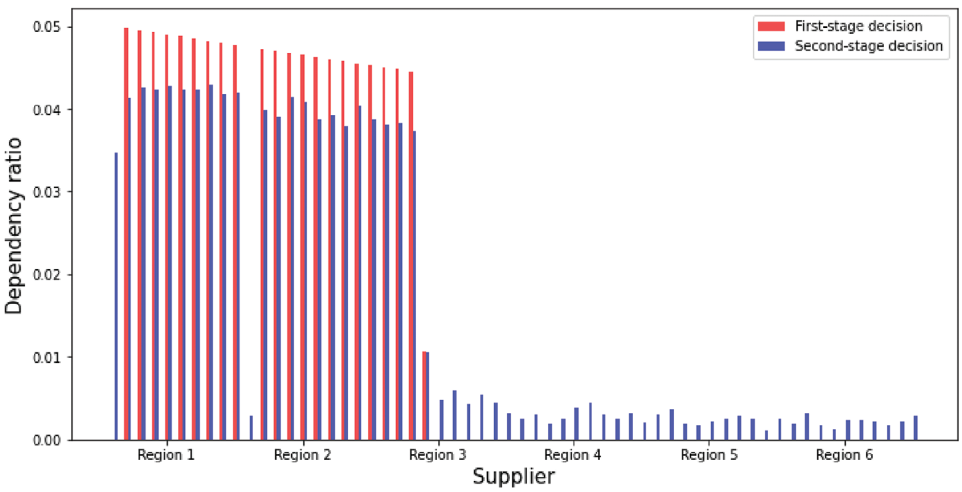

Fig. 6. Expected supplier dependency ratios in the responsiveness model.

service level of 0.98 is achieved. No matter how much we prepare for disruption, this suggests that unsatisfied items may exist in large-scale disruption.

Figures 7 and 8 show the expected regional dependency ratios of the risk-neutral and risk-averse models, respectively. We confirm the recovery strategies for flexibility and redundancy for each model. The risk-neutral model contracts regions 1–3 for flexibility and region 6 for redundancy. On the other hand, the risk-averse model contracts with all regions to confirm that it was costly but copes well with supply disruptions and demand fluctuations by contracting regions 1–3 for flexibility and regions 4–6 for redundancy. Figure 9 shows the expected regional dependency ratios of the responsiveness model. Overall, decision-making strategies are similar to the risk-averse

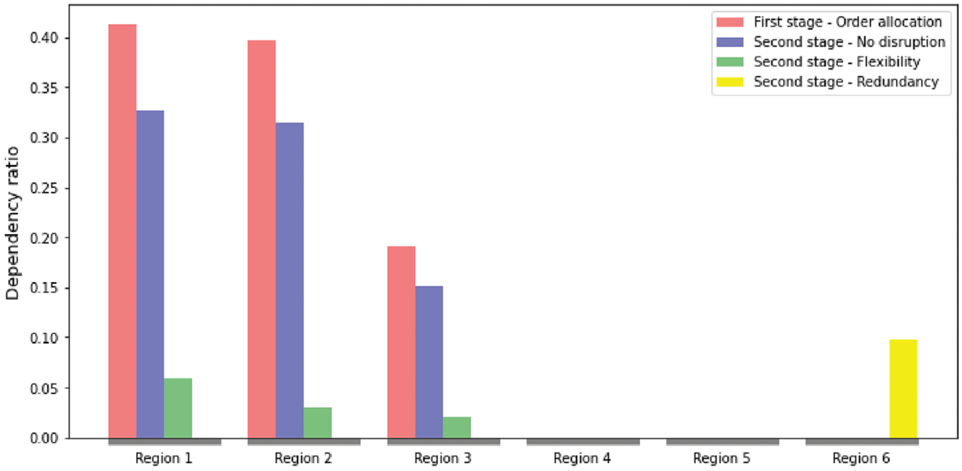

Fig. 7. Expected regional dependency ratios of the risk-neutral model.

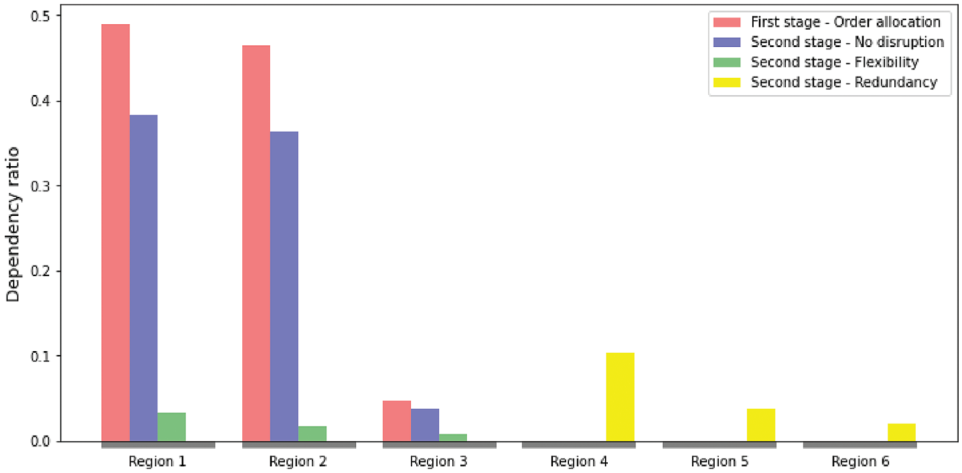

Fig. 8. Expected regional dependency ratios of the risk-averse model.

model. Eventually, in a disruption situation, the contracted prime suppliers temporarily increase production while the contracted backup suppliers urgently supply items.

5.2. Stochastic measures

As previously stated, we calculate the stochastic measures to demonstrate the efficacy of our models. Table 7 shows stochastic measures, including the VSS and EVPI for the risk-neutral model. Table 7 also shows the relative values of EVPI and VSS divided by the optimal objective function value of the risk-neutral model. The analysis of VSS measures suggests that efforts to solve the risk-neutral model rather than a deterministic model are critical and have the potential to reduce the expected

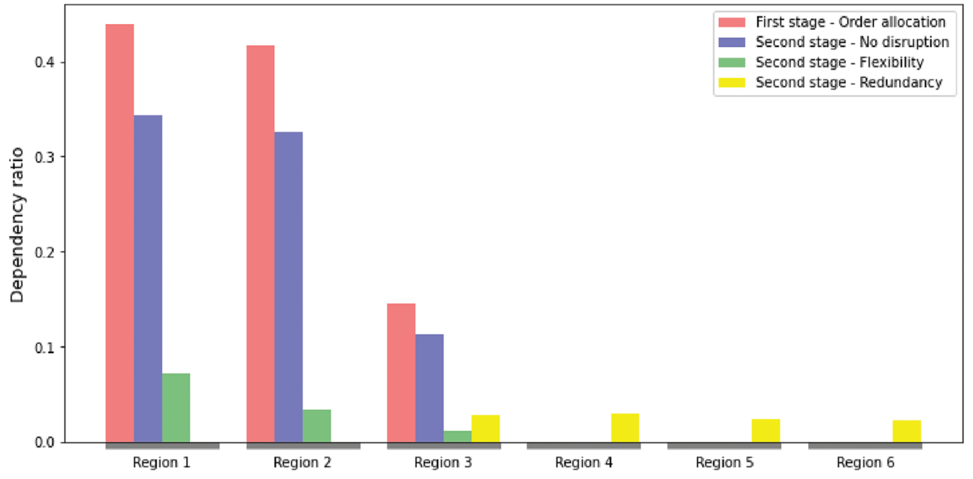

Fig. 9. Expected regional dependency ratios of the responsiveness model.

Table 7
Results of the stochastic measures according to the demand fluctuation parameter θ

θ	1	2	3	4	5
Z_{SP}	330,479	587,852	1,105,454	1,737,503	2,456,211
Z_{EEV}	720,989	1,276,148	1,815,167	2,369,486	2,961,407
Z_{WS}	212,059	427,891	844,003	1,462,352	2,177,836
$EVPI$	118,420	159,961	261,451	275,151	278,375
VSS	390,510	688,297	709,713	631,982	505,196
$EVPI/Z_{SP}$	0.358	0.272	0.237	0.158	0.113
VSS/Z_{SP}	1.182	1.171	0.642	0.364	0.206

Table 8
Results for the risk-averse model according to tolerance level α

Toleranc level	1	0.5	0.25	0.2	0.15	0.10	0.05	0.02	0.01
Z_{RSP_α}	330,479	395,840	497,754	543,105	613,890	752,556	1,164,289	2,391,155	4,428,858
Z_{REV_α}	721,000	1,200,777	2,159,065	2,638,125	3,436,689	5,033,806	9,829,704	24,199,390	48,144,644
Z_{RWS_α}	158,705	163,481	163,563	163,601	163,660	163,774	164,115	165,138	166,842
$RVPI_\alpha$	171,774	232,360	334,191	379,504	450,230	588,782	1,000,173	2,226,017	4,262,017
$RVSS_\alpha$	390,521	804,936	1,661,311	2,095,020	2,822,799	4,281,250	8,665,415	21,808,235	43,715,786
$RVPI_\alpha/Z_{RSP_\alpha}$	0.520	0.587	0.671	0.699	0.733	0.782	0.859	0.931	0.962
$RVSS_\alpha/Z_{RSP_\alpha}$	1.182	2.033	3.338	3.857	4.598	5.689	7.443	9.120	9.871

total cost significantly. Furthermore, the analysis of EVPI measures indicates that obtaining perfect information about disruption and demand uncertainty can significantly reduce the expected total cost. An increase in the demand fluctuation parameter means an increase in uncertainty. Therefore, it can be confirmed that the values of $EVPI/Z_{SP}$ and VSS/Z_{SP} tend to decrease.

We also calculate the $RVPI_\alpha$ and $RVSS_\alpha$ for a given set of tolerance levels. Table 8 records the

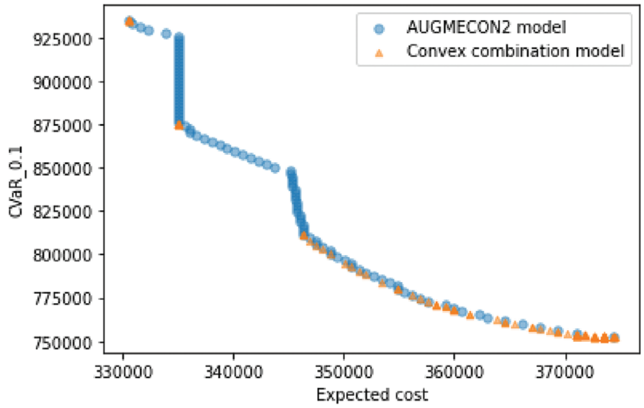

Fig. 10. Result of the biobjective model that combines risk-neutral and risk-averse models.

results of stochastic measures for the risk-averse model. According to the results, the risk-averse value of the stochastic solution (RVSS) value is significantly larger than the Z_{RSP_α} value, especially when the tolerance level is very small. It indicates that solving the risk-averse model is worthwhile in extreme situations. Furthermore, $RVPI_\alpha/Z_{RSP_\alpha}$ values decrease monotonously as the tolerance level alpha increases. $RVSS_\alpha/Z_{RSP_\alpha}$ values indicate that the solutions are more robust than the deterministic model once disruption and demand uncertainties are considered.

5.3. *Experiment results for the multiobjective model*

We present the results of the experiments on the MOMP discussed in Section 4. The goal is to make robust decisions by simultaneously considering risk-neutral, risk-averse, and responsiveness models. We constructed a Pareto frontier by combining the nondominated solutions from each model.

First, we experimented with three combinations of biobjective models that can be derived through the risk-neutral, risk-averse, and responsiveness models. Through this, we confirm the trade-off relationship that exists between each model. The results of AUGMECON2 and the convex combination model are compared. The convex combination model derives the result by assigning weight to the objective function of each model. At this time, the weight is divided into 100 grid points between 0 and 1. We experimented with the biobjective model that combines risk-neutral and risk-averse models, as shown in Fig. 10. Both models equally searched 100 points; the convex combination model found 67 overlapping solutions, and the AUGMECON2 model found all 100 different solutions. This implies that the AUGMECON2 model derives more sophisticated solutions when estimating the Pareto frontier. Figure 11 shows the $CVaR_{0.1}$ measures and service levels resulting from risk-averse and responsiveness models. Both models found six different solutions. The difference is that the convex combination model conducted 100 experiments to obtain six nondominated solutions. In contrast, the AUGMECON2 model conducted only six experiments to find six nondominated solutions through bypass coefficients. Because when creating the payoff table, the model already searched for high-quality solutions and could not find a more improved solution. This suggests that the risk-averse and responsiveness models eventually choose similar

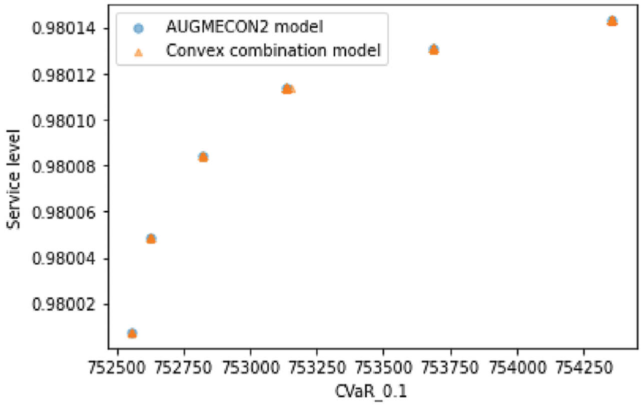

Fig. 11. Result of the biobjective model that combines risk-averse and responsiveness models.

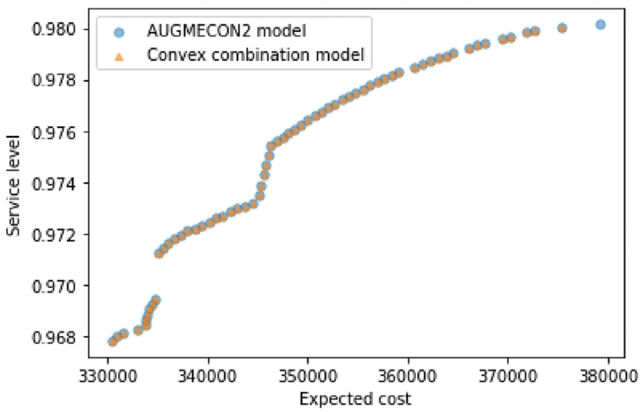

Fig. 12. Result of the biobjective model that combines risk-neutral and responsiveness models.

strategies to cope with disruption. Figure 12 shows the result of the biobjective model combining the risk-neutral and responsiveness model. Since the x-axis is the expected total cost and the y-axis is the service level, the solutions have a concave shape. The AUGMECON2 model found 65 unique nondominated solutions, whereas the convex combination model found 29 unique solutions out of 100. As a result, it suggests that the expected total cost must be compromised in order to increase the service level.

Finally, we experiment with a supply chain resilience model that integrates the three models. As the first process of the AUGMECON2 model, we create a payoff table as shown in Table 9 through lexicographic optimization. What can be seen through the payoff table is that the results of *min* F_2 and *max* F_3 are similar to each other. This is because risk and responsiveness are opposite concepts, and, as a result, similar strategies are selected.

There is a clear trade-off between the objective functions. According to the AUGMECON2 solutions, the decision-maker has access to a broad range of solutions from which to select the most preferred solution. Figure 13 shows a Pareto frontier derived from these nondominated solutions.

Table 9
Payoff table of the AUGMECON2 model

Sequence	*min* F_1	*min* F_2	*max* F_3
F_1	**330,479**	374,480	379,135
F_2	934,791	**752,556**	754,358
F_3	0.96783	0.98001	**0.98014**
Objective function	F_1	F_2	F_3
Lower bound	330,479	752,556	0.96783
Upper bound	379,135	934,791	0.98014
Range	48,656	182,236	0.01232

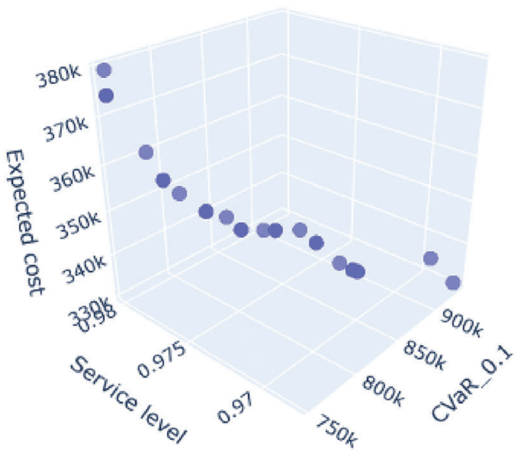

Fig. 13. Result of the AUGMECON2 model with the 10 grid points.

While we have to experiment with 100 iterations in AUGMECON, we can get the same nondominated solutions in AUGMECON2 with only 54 experiments with the bypass coefficient. Figure 14 shows the result by dividing the range into 100 grid points. This results from investing much computation time and searching for a sophisticated Pareto frontier. Similarly, with the bypass coefficient, the result can be obtained with 3126 experiments instead of 10,000. As a result, it aids in understanding the trade-offs among nondominated solutions at a glance. The solutions provide the decision-makers with nondominated solutions to select the best solution based on their priorities.

5.4. *Managerial insights*

This study presents three models for enhancing supply chain resilience to help business practitioners decide on optimal supplier selection and order allocation. Our models aim to explore various strategies through flexibility and redundancy. This study offers decision-makers valuable perspectives on effective supply chain risk management.

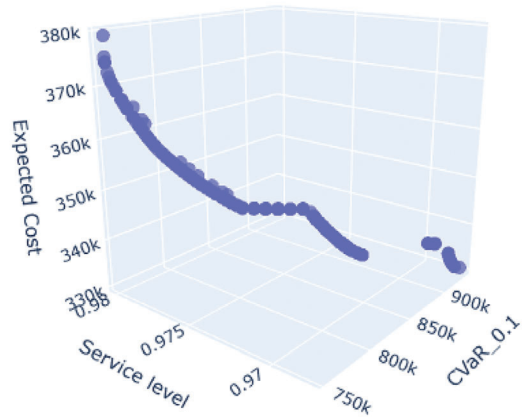

Fig. 14. Result of the AUGMECON2 model with the 100 grid points.

From the risk-neutral model with a set of demand fluctuation parameters, we found that various strategies can cope well in disruption situations through flexibility and redundancy. We explored appropriate strategies through various scenario analyses on demand fluctuations. Additionally, we conducted experiments on a risk-averse model based on nine tolerance levels. Our observations indicated that the expected total cost increased steadily as the tolerance level decreased, whereas the $CVaR$ measure surged exponentially. This suggests that it is possible to offset the significant costs associated with a disruption situation by accepting higher expected total costs. The responsiveness model has similar decision-making strategies to the risk-averse model in a disruption situation, with prime suppliers increasing production and backup suppliers urgently supplying items.

Stochastic measures, including VSS and EVPI, demonstrate the efficacy of the models. The results indicate that efforts to solve the two-stage stochastic programming are critical, and obtaining perfect information about disruption and demand uncertainty can significantly reduce the expected total cost. In the risk-averse model, smaller tolerance levels resulted in contracting all regions to mitigate disruption risk, and backup suppliers are contracted more than prime suppliers in extreme situations with high risk.

We present the results of experiments on MOMP for supply chain resilience. We aim to make rational decisions by simultaneously considering risk-neutral, risk-averse, and responsiveness models. The AUGMECON2 and convex combination models were compared, deriving more sophisticated solutions when estimating the Pareto frontier. The results reveal a Pareto frontier that derived from nondominated solutions, offering decision-makers a spectrum of alternatives to choose the most suitable solution with their priorities. We demonstrate that AUGMECON2 is more efficient and helps find more sophisticated solutions than the convex combination model.

6. Conclusions

This study discussed supply chain resilience models that consider the uncertainties about supply disruptions and demand fluctuations. We propose scenario-based two-stage stochastic programming with risk-neutral, risk-averse, and responsiveness models. We analyzed the recovery strategies through flexibility and redundancy to deal with situations that arise after disruptions. Furthermore, quantifying the stochastic measures demonstrates that considering uncertainty in our models produces more robust results than the deterministic model. We also proposed a multiobjective model that integrates the three models and implemented the recently developed solution approach. We presented the Pareto frontier through the experimental results and derived managerial insights. Consequently, employing various strategies that consider supplier and regional dependency ratios can enhance the risk management of the global supply chain.

Nonetheless, this research has some limitations, and future studies should consider the following aspects. First, there is a need to concentrate on monitoring the decisions made in a multiperiod setup. This approach can recognize the progress and variation in diverse decisions when viewed from a long-term perspective. Moreover, a mathematical model that accurately reflects real-life scenarios is essential for refining and enhancing some simplified assumptions. Although the probability of disruption was set randomly in our model, it is necessary to accurately estimate the probability and conduct sensitivity analysis according to the probability.

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