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Supplier selection and order allocation problems considering regional and supplier disruptions with a risk-averse strategy

Jongmin Lee [a], Ilkyeong Moon [a,b,*]

[a] Department of Industrial Engineering, Seoul National University, 1 Gwanak-ro, Gwanak-gu, Seoul, Republic of Korea
[b] Institute of Engineering Research, Seoul National University, 1 Gwanak-ro, Gwanak-gu, Seoul, Republic of Korea

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ABSTRACT

This paper studies optimal supplier selection and order allocation problems considering regional and supplier disruptions. We suggest a pricing policy that takes into account disruption probability, which reflects the trade-off relationship between cost and risk. We present a risk-neutral model considering the expected cost and a risk-averse model considering the *conditional value-at-risk* ($CVaR$) measure. We also present a weighted $CVaR$ model that considers various tolerance levels simultaneously. Several multi-objective models that consider both risk-averse and risk-neutral models are proposed. We develop methodologies to solve multi-objective models by applying a convex combination or a modified augmented Tchebycheff distance. Finally, we show the performance of solution approaches through numerical experiments and present the supplier dependency ratio, which can construct an appropriate portfolio. We offer a Pareto frontier as the result of the multi-objective model and derive managerial insights, suggesting a decision-making criterion between disruption risk and the expected cost.

1. Introduction

Supply chain risk management has become an essential agenda in a rapidly changing environment (Taghizadeh & Venkatachalam, 2022). In particular, while experiencing the COVID-19 pandemic, the supply chain has experienced a lot of disruption situations and is still experiencing disruptions for various reasons. Disruption of a single supplier adversely affects many components of the supply chain network through bullwhip consequences, and many studies considering this have been conducted recently (Dolgui & Ivanov, 2021; Moosavi, Fathollahi-Fard, & Dulebenets, 2022; Nooraie et al., 2020). Even though disruption in the supply chain has a low probability, it should be viewed as an essential characteristic with serious and catastrophic consequences. To deal with this disruption situation, estimating the supplier dependency ratio and intensively managing products based on the ratio is necessary. In other words, the risk of disruption can be spread out through a strategy of receiving items from various and reliable suppliers.

The competitive nature of the global market forces companies to be supplied certain products through outsourcing in the supply chain (Torabi, Baghersad, & Mansouri, 2015). Supplier selection and order allocation problems are traditionally addressed in supply chain management (Aissaoui, Haouari, & Hassini, 2007; Ekici, Özener, & Elyasi, 2021; Minner, 2003; Venkatesan & Goh, 2016). These problems involve determining which suppliers to select and how to allocate orders when dealing with multiple suppliers. Supplier selection is the process of choosing among various available suppliers. This selection is based on reliability, price, and more. Supplier reliability refers to the probability of receiving products at the required time, while price refers to the cost of procuring the products (Shahed, Azeem, Ali, & Moktadir, 2021). Considering these factors, the most suitable supplier is selected. In addition, order allocation involves determining how to allocate orders from the selected suppliers to the retailer. This process considers disruption probability, transportation costs, and more.

This paper also deals with supplier selection and order allocation with a risk-averse strategy. We consider *conditional value-at-risk* ($CVaR$), which is known as a popular risk measure and defined as the expectation of the worst α-tail scenarios (Zhou & Tokekar, 2018). In other words, CVaR quantifies the expected cost that occurs beyond the *value-at-risk* (VaR). Specifically, we consider minimizing the $CVaR$ measure to avoid the worst case by creating scenarios for disruption. In this way, this risk-averse model is more likely to make rational decisions in uncertain situations.

Multi-objective mathematics programming (MOMP) aims to find solutions as close to the Pareto frontier as possible. The Pareto frontier comprises a set of non-dominated points, which are solutions in which improving one objective function does not increase the performance of

* Corresponding author at: Department of Industrial Engineering, Seoul National University, 1 Gwanak-ro, Gwanak-gu, Seoul, Republic of Korea.
E-mail address: ikmoon@snu.ac.kr (I. Moon).

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at least one other objective function (Chiandussi, Codegone, Ferrero, & Varesio, 2012; Petrelli, Fioriti, Berizzi, Bovo, & Poli, 2021). The ϵ-constraint method, which optimizes one objective while setting the others as constraints parametrized by an ϵ, is a well-known technique for generating the Pareto frontier. One of the critical drawbacks of the ϵ-constraint method is that the resulting solutions cannot be guaranteed to be efficient because the parameter vector must fall within the domain of the objective functions. Previous studies have also been carried out on the augmented weighted Tchebycheff scalarization method for generating non-dominated points (Dächert, Gorski, & Klamroth, 2012; Steuer & Choo, 1983).

Disruption can lead to severe and disastrous consequences in the supply chain network. Therefore, these uncertainties should not be ignored. Heckmann, Comes, and Nickel (2015) defined supply chain disruption and reviewed existing approaches related to supply chain risk management. Watanabe and Kusukawa (2015) proposed optimal ordering policy in a dual-sourcing supply chain considering supply disruptions. Falsafi, Masera, Mascolo, and Fornasiero (2022) proposed a decision-support model that takes into account inbound logistics disruptions in the automotive sector. Recently, it has become necessary to consider the disruption of individual suppliers and the disruption of entire suppliers within the same region (Esmaeili-Najafabadi, Azad, Pourmohammadi, & Nezhad, 2021; Rezaei, Aghsami, & Rabbani, 2021; Venkatesan & Goh, 2016). The reasons are geographical differences such as culture, politics, and economy, as well as business-friendly conditions such as labor cost, intellectual property protection, and workplace safety. Therefore, by considering the regional factors, it is possible to reflect the disruption from all suppliers belonging to the region and the national investment for trade with a specific country as a regional fixed cost. Fan, Zhou, Yeung, Lo, and Tang (2022) analyzed the impact of the U.S.–China trade war considering geopolitical risk with supply diversification. In addition, Kamalahmadi, Shekarian, and Mellat Parast (2022) analyzed the impact on supply chain responsiveness considering the occurrence of a semi-super event that results in regional disruption. This paper presents optimization models considering regional and supplier disruptions, and a comparative analysis of dependency ratio by region and supplier is presented.

The remaining sections of the paper are structured as follows. Section 2 reviews the literature related to our research and emphasize the research gaps with significant contributions. Section 3 presents the problem statement for the risk-neutral problem and risk-averse problem considering multiple $CVaR$ measures. Section 4 covers the problem statement for the multi-objective model by combining the risk-neutral and risk-averse models. Section 5 provides numerical experiments for the single and multi-objective models. We analyze the performance of each model from various perspectives. We derive managerial insights and conclude the paper in Section 6.

2. Literature review

In this section, we conduct a thorough literature review to identify and emphasize the research gaps that this paper addresses.

2.1. Supplier selection and order allocation problems

Supplier selection and order allocation problems have been crucial in improving the supply chain from long ago until now (Aissaoui et al., 2007; Venkatesan & Goh, 2016). When multiple potential suppliers are competing, the presence of multiple supply alternatives and the option to merge sources enhances the negotiation power of the retailer (Minner, 2003). In particular, a systematic approach to procurement decision-making is crucial, when identifying suitable suppliers and the allocation of orders among them (Aissaoui et al., 2007). Meena and Sarmah (2016) studied supplier selection and demand allocation problems considering supplier disruptions. A stepwise solution procedure was proposed to solve the problem considering quantity discount. Mohammed, Harris, and Govindan (2019) proposed a sustainable supplier selection and order allocation problem by using a fuzzy multi-objective optimization approach. Moheb-Alizadeh and Handfield (2019) also addressed the sustainable supplier selection and order allocation problem through a multi-objective programming model. They developed a solution approach combining the ϵ-constraint method and the Benders decomposition algorithm. This paper proposes supplier selection and order allocation problems with multi-products and solves a multi-objective optimization problem considering the risk-neutral and risk-averse models. Therefore, this study has contributed to advancing the research on supplier selection and order allocation problems.

2.2. Supply chain disruption

Several previous studies considering disruption in the supply chain network exist. Qi, Bard, and Yu (2004) investigated supply chain coordination considering demand disruptions in a one-supplier–one-retailer supply chain. Sawik (2015) proposed a supplier selection model to optimize a customer service level and overall cost considering supply chain disruption risks. Yu, Zeng, and Zhao (2009) compared single and dual sourcing methods considering supply chain disruption risk and price-sensitive demand. Serrano, Oliva, and Kraiselburd (2018) studied how the payment variability of suppliers in the supply chain propagates upstream. Tang, Jin, and Lu (2022) proposed a berth allocation problem considering the disruptions in container ports and developed a heuristic algorithm to solve a large-scale problem. This paper proposes the concept of regional disruption separately from supplier disruption as the uncertainties. Regional disruption is defined as the disruption of entire suppliers within the same region. In a regional disruption situation, all suppliers belonging to the region cannot deliver products. Therefore, by separating regional and local disruptions, more diverse situations can be reflected when creating scenarios, and optimal strategies can be suggested accordingly.

2.3. Conditional value-at-risk

Few studies exist on minimizing *conditional value-at-risk* ($CVaR$) in theoretical and practical ways to deal with uncertain situations. We can make rational decisions by minimizing the $CVaR$ measure in situations that lead to catastrophic consequences due to disruption. This risk-averse measure was applied in various fields, such as in routing and inventory problems (Gao, Chen, & Chao, 2011; Zhong et al., 2020). Rockafellar, Uryasev, et al. (2000) introduced an auxiliary function to make $CVaR$ more tractable. Esmaeili-Najafabadi et al. (2021) proposed an outsourcing strategy considering the $CVaR$ measure in the dual-sourcing inventory model. For disaster management, Noyan (2012) determined the facility location and inventory level. In particular, the study proposed a two-stage stochastic model considering the value of perfect information and the value of the stochastic solution. Nazemi, Parragh, and Gutjahr (2021) proposed a two-stage bi-objective facility-location model under demand uncertainty. They applied a last-mile network in disaster relief considering the $CVaR$ measure. Zhu, Wen, Ji, and Qiu (2020) proposed a decision-making model considering the CVaR measure in the dual-channel supply chain. Mansini, Ogryczak, and Speranza (2007) first introduced weighted *conditional value-at-risk* ($WCVaR$) considering multiple $CVaR$ measures. Since then, the $WCVaR$ model has been widely applied in portfolio optimization (Filippi, Guastaroba, & Speranza, 2020; Guastaroba, Mansini, Ogryczak, & Speranza, 2020; Sehgal & Mehra, 2019). Nevertheless, this approach has not yet been applied in supply chain research.

Table 1
Recent models for supplier selection and order allocation problems with disruption risk.

Source	Multi objective	Multi product	Risk measure	Types of distribution	Solution methodology
Ruiz-Torres, Mahmoodi, and Zeng (2013)	–	–	–	Local	Decision tree
Sawik (2014)	–	✓	CVaR	Local, regional	Stochastic MIP
Torabi et al. (2015)	✓	✓	–	Local	Two-stage stochastic programming
Meena and Sarmah (2016)	–	–	–	Local, super	Stepwise solution procedure
Venkatesan and Goh (2016)	✓	–	–	Local, regional	Particle Swarm Optimization
Hosseini et al. (2019)	✓	–	VaR	Local	Augmented ϵ-constraint method
Esmaeili-Najafabadi et al. (2021)	–	✓	CVaR	Local, regional	Particle Swarm Optimization
Rezaei et al. (2021)	✓	–	–	Local, environmental	Grasshopper Optimization Algorithm
Kamalahmadi et al. (2022)	–	–	–	Local, regional	Two-stage stochastic programming
Our study	✓	✓	CVaR, WCVaR	Local, regional	Stochastic MILP

2.4. Multi-objective mathematics programming

The concept of the Tchebycheff norm was first proposed by Bowman (1976) to generate all non-dominated points of multi-objective mathematics programming (MOMP). Expanding on this concept, the augmented weighted Tchebycheff method was suggested by Steuer and Choo (1983). This idea is based on the weighted distance metric of a specific solution from the ideal solution. Recently, MOMP using a modified augmented weighted Tchebycheff norm was presented to generate entire non-dominated points without supervision (Holzmann & Smith, 2018). Sawik (2010, 2011) proposed bi-objective models based on an augmented weighted Tchebycheff (MAWT) metric to control disruption risks for the supply portfolio. Therefore, the weighted Tchebycheff scalarization model is commonly applied in various ways to solve MOMP. Additionally, it has been used in many recent studies to solve multi-objective models efficiently (Domínguez-Ríos, Chicano, & Alba, 2021; Holzmann & Smith, 2019; Tsionas, 2019; Varas, Basso, Maturana, Osorio, & Pezoa, 2020). Therefore, this paper presents a methodology to solve MOMP, deriving a solution through MAWT norm scalarization.

Table 1 shows recent models for supplier selection and order allocation problems with disruption risk. We identify and emphasize the research gaps based on the thorough literature review. This paper presents supplier selection and order allocation problems considering regional and supplier disruption risks for multi-products. In addition, most studies have addressed the supplier selection and order allocation problem with risk-neutral decision-making in the existing literature. However, this paper proposes a risk-averse model considering CVaR and WCVaR as risk measures. Finally, we proposed a multi-objective model combining risk-neutral and risk-averse models. Based on the thorough literature review in Table 1, we believe that our study on supplier selection and order allocation problems presented in this paper is the first.

This paper presents several significant contributions, which can be summarized as follows:

- We define supplier selection and order allocation problems while considering regional and supplier disruptions. In particular, by considering both regional and supplier disruptions simultaneously, it realistically reflects the potential uncertainties that may arise. We also propose a pricing policy considering reliability, because these uncertainties should not be overlooked.
- We present the risk-neutral model considering the total expected cost and the risk-averse model considering the $CVaR$ measure. By measuring the $CVaR$ using an equivalent equation, a scenario-based risk-averse model that considers disruption significantly is proposed. A weighted $CVaR$ model combining various $CVaR$ measures is also presented. In particular, the $WCVaR$ model is first applied to the supply chain domain and verified to derive a solution effectively.
- We develop multi-objective models, considering both risk-neutral and risk-averse models. These models that consider both disruption risks and expected costs allow the decision maker to check the extent of the increased cost to mitigate the risk.
- We provide the supplier dependency ratio, which refers to the proportion of total demand supplied by each supplier. The performance of several models is compared and analyzed through numerical experiments. As a result of the multi-objective model, we provide a Pareto frontier and derive managerial insights.

3. Risk-neutral and risk-averse models

This section defines supplier selection and order allocation problems for the risk-neutral and risk-averse models. In a supply chain network, the retailer purchases products from suppliers and sells them to customers. In this paper, we segregate suppliers according to regional characteristics. We separated them into total L regions and assumed that the number of suppliers in region k is M_k. Similarly, the same consideration also follows for models classified by price, reliability, preference, and other factors. Each supplier provides various products to the retailer, and the retailer finally sells the multi-products to customers. Disruption may occur unexpectedly in the supply chain. In this study, we define a disruption as an interruption of a supplier. In other words, the retailer will not be able to receive the ordered products from the disrupted supplier. In a regional disruption situation, all suppliers belonging to the same region cannot deliver products. As a result, regional disruption can have a significant impact on the retailer. Therefore, the retailer needs to make decisions considering these uncertain situations.

This novel supply chain structure can be presented as shown in Fig. 1. A risk-neutral model that considers the cost point of view would choose inexpensive suppliers in reasonable regions. However, a risk-averse model that significantly considers the impact of disruption risk would prefer a mixture of expensive but reliable suppliers.

We define the disruption probability of supplier i located in region k as β_{ik}. Regional disruption means that all suppliers located in the same region are disrupted. We define the regional disruption probability of region k as η_k. The reliability parameter can affect the production and material cost in a general production line (Cheng, 1989; Moon, Yun, & Sarkar, 2022; Sarkar, 2012). In addition, the reliability of suppliers can affect the value of the product to offset part of risk costs by providing a price discount (Ganeshan, Tyworth, & Guo, 1999). Similarly, by applying this concept to the supplier, we assume products are supplied without disruption and delivered on time when the supplier is reliable. We reflect the relationship through the disruption probability inversely proportional to the reliability. Therefore, if the disruption risk of the supplier is high, the retailer evaluates the value of the product as relatively low. When the original price of product j is c_j, the value of product j decreases as the disruption probabilities β_{ik} and η_k increase. The reliability parameter indicates the impact of disruption probability on product price. As a result, we propose a pricing policy considering regional and supplier disruptions based on the reliability parameter θ_j with the linear equation:

$$c_{ijk} = c_j - \theta_j \beta_{ik} - \theta_j \eta_k \tag{1}$$

We assume that there is a set of finite disruption scenarios $\omega \in \Omega = \{\omega_1, \omega_2, \dots, \omega_S\}$ and that the probability of each scenario ω is P_ω.

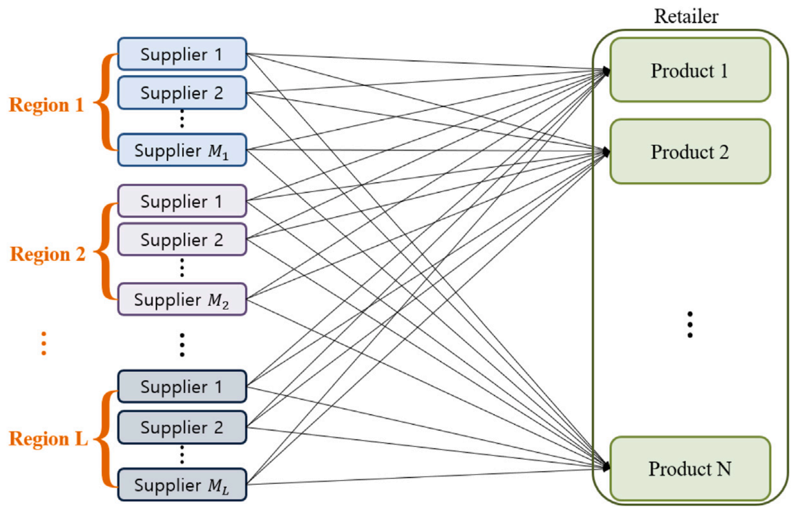


Fig. 1. Supply chain structure classified by regional characteristics.

Table 2
Indices and parameters.

i	Index of supplier's type $i \in I = \{1, 2, \dots, M_k\}$
j	Index of product's type $j \in J = \{1, 2, \dots, N\}$
k	Index of region's type $k \in K = \{1, 2, \dots, L\}$
ω	Index of disruption scenario $\omega \in \Omega = \{\omega_1, \omega_1, \dots, \omega_S\}$
c_j	Original price of product j
k_{ik}	Capacity of supplier i located in region k
t_{ik}	Transportation cost from supplier i located in region k
r_k	Regional fixed cost of region k
d_j	Market demand of product j
s_j	Unit shortage cost of product j
P_ω	Probability of disruption scenario ω
β_{ik}	Disruption probability of supplier i located in region k
η_k	Disruption probability of all suppliers located in region k
α	Tolerance level
θ_j	Reliability parameter of product j

For scenario generation, we consider supplier and regional disruptions and non-disruption situations, resulting in a total number of scenarios of $M_1 + M_2 + \cdots + M_k + k + 1$. We do not consider the scenarios of $2^{M_1+M_2+\cdots+M_K+k+1}$ to solve our problems in a reasonable time. Although it does not significantly affect the result value, the computational complexity increases exponentially in proportion to the number of suppliers. k_{ik} is the capacity of supplier i located in region k, and t_{ik} is the transportation cost from supplier i located in region k, respectively. r_k is defined as the regional fixed cost of region k. d_j and s_j are the market demand and unit shortage cost of product j, respectively. α is the tolerance level for the risk measure in the risk-averse model. Table 2 shows definitions of all indices and parameters.

Decision variables are summarized in Table 3. When a retailer handles various products, that retailer decides how many products to receive from supplier i located in region k. As a result, the dependency ratio of supplier i located in region k can be calculated and expressed as $x_{ik} = \sum_{j\in J} q_{ijk}/d_j$ as the result of each model. By summing up the ratios of individual suppliers, the dependency ratio of region k can be obtained and expressed as $X_k = \sum_{i\in I} x_{ik}$. y_{ik} and z_k are binary variables depending on whether supplier i or region k is selected. τ_s, *value-at-risk* (VaR), and *conditional value-at-risk* ($CVaR$) are decision variables in the risk-averse model, which will be described in detail in Section 2.2.

3.1. Risk-neutral model

In the risk-neutral model, we aim to minimize the expected total cost. We define $\overline{Q}$ as a three-dimensional vector in which the decision variable q_{ijk} is determined. $\omega \in \Omega$ is a random variable representing a

Table 3
Decision variables.

q_{ijk}	Ordering quantity of product j ordered from supplier i located in region k
x_{ik}	Dependency ratio of supplier i located in region k
X_k	Dependency ratio of region k
y_{ik}	1 if supplier i located in region k is selected; otherwise 0
z_k	1 if region k is selected; otherwise 0
τ_ω	Tail cost of scenario ω
VaR_α	*value-at-risk* measure with tolerance level α
$CVaR_\alpha$	*conditional value-at-risk* measure with tolerance level α

disruption scenario independent of $\overline{Q}$. The objective function $\mathbb{E}[f_\omega(\overline{Q})]$ consists of purchase costs, transportation costs from the suppliers, regional fixed costs, and shortage cost for each scenario with uncertainty. In particular, the shortage cost should be charged with a much higher cost for undelivered products caused by disruptions

$$\min\ \mathbb{E}[f_\omega(\overline{Q})] = \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}(c_j - \theta_j\beta_{ik} - \theta_j\eta_k)q_{ijk}/\sum_{j\in J} d_j + \sum_{i\in I}\sum_{k\in K} t_{ik}y_{ik}/\sum_{j\in J} d_j$$
$$+ \sum_{k\in K} r_k z_k/\sum_{j\in J} d_j + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{\omega\in\Omega} P_\omega\{s_j - (c_j - \theta_j\beta_{ik} - \theta_j\eta_k)\}q_{ijk}/\sum_{j\in J} d_j \quad (2)$$

$$\text{subject to} \sum_{i\in I}\sum_{k\in K} q_{ijk} = d_j \quad \forall j \in J \quad (3)$$

$$\sum_{j\in J} q_{ijk} \le k_{ik} y_{ik} \quad \forall i \in I,\ \forall k \in K \quad (4)$$

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

$$\sum_{i\in I}\sum_{j\in J} q_{ijk} \le \sum_{j\in J} d_j z_k \quad \forall k \in K \quad (6)$$

$$y_{ik} \in \{0, 1\} \quad \forall i \in I,\ \forall k \in K \quad (7)$$

$$z_k \in \{0, 1\} \quad \forall k \in K \quad (8)$$

$$q_{ijk} \in \mathbb{Z} \quad \forall i \in I,\ \forall j \in J,\ \forall k \in K \quad (9)$$

Constraint (3) indicates that the total order quantity for each product satisfies the given demand. Constraint (4) ensures that the order quantity does not exceed the capacity of each supplier. Constraint (5) restricts that the supplier in the region should be selected only when the region is available. Constraint (6) mandates that order allocation from suppliers in the region is possible when the region is available. Constraints (7)–(9) are binary and integer conditions for each decision variable.

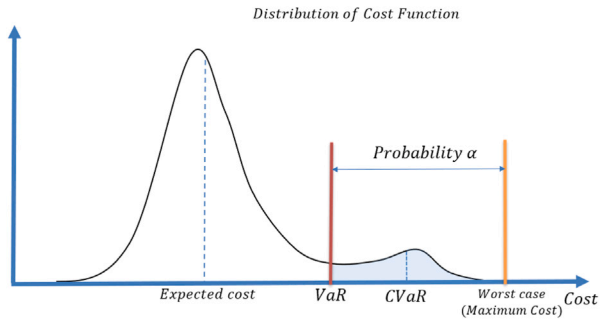


Fig. 2. An illustration of risk measures VaR and $CVaR$.

3.2. Risk-averse model

In the risk-averse model, we consider uncertainty about disruption. Especially in a situation of high variability, there is a high possibility that the risk-neutral model may find risky solutions. Recent research has concentrated on risk-averse optimization rather than on a risk-neutral model to rationally reflect the risk from the uncertainty (Zhou & Tokekar, 2018).

Risk-averse decisions are important when the disruption leads to serious consequences. For a given tolerance level $\alpha \in (0,1]$, *value-at-risk* (VaR) means the (right) α-percentile of the random variable $f_\omega(\overline{Q})$. VaR is known as a general risk measure in the financial industry (Brusset & Bertrand, 2018; Saidane, 2017; Sehgal, Sharma, & Mansini, 2023). We define VaR as follows, for a given tolerance level $\alpha \in (0,1]$:

$$VaR_\alpha(f_\omega(\overline{Q})) = \min\{\tau : \text{Prob}[\tau \le f_\omega(\overline{Q})] \ge \alpha, \tau \in \mathbb{R}\} \tag{10}$$

On the other hand, *conditional value-at-risk* ($CVaR$) is the expectation of $f_\omega(\overline{Q})$ from α-percentile cases. Due to its computational tractability, $CVaR$ is a more widely used measure than VaR (Artzner, Delbaen, Eber, & Heath, 1999; Gao, Simchi-Levi, Teo, & Yan, 2019). This property makes $CVaR$ more appropriate in both theoretical and practical models (Maehara, 2015). Therefore, we use $CVaR$ as a risk measure, and the definition of $CVaR$ is as follows, for a given tolerance level $\alpha \in (0,1]$:

$$CVaR_\alpha(f_\omega(\overline{Q})) = \mathbb{E}[f_\omega(\overline{Q}) | f_\omega(\overline{Q}) \ge VaR_\alpha(f_\omega(\overline{Q}))] \tag{11}$$

Fig. 2 shows an illustration of risk measures for the concept of VaR and $CVaR$.

The equivalent equation is introduced to make the optimization problem more tractable:

$$CVaR_\alpha(f_\omega(\overline{Q})) = \tau + \frac{1}{\alpha}\mathbb{E}\big([f_\omega(\overline{Q}) - \tau]_+\big) \tag{12}$$

where $[f_\omega(\overline{Q}) - \tau]_+$ is defined as $\max(f_\omega(\overline{Q}) - \tau, 0)$ (Rockafellar et al., 2000). It is known that minimizing (11) and (12) are equivalent.

We present the scenario-based optimization model through constraints for the calculation of expectations. The risk-averse model is effective in reducing the risk of the worst case by minimizing the $CVaR$ measure. It means that the risk-neutral model focuses on minimizing the expected cost of the retailer, whereas the risk-averse model aims to improve performance in the worst-case scenario. Therefore, the risk-averse model that minimizes $CVaR$ at a given tolerance level $\alpha \in (0,1]$ is as follows ($CVaR$ model):

$$\min\ CVaR_\alpha(f_\omega(\overline{Q})) = \tau + \frac{1}{\alpha}\sum_{\omega\in\Omega} P_\omega \tau_\omega \tag{13}$$

subject to (3)–(9)

$$\tau_\omega \ge f_\omega(\overline{Q}) - \tau \quad \forall \omega \in \Omega \tag{14}$$

$$\tau_\omega \ge 0 \quad \forall \omega \in \Omega \tag{15}$$

Constraints (3)–(9) are the same conditions in the risk-neutral model. τ_ω is the tail cost for scenario ω, and τ is the tail cost corresponding to VaR when the tolerance level is α. Constraint (14) searches for a case where $f_\omega(\overline{Q})$ exceeds τ in the scenario ω. Constraint (15) is a non-negative condition for each scenario.

Mansini et al. (2007) provided that a more detailed risk-averse model can be achieved by considering multiple $CVaR$ measures simultaneously. Each given tolerance level is combined into a single risk measure as a weighted sum. In more detail, they give a grid of m tolerance levels $0 = \alpha_0 < \alpha_1 < \cdots < \alpha_r < \cdots < \alpha_m$ and combine the $CVaR$ measures to create the weighted *conditional value-at-risk* ($WCVaR$) measure. The definition of the $WCVaR$ model for a given set of finite tolerance level $\alpha = \{\alpha_1, \alpha_2, \ldots, \alpha_m\}$ is as follows ($WCVaR$ model):

$$WCVaR_{\{\alpha_1,\alpha_2,\ldots,\alpha_m\}}(f_\omega(\overline{Q})) = \sum_{r=1}^{m} w_r CVaR_{\alpha_r}(f_\omega(\overline{Q})) \tag{16}$$

where $w_r = \frac{\alpha_r(\alpha_{r+1}-\alpha_{r-1})}{\alpha^2}$ for $r = 1,2,\ldots,m-1$, and $w_m = \frac{\alpha_m(\alpha_m-\alpha_{m-1})}{\alpha^2}$ (Guastaroba et al., 2020; Mansini et al., 2007). This formulation enables us to optimize the entire $CVaR$ measures considering several tolerance levels with determined weights.

4. Multi-objective model

4.1. Bi-objective mathematical programming

The bi-objective model simultaneously optimizes the risk-neutral and risk-averse models discussed in Section 2. The goal is to minimize the expected total cost in the risk-neutral model while minimizing the *conditional value-at-risk* ($CVaR$) measure in the risk-averse model. When we connect the non-dominated solutions, we can get a Pareto frontier. This reveals the trade-off relationship between cost and risk, and provides a decision-making criterion depending on where the weights are placed. The convex combination of the risk-neutral and risk-averse models with weight λ is expressed as follows ($ECVaR$ model):

$$\min\ ECVaR_\alpha(f_\omega(\overline{Q})) = \lambda\mathbb{E}[f_\omega(\overline{Q})] + (1-\lambda)CVaR_\alpha(f_\omega(\overline{Q})) \tag{17}$$

subject to (3)–(9), (14), (15)

We also optimize the bi-objective model through modified augmented weighted Tchebycheff (MAWT) norm scalarization. This is for finding the optimal solution by scalarizing the point that minimizes the MAWT distance from the ideal solutions, which are the lower bounds for each model represented as $\underline{\mathbb{E}}$ and $\underline{\mathbb{C}}$. These values are set as the lower bound in the bi-objective model because it is impossible to achieve results smaller than them in both the risk-neutral and risk-averse models. The definition for the MAWT norm was proposed as follows:

$$\|\mathbf{z}\|^{\mathbf{w},\epsilon} = \|\mathbf{z}\|^{\mathbf{w}}_\infty + \epsilon\|\mathbf{z}\|^{\mathbf{w}}_1 = \max_{k\in P}\{w_k|z_k|\} + \epsilon\sum_{k\in P} w_k|z_k| \tag{18}$$

where $\mathbf{w} \ge 0$ and $\epsilon \ge 0$ (Holzmann & Smith, 2018). $\mathbf{z}$ is set as a p-dimensional vector and means the difference between the objective function of risk-neutral and risk-averse models and the lower bound corresponding to the ideal solution. $\mathbf{w}$ is also set as a p-dimensional vector and means weights for multi-objective functions. We formulate the maximization term as a constraint through γ as follows ($MAWT$ model):

$$\min\ \gamma + \epsilon(\lambda\mathbb{E}[f_\omega(\overline{Q})] + (1-\lambda)CVaR_\alpha(f_\omega(\overline{Q}))) \tag{19}$$

subject to (3)–(9), (14), (15)

$$\lambda(\mathbb{E}[f_\omega(\overline{Q})] - \underline{\mathbb{E}}) \le \gamma \tag{20}$$

$$(1-\lambda)(CVaR_\alpha(f_\omega(\overline{Q})) - \underline{\mathbb{C}}) \le \gamma \tag{21}$$

$$\gamma \ge 0 \tag{22}$$

The objective function is equivalent to the MAWT norm for minimization. We set ϵ of the objective function to a tiny value of 0.01 and λ for the weight value. Constraints (20) and (21) are for figuring out γ, which is the maximum value in the MAWT norm. $\underline{\mathbb{E}}$ and $\underline{\mathbb{C}}$ are ideal solutions corresponding to the lower bounds. Constraint (22) is a non-negative condition for γ.

4.2. Multi-objective mathematical programming

We extend to this multi-objective mathematical programming (MOMP) that optimizes the expected cost and individual $CVaR$ measures to more than only one $CVaR$ measure. We conjugate the risk-averse model to optimize the weighted *conditional value-at-risk* ($WCVaR$) by combining various $CVaR$ measures. Therefore, we combine the risk-neutral model with the $WCVaR$ model, and it can be expressed as follows ($EWCVaR$ model):

$$\min \ EWCVaR_{\{\alpha_1,\ldots,\alpha_m\}}(f_\omega(\overline{Q}))$$

$$= \lambda\mathbb{E}[f_\omega(\overline{Q})] + (1-\lambda)\sum_{r=1}^{m} w_r CVaR_{\alpha_r}(f_\omega(\overline{Q})) \tag{23}$$

subject to (3)–(9), (14), (15)

$$\sum_{r=1}^{m} w_r = 1 \tag{24}$$

$$w_r \geq 0 \quad for\ r = 1, 2, \ldots, m \tag{25}$$

Weight λ is set to a value between 0 and 1, and analysis is performed according to the λ through experiments. Constraints (24) and (25) are for weight values determined by Eq. (16).

We also expand the $MAWT$ model from a bi-objective function to a multi-objective function. Various tolerance levels are taken into account when considering $CVaR$ measures. Therefore, we present the extended form of the $MAWT$ model and express it as follows ($MAWT-M$ model):

$$\min \ \gamma + \epsilon(\lambda\mathbb{E}[f_\omega(\overline{Q})] + (1-\lambda)\sum_{r=1}^{m} w_r CVaR_{\alpha_r}(f_\omega(\overline{Q}))) \tag{26}$$

subject to (3)–(9), (14), (15), (24), (25)

$$\lambda(\mathbb{E}[f_\omega(\overline{Q})] - \underline{\mathbb{E}}) \leq \gamma \tag{27}$$

$$(1-\lambda)(w_r CVaR_{\alpha_r}(f_\omega(\overline{Q})) - \underline{\mathbb{C}_r}) \leq \gamma \quad \forall r = 1, 2, \ldots, m \tag{28}$$

$$\gamma \geq 0 \tag{29}$$

As more tolerance levels are considered in the $WCVaR$ model, the number of constraints increases by that amount.

5. Computational experiments

5.1. Experiment results for the single-objective model

In this subsection, we conduct computational experiments to show the performance of the single-objective model. We modified the experimental parameters setup from a case study conducted by Kamalahmadi et al. (2022). Their data set was based on the observations of an appliance manufacturer. We assume that there are a total of 60 suppliers located in 6 regions, each supplying 20 kinds of products. Regions are sorted in order by parameters. As a result, suppliers belonging to a low-numbered region have a high disruption probability and a high transportation cost but have increased capacity and low regional fixed cost. This reflects economies of scale and the characteristics of each supplier level practically. Because regional disruption is a severe event, the occurrence probability is set very low. Additionally, we set the probability of a non-disruption situation to be very high, reflecting realistic situations. Tables 4 and 5 show the parameter set considering each

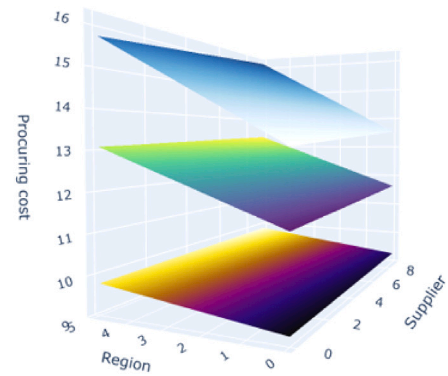


Fig. 3. Procuring costs with the pricing policy applied.

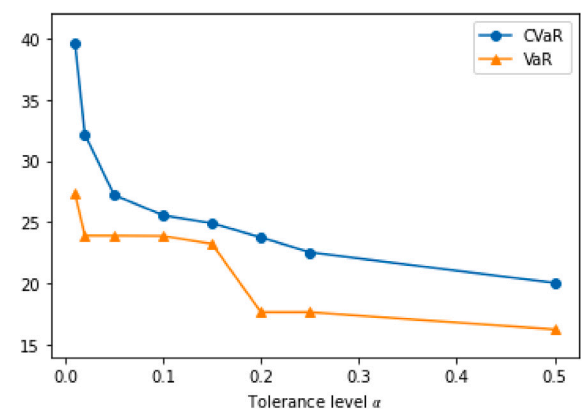


Fig. 4. Measures of the VaR and $CVaR$ for each tolerance level α.

region's and supplier's characteristics and the parameter set considering each product's characteristics, respectively.

The procuring cost for each region and each supplier varies according to the aforementioned pricing policy. Fig. 3 shows the procuring costs of 3 out of 20 products with the pricing policy applied to a particular product purchased from supplier i located in the region k. Even for the same product, we suggest that the lower the disruption probability, the greater the value of the product. All tests were run on a Python 3, including CPLEX ver.21.1.2 with 3.70 GHz AMD Ryzen 7 2700X and 16 GB RAM. The computation time for each model was less than 10 s, and the differences in computation time were deemed insignificant. Therefore, the analysis procedure for the computation time was not performed.

First, we aimed to find an appropriate range of the reliability parameter θ_j in computational experiments. We conducted experiments through each parameter setting mentioned in Tables 4 and 5. Therefore, we performed a sensitivity analysis for five cases (in order, $Uniform(12.5, 112.5)$, $Uniform(25, 225)$, $Uniform(50, 450)$, $Uniform(100, 900)$, and $Uniform(200, 1800)$) through a risk-neutral model. As the reliability parameter θ_j increased, the pricing policy imposed a higher penalty on the original price. Therefore, the number of suppliers and regions selected also tended to decrease. We experimented with five cases of the reliability parameter set. In Case 4 ($Uniform(100, 900)$), 2 out of 6 regions and 13 out of 60 suppliers are selected, and the expected total cost is 17.64. The selected suppliers are located in regions 1 and 2. The characteristics of the selected suppliers are cost-efficient and have sufficient capacity, as can be seen in Table 4. This reliability parameter can be an effective indicator that can compare the results of the risk-averse and the risk-neutral models. Therefore, we concluded that Case 4 ($Uniform(100, 900)$) is a representative reliability

Table 4
Regions' and suppliers' characteristics.

Parameters	Region1	Region2	Region3	Region4	Region5	Region6
η_k	0.0007	0.0006	0.00005	0.0004	0.0003	0.0002
β_{ik}	$Uniform(0.006, 0.004)$	$Uniform(0.005, 0.006)$	$Uniform(0.004, 0.005)$	$Uniform(0.003, 0.004)$	$Uniform(0.002, 0.003)$	$Uniform(0.001, 0.002)$
k_{ik}	$Uniform(6000, 7000)$	$Uniform(5000, 6000)$	$Uniform(4000, 5000)$	$Uniform(3000, 4000)$	$Uniform(2000, 3000)$	$Uniform(1000, 2000)$
r_k	5000	8000	11 000	14 000	17 000	20 000
t_{ik}	$Uniform(600, 700)$	$Uniform(500, 600)$	$Uniform(400, 500)$	$Uniform(300, 400)$	$Uniform(200, 300)$	$Uniform(100, 200)$

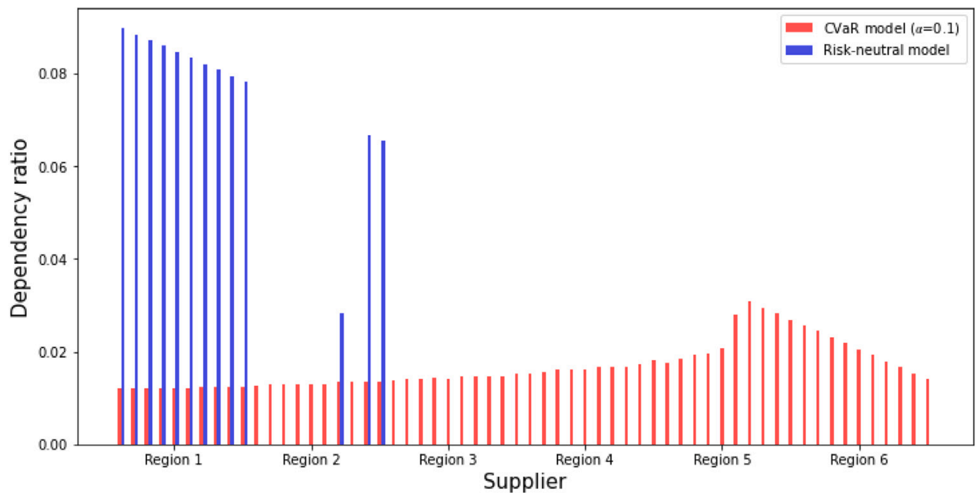


Fig. 5. The dependency ratios for each supplier.

Table 5
Products' characteristics.

Parameters	Product
c_j	$Uniform(10, 25)$
d_j	$Uniform(2000, 6000)$
s_j	$Uniform(200, 600)$

Table 6
Results of the $CVaR$ model according to the reliability parameter set.

θ_j	Case 1	Case 2	Case 3	Case 4	Case 5
Expected cost	20.25	20.03	19.43	17.64	13.67
No. of suppliers	31	24	20	13	13
No. of regions	4	3	2	2	2

Table 7
Results for the $CVaR$ model according to tolerance level α.

Tolerance level	0.5	0.25	0.2	0.15	0.1	0.05	0.02	0.01
VaR measure	16.26	17.66	17.66	23.22	23.88	23.90	23.91	27.33
$CVaR$ measure	20.05	22.54	23.76	24.92	25.55	27.21	32.17	39.60
Expected cost	18.15	18.88	18.88	19.06	18.94	18.93	18.93	19.00
No. of suppliers	20	31	31	60	60	60	60	42
No. of regions	2	4	4	6	6	6	6	6

parameter set, and we used it in subsequent experiments. Table 6 shows the results of five cases according to the reliability parameter set.

In the risk-averse model, we conducted experiments based on each of the eight tolerance levels. As the tolerance level α became smaller, there were cases ($\alpha = 0.15, 0.1, 0.05, 0.02$) in which all suppliers were selected to hedge the disruption risk. When the tolerance level α was extremely small ($\alpha = 0.01$), suppliers with high reliability in all regions were selected regardless of cost. This indicated that diversification strategies were no longer needed in extreme situations. Table 7 summarizes the results for the $CVaR$ model according to tolerance level α.

Fig. 4 shows the measures of the VaR and $CVaR$ according to tolerance level α in the $CVaR$ model. As the tolerance level α decreases, the focus shifts toward the smaller tail of the cost distribution. We confirmed that the measures of the VaR and $CVaR$ increased significantly as the tolerance level α decreased. This means that the cost incurred in the worst case can be more than doubled compared to the expected cost when the tolerance level α is small. In other words, the CVaR measure can be significantly higher than the expected cost, and the cost difference can be more than doubled in the worst case.

Fig. 5 shows the results of the supplier dependency ratios in the $CVaR$ model ($\alpha = 0.1$) and the risk-neutral model. The risk-neutral model selects all suppliers located in region 1 and three suppliers located in region 2, and the expected cost is 17.64. Conversely, the $CVaR$ model is diversely supplied by all suppliers, and the expected cost is high, at 18.94.

When the tolerance level becomes extremely small ($\alpha = 0.01$), only suppliers with high reliability are selected, and the expected cost is very high, at 19.00. Fig. 6 shows that the $CVaR$ model ($\alpha = 0.01$) tends to make quite a different decision compared to the risk-neutral model. In detail, the risk-neutral model focuses on minimizing the expected cost by selecting suppliers only from regions 1 and 2. On the contrary, the $CVaR$ model focuses on reducing the risk in the worst case by contracting with all regions and selecting a larger number of suppliers.

Next, we considered three different sets of tolerance levels for the $WCVaR$ model. Table 8 shows the sets of tolerance levels and determined weights from Eq. (16). For Case 1, we focused on the tail cost and emphasized the worst-case situation. For Case 2, tolerance levels mainly applied for statistical analysis were combined. Case 3 is a combination uniformly separated from the overall distribution.

Looking at Case 1, the $WCVaR$ measure is 25.17, and all regions and suppliers are selected. This is because Case 1 focuses on the tail cost, and this combination produces results similar to the $CVaR$ model of tolerance levels, with 0.1 and 0.15. In Case 2, comparable results were obtained when the tolerance level α was between 0.2 and 0.25, and the expected total cost was 18.88. Case 3, in which the tolerance levels are evenly distributed, shows similar results when the tolerance

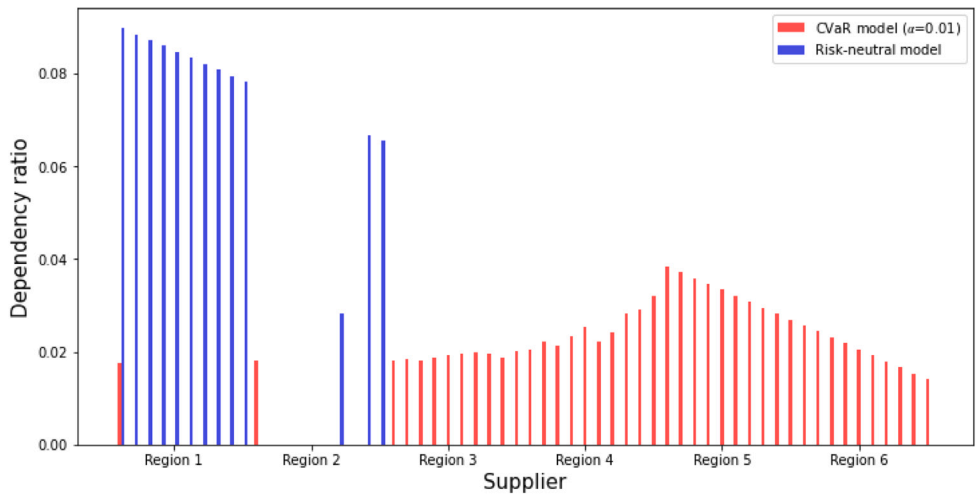


Fig. 6. The dependency ratios for each supplier.

Table 8
Sets of tolerance levels and determined weights for the $WCVaR$ model.

Set	Tolerance levels	Determined weights
Case 1	$\alpha_1 = 0.01, \alpha_2 = 0.1, \alpha_3 = 0.25$	$w_1 = 0.016, w_2 = 0.384, w_3 = 0.6$
Case 2	$\alpha_1 = 0.01, \alpha_2 = 0.1, \alpha_3 = 0.25, \alpha_4 = 0.5$	$w_1 = 0.004, w_2 = 0.096, w_3 = 0.4, w_4 = 0.5$
Case 3	$\alpha_1 = 0.2, \alpha_2 = 0.4, \alpha_3 = 0.6, \alpha_4 = 0.8, \alpha_5 = 1$	$w_1 = 0.08, w_2 = 0.16, w_3 = 0.24, w_4 = 0.32, w_5 = 0.2$

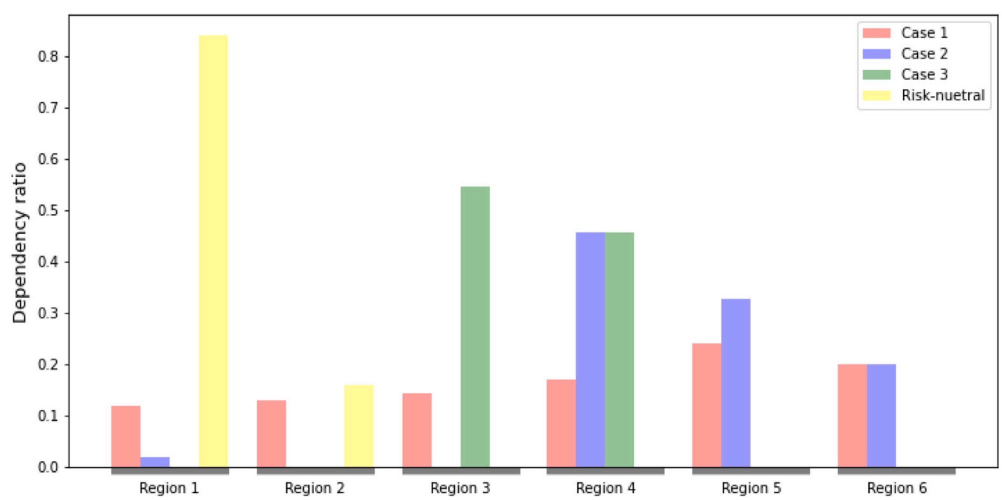


Fig. 7. Dependency ratios for each region.

Table 9
Results of the $WCVaR$ model according to the cases.

Model	Case 1	Case 2	Case 3	Risk-neutral
$WCVaR$ measure	25.17	22.49	19.66	–
Expected cost	18.99	18.88	18.12	17.64
VaR measure	23.66	17.66	16.20	–
No. of suppliers	60	31	20	13
No. of regions	6	4	2	2

level α is 0.5. Table 9 summarizes the results of the $WCVaR$ model according to the three cases compared with the risk-neutral model.

Fig. 7 shows the results of the dependency ratios for each region according to the three cases and the risk-neutral model. The risk-neutral model selects only regions 1 and 2, with dependency ratios of 0.84 and 0.16, respectively. However, the $WCVaR$ model takes different strategies for each case. Case 1 decentralizes the risk by choosing all regions and suppliers. Contrarily, Case 2 mainly selects regions 1, 4, 5, and 6, which have relatively high reliability with dependency ratios of 0.46, 0.33, and 0.20. Note that Case 3 takes a strategy that considers cost and risk simultaneously by selecting all suppliers in regions 3 and 4 with 0.54 and 0.46, respectively.

5.2. Experiment results for the multi-objective model

This subsection shows the experiment results on the multi-objective mathematical programming (MOMP) constructs, such as the $ECVaR$ model, the $MAWT$ model, the $EWCVaR$ model, and the $MAWT-M$ model discussed in Section 3. The goal is to make rational decisions by considering both risk-neutral and risk-averse models at the same time. In particular, we derived a Pareto frontier that combined non-dominated solutions from each model.

Table 10
Results of the $ECVaR$ model according to the λ values.

λ	0.01	0.1	0.25	0.5	0.75	0.9	0.99
Expected cost	18.94	18.94	18.93	18.93	18.58	18.28	17.64
$CVaR$ measure	25.55	25.55	25.56	25.55	26.53	28.23	43.91
VaR measure	23.88	23.89	23.90	23.90	24.69	26.21	14.72
Objective function	25.49	24.89	23.90	22.24	20.57	19.27	17.90
No. of suppliers	60	60	60	60	50	40	13
No. of regions	6	6	6	6	5	4	2

Table 11
Results of the $MAWT$ model according to the λ values.

λ	0.01	0.1	0.25	0.5	0.75	0.9	0.99
Expected cost	18.93	18.92	18.88	18.58	18.50	18.20	17.76
$CVaR$ measure	25.56	25.69	25.97	26.53	28.14	30.59	38.01
VaR measure	23.90	24.02	24.26	24.69	26.20	28.49	35.17
Objective function	0.27	0.38	0.55	0.71	0.86	0.70	0.30
No. of suppliers	60	60	59	50	43	33	20
No. of regions	6	6	6	5	5	4	2

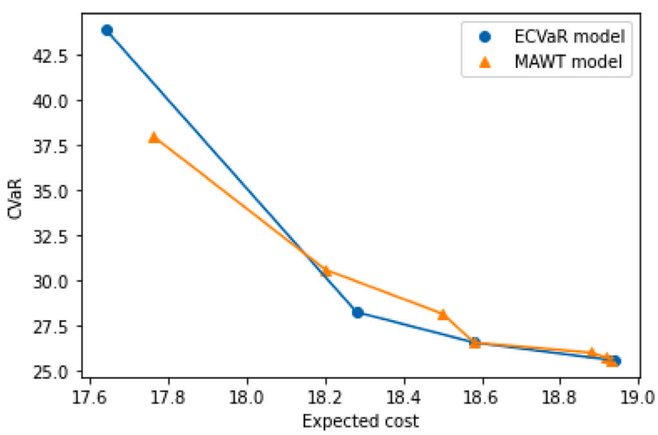


Fig. 8. Linear Pareto frontier of each model.

First, we experimented with the $ECVaR$ model that combines the risk-neutral model and the $CVaR$ model. We proceeded with the analysis according to the λ values. As the λ value increased, the $ECVaR$ model selected a relatively small number of suppliers because the expected cost was heavily weighted. When the λ value was very small ($\lambda = 0.01$), we got the same result as in the $CVaR$ model. Contrarily, when the λ value was very large ($\lambda = 0.99$), we got the same result as in the risk-neutral model. Table 10 summarizes the results of the $ECVaR$ model for each λ.

Next, we experimented on the $MAWT$ model according to the λ values. For the ideal solution, the results of the risk-neutral and the $CVaR$ model were set to $\underline{\mathbb{E}}$ and $\underline{\mathbb{C}}$ as lower bounds, respectively. We confirmed a similar trend to the $ECVaR$ model according to the λ values. In other words, as the value of the λ increased, the distance of the expected cost was weighted, and a relatively small number of suppliers were selected. Table 11 summarizes the results of the $MAWT$ model for each λ.

Fig. 8 shows the linear Pareto frontier obtained by the $ECVaR$ and $MAWT$ models. The three solutions of the $MAWT$ model are clustered at the extreme point, whereas the four solutions of the $ECVaR$ model are concentrated at the same extreme point. In terms of solution diversity, $MAWT$ performs better. However, the $ECVaR$ model tends to find solutions that exist in more extreme points. The solutions can provide a decision criterion for the importance between the expected cost and the $CVaR$ measure. That is, the high cost in the worst case can be offset by slightly increasing the expected cost.

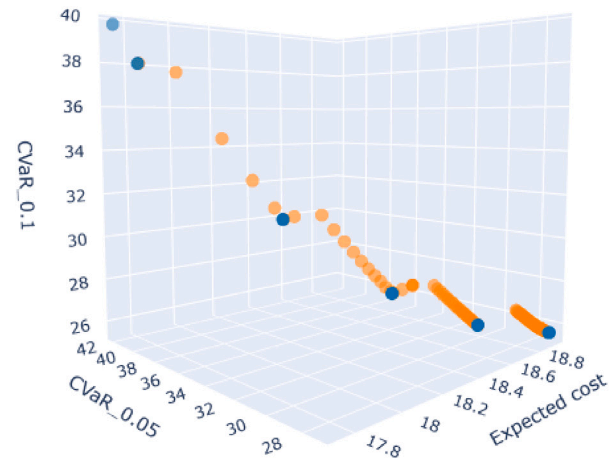
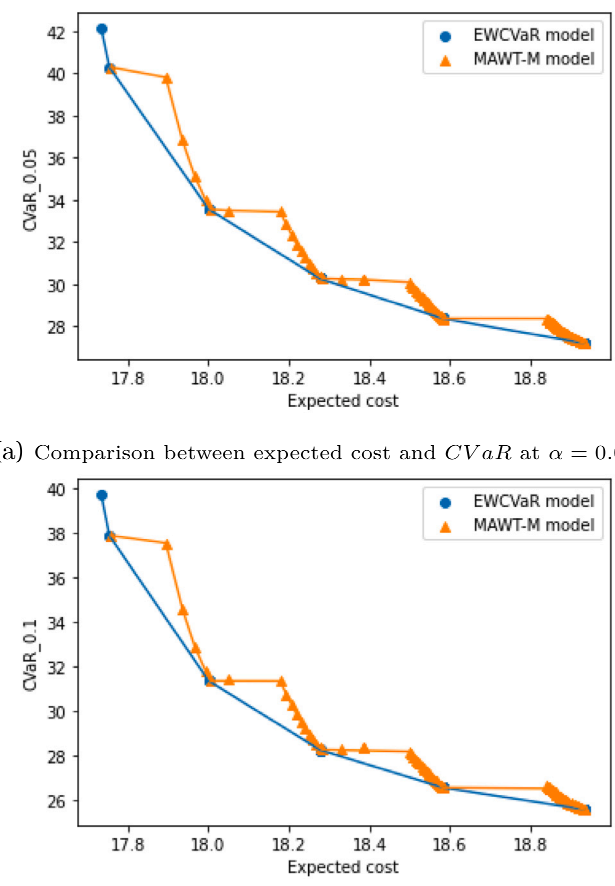


Fig. 9. 3D results of the $EWCVaR$ and $MAWT-M$ models.



(a) Comparison between expected cost and $CVaR$ at $\alpha = 0.05$

(b) Comparison between expected cost and $CVaR$ at $\alpha = 0.1$

Fig. 10. Results of the $EWCVaR$ and $MAWT-M$ models.

Next, we extended an experiment on the $EWCVaR$ and $MAWT-M$ models considering the two $CVaR$ measures and the expected cost when the tolerance levels were 0.05 and 0.1. We established the parameter set of the λ between 0 and 1 uniformly divided by 100 grid points. For the ideal solution, the results of the risk-neutral and the $CVaR$ models were set to $\underline{\mathbb{E}}$, $\underline{\mathbb{C}_1}$, and $\underline{\mathbb{C}_2}$ as lower bounds, respectively.

Fig. 9 shows the scatter plot for the 3D results of the $EWCVaR$ and $MAWT-M$ models. The solutions of each model are dispersed as 100 points. The blue dots are the results of the $EWCVaR$ model, and the

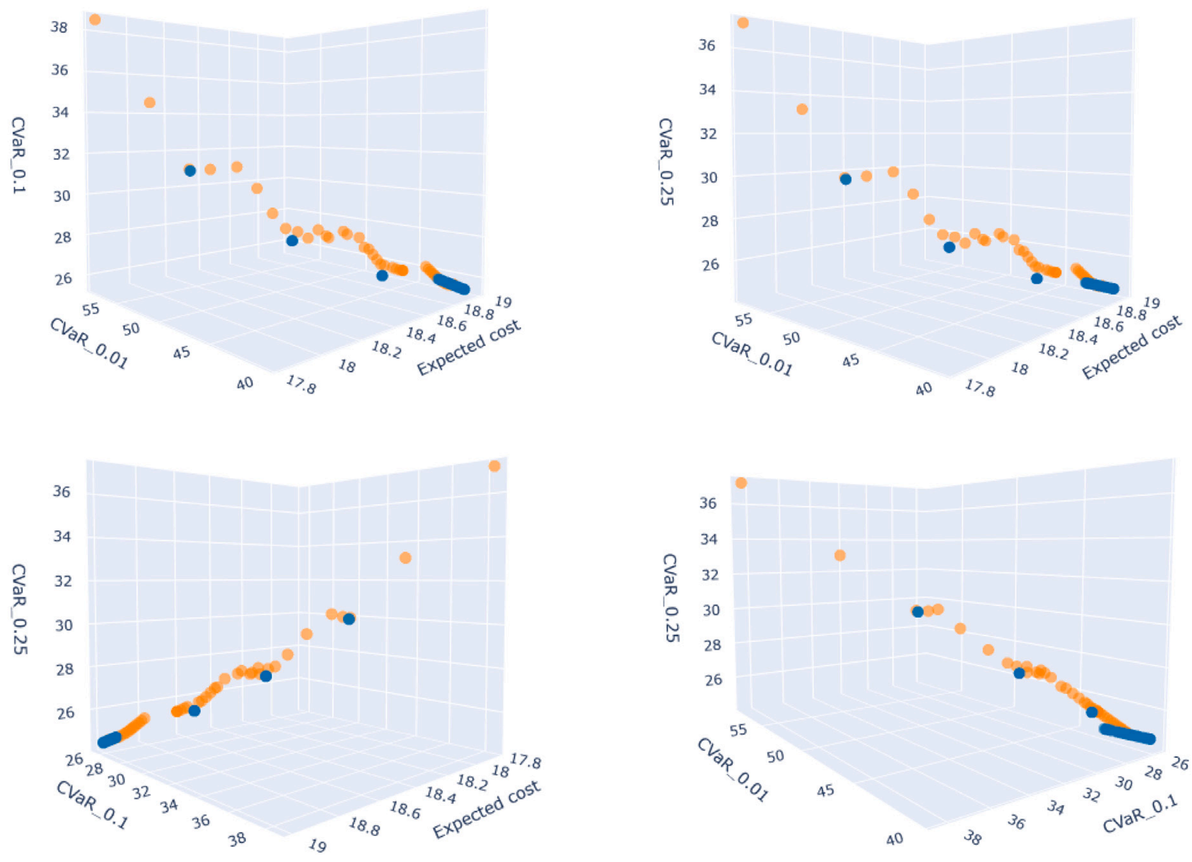


Fig. 11. 3D results of the $EWCVaR$ and $MAWT-M$ models.

red dots are the results of the $MAWT-M$ model. As the expected cost decreased, the two $CVaR$ measures tended to increase significantly in both models. In the $EWCVaR$ model, the solutions are clustered at five points. Conversely, in the $MAWT-M$ model, the solutions are distributed over various points. In other words, the $MAWT-M$ model hedges disruption risks through multiple strategies.

To show the Pareto frontier composing a set of non-dominated points, we divided the 3D plot into two 2D plots with the x-axis and y-axis in Fig. 10. In Fig. 10(a) and (b), the x-axis represents the expected cost and the y-axis represents the CVaR measures at $\alpha = 0.05$ and $\alpha = 0.1$, respectively. We connected non-dominated points to compose the Pareto frontier. First, Fig. 10(a) shows that each model selects two regions near the point where the expected cost is 17.8 and the $CVaR$ measure is 40. Subsequently, three regions are selected near (18.0, 34), four regions are selected near (18.3, 30), five regions are selected near (18.6, 28), and all regions are selected near (18.9, 27). Next, Fig. 10(b) shows that each model selects two regions near the point where the expected cost is 17.8 and the $CVaR$ measure is 38. Subsequently, three regions are selected near (18.0, 31), four regions are selected near (18.3, 28), five regions are selected near (18.6, 27), and all regions are selected near (18.9, 26). Points with a large change are determined by whether a region is selected or not. The $EWCVaR$ model tends to select all suppliers in the selected region. Therefore, the solutions are not diversified and are approached only from the perspective of high cost. Contrarily, the $MAWT-M$ model selects several suppliers through various strategies while selecting regions, and the solutions are distributed throughout. Therefore, the $MAWT-M$ model derives more sophisticated solutions when estimating the Pareto frontier.

We also experimented with three tolerance levels corresponding to Case 1 in the $WCVaR$ model ($\alpha_1 = 0.01$, $\alpha_2 = 0.1$, $\alpha_3 = 0.25$). We compared the various $CVaR$ measures with the expected cost to clarify the characteristics of the $EWCVaR$ and $MAWT-M$ models.

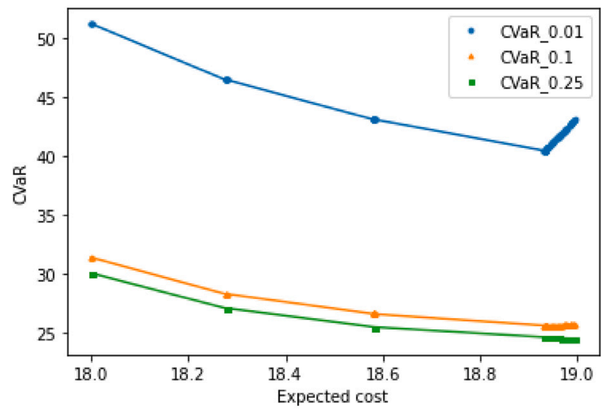
Fig. 11 shows the three $CVaR$ measures and the expected cost, which are the results of each model, through each subplot. The blue dots are the results of the $EWCVaR$ model, and the red dots are the results of the $MAWT-M$ model. The $EWCVaR$ model selects six strategies according to the λ values, while the $MAWT-M$ model selects twenty strategies. Therefore, the distributions of solutions are different for each model. We can lower the $CVaR$ measure significantly by taking some expected costs into account. In particular, the effect becomes more pronounced as the tolerance level decreases. The last subplot can identify the range of $CVaR$ measures for each tolerance level.

Fig. 12 shows the results of the $EWCVaR$ and $MAWT-M$ models according to the three tolerance levels ($\alpha_1 = 0.01$, $\alpha_2 = 0.1$, *and* $\alpha_3 = 0.25$). This allows us to compare how the three $CVaR$ measures are distributed for each model. In the $EWCVaR$ model, 3, 4, 5, and 6 regions are selected near the points where the expected costs are 18.0, 18.3, 18.6, and 19, respectively. In addition, when the region is selected, all suppliers within that region are selected. In the $MAWT-M$ model, various combinations of supplier selection within the region are considered while selecting the region. In other words, the EWCVaR model obtained many of the same overlapping results, while the MAWT-M model found various solutions. Therefore, the $MAWT-M$ model presents a Pareto frontier by elaborately establishing various strategies.

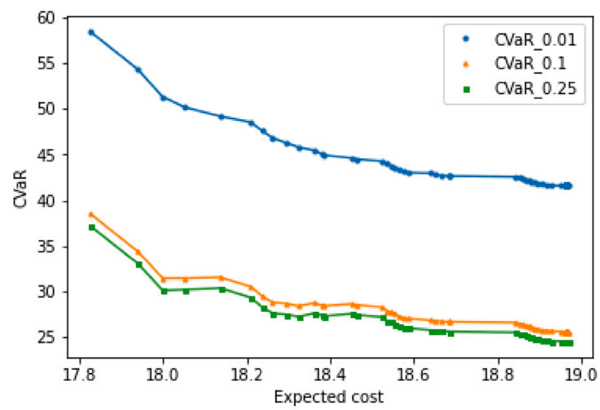
6. Conclusions

6.1. Managerial insights

This paper presents optimal supplier selection and order allocation problems that can help companies and countries make decisions. Our models aim to explore various strategies for risk-neutral and risk-averse



(a) Results of the $EWCVaR$ model according to the three tolerance levels



(b) Results of the $MAWT-M$ model according to the three tolerance levels

Fig. 12. Results of the $EWCVaR$ and $MAWT-M$ models according to the three tolerance levels.

models. By comparing the experimental results of the risk-neutral and risk-averse models, we provide the cost difference between expected cost and CVaR measure in the worst case. In particular, we observed that the risk-averse model chooses a strategy of contracting with suppliers from most regions and selecting a larger number of suppliers. This can be generally interpreted as mitigating disruption risk by investing money to secure various supply routes. Furthermore, by presenting supplier dependency ratios, we visually demonstrated how the order allocation is configured for each supplier. Therefore, this study can benefit decision-makers by providing valuable insights into effective supply chain risk management.

From the risk-neutral model with a reliability parameter, we found that appropriate strategies can cope well in disruption situations. We also conducted experiments on a risk-averse model based on eight tolerance levels. We found that the expected total cost increased monotonically as the tolerance level decreased while the $CVaR$ and VaR measures increased exponentially. Findings suggest that it is possible to offset more than twice the costs associated with a disruption situation by accepting higher expected total costs.

We present the results of experiments on MOMP. We aim to make rational decisions by simultaneously considering risk-neutral and risk-averse models. The $EWCVaR$ and $MAWT-M$ models were compared, and the $MAWT-M$ model is more efficient and helps find more sophisticated solutions when estimating the Pareto frontier. The results show a Pareto frontier derived from non-dominated solutions. The solutions provide decision makers with a range of options, to choose the best solution based on their priorities. In particular, from the perspective of a retailer handling multiple products, it supports reasonable decision-making by considering uncertainty in the supply chain. Through this, the risk cost according to the disruption scenario can be confirmed, and an appropriate supply portfolio can be formed.

6.2. Conclusion and future studies

The ultimate objective of this study was to present criteria for rational decision-making by simultaneously considering disruption risks and expected costs. For this, we covered supplier selection and order allocation problems considering regional and supplier disruption risks. We presented the risk-neutral and risk-averse models with the $CVaR$ measure. The risk-averse model that considers disruption significantly was developed using an equivalent equation to calculate the $CVaR$ measure. We proposed the problem of composing a multi-product supply portfolio. Through the portfolio, we determined which suppliers to select and how to allocate orders when dealing with multiple suppliers. we developed a $WCVaR$ model with various tolerance levels. In particular, we first applied the $WCVaR$ model to the supply chain domain and successfully derived effective solutions. We confirmed that various strategies were taken depending on the tolerance levels. In addition, we proposed a multi-objective model that combines multiple models. Through the experimental results, we explored various strategies for risk-neutral and risk-averse models with supplier dependency ratios. The ratios effectively demonstrate how the order allocation is structured for each supplier, providing a clear visualization. Furthermore, we presented the Pareto frontier and derived managerial insights. Our findings revealed that the MAWT-M model outperforms the EWCVaR model in terms of efficiency and the ability to derive more sophisticated solutions. As a result, effective strategies considering supplier and regional dependency ratios can improve global supply chain risk management.

However, this study has certain limitations, and it is necessary to consider the following in future research. First, validating the models through practical application with real data in future research can be crucial. Real-world implementation can help assess the effectiveness and applicability of the proposed models. In addition, digitalization of supply chain management can facilitate real-time improvements in decision-making processes (Holmström, Holweg, Lawson, Pil, & Wagner, 2019). Second, further research should focus on tracking decisions made at each stage of a multi-period decision process. Understanding the dynamics of decision-making over time can provide valuable insights into optimizing supply chain strategies. In addition, it may be possible to alleviate certain simplified assumptions. For example, the binary nature of disruptions could be substituted with more complex scenarios involving multi-level disruptions. Lastly, This paper presents a proactive approach to handle the disruptions but a reactive approach considering the concept of recoverable robust optimization as a future research direction (Iris & Lam, 2019). Therefore, future research should explore strategies for enhancing supply chain resilience and recovery capabilities to manage post-disruption situations effectively.

CRediT authorship contribution statement

Jongmin Lee: Conceptualization, Data curation, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Ilkyeong Moon:** Conceptualization, Supervision, Validation, Writing – review & editing.

Data availability

Data will be made available on request.

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