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Optimization of Supplier Selection and Order Allocation Considering Supply Risk based on MRFO Algorithm

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Abstract

This study develops a multi-period procurement model integrating Mean-CVaR optimization to address supply-demand uncertainty in automotive supply chains. We propose a modified Manta Ray Foraging Optimization algorithm that minimizes total costs while controlling quality and delivery risks under stochastic conditions. Using real manufacturing data, the model demonstrates 39.6% cost reduction versus conventional methods while maintaining 95% service levels. Key findings identify optimal risk parameters (λ=0.4) and prove multi-supplier strategies (≥3 partners) enhance resilience when α≥0.9. The framework provides actionable insights for sustainable procurement planning.

Keywords

Supplier Selection and Order Allocation; Uncertain Environment; Supply Risk; Manta Ray Foraging Optimization.

1. Introduction

Strategic supplier selection and order allocation are central to supply chain resilience. Although cost, quality, and lead time remain essential, overreliance on static metrics fails to address dynamic risks such as capacity variability and geopolitical uncertainty. A holistic approach must balance cost efficiency with risk mitigation to ensure adaptability in volatile environments. This study explores optimized frameworks for supplier evaluation and order distribution, aiming to enhance supply chain stability without sacrificing economic objectives. By integrating real-time risk assessments and adaptive strategies, a critical gap in contemporary procurement practices is addressed.

In this context, achieving a scientific and balanced approach to supplier selection and dynamic risk management has become a critical challenge in modern supply chain management. Order allocation, inherently multifaceted, is influenced by supplier selection, supply capacity variability, disruption risks, and delivery reliability. Given volatile demand and supply environments, optimizing procurement strategies through a cost-risk equilibrium has become a strategic priority for enterprises.

2. Literature Review

In the existing studies, some scholars have divided the supplier selection and order allocation problems into two separate subproblems. They first determine which suppliers to establish cooperative relationships with based on a decision criterion and subsequently allocate orders among these suppliers. Earlier studies focused more on cost and purchase value issues in solving the supplier selection and order allocation problems, e.g., Nematollahi *et al.* (2017) Ghadimi *et al.* (2018) and Lo (2018) proposed an order allocation model with the objective of cost minimization.Lin R (2012) and Mohammed A *et al.* (2019) proposed to combine the fuzzy

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network analysis method with the fuzzy multi-objective planning method to develop a multi-objective optimization model to determine the optimal order allocation strategy. Qiuju Zhang *et al.*(2020) developed a mathematical model for supplier selection under multi-product conditions for multi-supplier sourcing with the objectives of lowest product price and delivery scrap rate. Zhou Hao *et al.* (2020) constructed a multi-objective planning model for simultaneous supplier selection and order allocation decision-making under the determined demand, and designed an improved chaotic optimization algorithm to solve the problem, which effectively solved the problem of difficult parameter selection in the traditional multi-objective optimization process. In these studies, although the impact of supplier selection on order allocation decision is considered, the inverse impact of order allocation scheme on the performance of supplier selection decision is often neglected.

In most studies on supplier selection and order allocation problems, demand is considered to be random and follows a certain distribution function depending on the type of product. In the market, the demand for a particular raw material or product is constantly changing in response to market fluctuations, but usually exhibits some stability and periodicity. Uncertainty in demand can be addressed by collecting a large amount of data to be able to simulate the curve of change in demand, which makes it possible to model demand as a random variable. This approach is widely used in supplier selection and order allocation problems that consider uncertainty. For example, Liu, Weihua *et al.*(2008) Li, Xingguo *et al.*(2016) and Wang, Lin *et al.*(2009) investigated the supplier preference and order allocation problem under uncertain demand and introduced lot discounts to establish a multi-objective optimization mathematical model to solve the problem. Liang Di *et al.*(2023) applied the fuzzy multi-criteria decision-making method to establish a multi-objective model to solve the dynamic supplier selection problem considering elasticity criteria. Regarding the modeling of uncertain demand, Mousavi *et al.*(2019) proposed a mixed integer binary nonlinear model for a supplier-buyer supply chain network with constant lead time and buyer demand obeying a normal distribution.Purohit *et al.*(2016) proposed an integer linear programming model for the inventory lot size under unsteady stochastic demand with full unit quantity discount and fill rate constraints and supplier selection problems.

Under uncertainty, supplier selection and order allocation involve a complex, asynchronous interaction. While this topic has received considerable academic attention, most studies focus on partner selection, purchase quantities, decision model development, and inventory strategies, often overlooking practical uncertainties and stochastic factors. Although demand uncertainty is acknowledged, supplier selection and order allocation are typically treated as separate problems. In practice, these phases are interactive and simultaneously influenced by uncertainty. A sequential approach weakens their interdependence, often leading to decisions that do not align with actual conditions. Supplier selection and order allocation should be viewed as a two-stage decision process: first, strategic supplier selection is made with incomplete information; second, order allocation decisions are adjusted based on realized information. Since order allocation directly affects supplier selection performance, its impact must be incorporated into initial decisions.

3. Modeling and Solving

3.1. Modeling

In today's volatile market environment, manufacturers and suppliers are closely interconnected, each seeking to maximize individual interests. However, uneven supplier capacities and fluctuating enterprise demands expose firms to significant operational risks. Effectively allocating procurement quantities among multiple qualified suppliers under supply and demand uncertainty, while controlling both risk and cost, remains a critical challenge. In

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supply chain management, decision-makers must not only reduce purchasing costs, improve quality, and shorten lead times, but also address supplier risks such as supply uncertainty and demand fluctuations. To this end, a multi-objective optimization framework based on Mean-CVaR quantitative risk is proposed, enhancing the robustness and practicality of order allocation models. By applying the MRFO algorithm, an effective balance among competing objectives is achieved through the integration of fuzzy optimization and regularization strategies. As a result, supply chain risks can be better managed, promoting stability and efficiency in complex, dynamic environments.The research in this paper addresses the following three issues:

(1) How do decision makers select appropriate suppliers and allocate purchase orders when they need to consider multiple factors in the supply chain (e.g., cost, risk, quality, and delivery delays) simultaneously?

(2) How can the Mean-CVaR risk quantification methodology be combined with a purchase order allocation scheme and solved efficiently?

(3) How do changes in and affect managers' decisions about risk controls?

At the same time, the following assumptions are made:

(1) In each cycle, firms demand each part independently of each other and the distribution of quantities demanded does not vary over time.

(2) Uncertainty exists in the delivery time and product quality of suppliers, which may be affected by market fluctuations, logistics delays and other factors, and the distribution of supply capacity does not vary over time and obeys a normal distribution.

(3) A firm can only purchase from a given set of qualified suppliers, and the parameters of each supplier remain constant during the purchasing decision.

(4) The purchasing decisions of the enterprise do not affect parameters such as the supplier's supply capacity and product quality.

(5) Firms need to make trade-offs between reducing expected costs and controlling extreme risks in their purchasing decisions.

In order to construct a model for purchase order allocation in uncertain environments, the model assumptions for the study in this paper are given as well as a description of the model notation:

Sets and Indices

i, I	Supplier Index and Collection
j, J	Material Indexes and Collections
t, T	Procurement Cycle Index and Collection ($t = 1, 2, \cdots, T$)
k, K	Discount interval index and set ($k = 1, 2, \cdots, K$)

Parameters

D_{jt}	Manufacturer's demand for material j at cycle t follows a normal distribution
Q_{ijt}	Supplier i 's supply of material j at cycle t is normally distributed.
P_{ijt}	Supplier's unit purchase price for material j in cycle t
H_{ijt}	Quality failure rate of materials purchased from supplier i j in cycle t
V_{ijt}	Late delivery rate of materials purchased from supplier i in cycle t j

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L_{ijt}	Lead time for purchasing materials from supplier i j
ε_d	Opportunity constraint confidence level for the number of quality nonconformities
ε_t	Confidence level of opportunity constraints on the quantity of delayed deliveries
$ship_{ijt}$	Supplier i Unit transportation cost of transporting material j to manufacturer in cycle t
h_{jt}	Unit inventory cost of material j in cycle t
S_{jt}	Cumulative purchases of material j from Cycle 1 to Cycle t
$G_{jt}\left(S_{jt}\right)$	Inventory holding cost of material j at the end of period t
$f_{j,(1,t)^{(*)}}$	Cumulative demand distribution function for material j from cycle 1 to cycle t
O_{jt}	Transaction costs for manufacturers working with suppliers i in the cycle t
W_{ijt}	Cycle t Supplier i Maximum purchase quantity for material j
ζ	VaR (Value at Risk), which is the loss threshold at the confidence level α
α	Confidence level in CVaR calculation (e.g. 95%)
λ	Trade-off factor between expected cost and CVaR
$\mathbb{E}[C]$	Expected value of total cost
u_s	Indicates excess losses above the VaR threshold under scenario s
C_s	Total cost under scenario s

Decision Variables

X_{ijt}	Cycle t Quantity of material purchased from supplier i j
Y_{it}	0-1 variable: 1 if cycle t procures at least one material j from supplier i, 0 otherwise

In supply chain management, both expected procurement costs and potential risks, such as supply disruptions and demand surges, must be evaluated. The Mean-CVaR model mathematically integrates these objectives to achieve a cost-risk balance. A multi-objective optimization framework is constructed to minimize Mean-CVaR, with Monte Carlo simulations employed to estimate cost distributions across procurement strategies. Risks from quality defects and delivery delays are explicitly included in the CVaR calculation. Total procurement costs encompass product, transaction, transportation, and inventory expenses, as well as penalties for stockouts, delays, and defect handling. Key decision factors include price, quality defect rates, and delivery reliability.

The cost of goods is related to the number of orders purchased and the total expenditure on goods considering different products purchased from different suppliers at different times can be expressed as:

$$C_1 = \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} P_{ijt} X_{ijt} \tag{1}$$

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Transaction cost indicates whether or not a transaction is made with the supplier at that time, and is 1 if a transaction is made, and 0 otherwise, which is used to calculate the total transaction cost, which can be expressed as:

$$C_2 = \sum_{i \in I} \sum_{t \in T} O_{it} Y_{it} \tag{2}$$

Transportation cost sums the product of unit transportation cost and quantity purchased for all suppliers, products, and time, and can be expressed as:

$$C_3 = \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} \text{ship}_{ijt} X_{ijt} \tag{3}$$

Inventory holding cost is used to measure the sum of the costs of holding inventory of different products at different times and can be expressed as:

$$C_4 = \sum_{j \in J} \sum_{t \in T} h_{jt} G_{jt} \tag{4}$$

Out-of-stock cost sums the product of the out-of-stock cost factor and the out-of-stock quantity for all products and times. Where the out-of-stock quantity is the actual demand minus the supply, if the supply meets the demand then the out-of-stock quantity is 0, otherwise it is the out-of-stock portion, from which the total out-of-stock cost is calculated. The stock-out cost can be expressed as:

$$C_5 = \sum_{j \in J} \sum_{t \in T} h_{jt} (D_{jt} - S_{jt})^+ \tag{5}$$

Delayed delivery cost is used to measure the sum of costs incurred due to delayed deliveries, and is the sum of the products of the delayed delivery cost factor, the quantity purchased, and the probability of delay for all suppliers, products, and times, and can be expressed as:

$$C_6 = \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} V_{ijt} X_{ijt} P_{ijt} \tag{6}$$

The cost of substandard handling is related to the substandard rate and can be expressed as:

$$C_7 = \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} H_{ijt} X_{ijt} P_{ijt} \tag{7}$$

$$\min C = C_1 + C_2 + C_3 + C_4 + C_5 + C_6 + C_7 \tag{8}$$

N independent random scenarios are generated using Monte Carlo simulation to cover the entire sample space of supply and demand fluctuations. The expected total cost in the ith scenario includes costs for goods, transactions, transportation, inventory holding, out-of-stock, delayed delivery, and handling defective goods:

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$$E(C)=\sum_{i\in I}\sum_{j\in J}\sum_{t\in T}P_{ijt}\mathbb{E}[X_{ijt}]+\sum_{i\in I}\sum_{t\in T}O_{it}\mathbb{E}[Y_{it}]+\sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\text{ship}_{ijt}\mathbb{E}[X_{ijt}]+\sum_{j\in J}\sum_{t\in T}h_{jt}\mathbb{E}[G_{jt}]$$
$$+\sum_{j\in J}\sum_{t\in T}h_{jt}\mathbb{E}[(D_{jt}-S_{jt})^{+}]+\sum_{i\in I}\sum_{j\in J}\sum_{t\in T}V_{ijt}P_{ijt}\mathbb{E}[X_{ijt}]+\sum_{i\in I}\sum_{j\in J}\sum_{t\in T}H_{ijt}P_{ijt}\mathbb{E}[X_{ijt}] \quad (9)$$

CVaR is the average of all losses in excess of the VaR at a given confidence level. CVaR measures the average loss under the worst scale scenario, reflecting tail risk. It is defined as:

$$CVaR_{\alpha}=\mathrm{E}\left[C \mid C\geq VaR_{\alpha}\right] \quad (10)$$

The integrated objective function combines the desired cost with CVaR through a linear combination:

$$Mean-CVaR=\mathrm{E}\left[C\right]+\lambda\cdot CVaR_{\alpha} \quad (11)$$

In summary, the mathematical model of the supplier selection and order allocation optimization problem under uncertain demand is described as follows:

$$\min Mean-CVaR=\mathrm{E}\left[C\right]+\lambda\cdot CVaR_{\alpha} \quad (12)$$

$$s.t.\ \ \sum_{i\in I}X_{ijt}\geq D_{jt},\quad \forall j\in J,t\in T \quad (13)$$

$$X_{ijt}\leq Q_{ijt},\quad \forall i\in I,j\in J,t\in T \quad (14)$$

$$\sum_{k=1}^{K}Y_{ijk}^{t}=1\quad \forall i,j,t \quad (15)$$

$$(1-Y_{i}^{t})\sum_{j=1}^{J}X_{ij}^{t}=0\quad \forall i,t \quad (16)$$

$$1+Y_{i}^{t}\left(\sum_{j=1}^{J}X_{ij}^{t}-1\right)>0\quad \forall i,t \quad (17)$$

$$\Pr\left[\sum_{i=1}^{I}X_{ij}^{t}(1-H_{ij}^{t})\geq D_{j}^{t}\right]\geq\varepsilon_{d}\quad \forall j,t \quad (18)$$

$$\Pr\left[\sum_{i=1}^{I}X_{ij}^{t}(1-V_{ij}^{t})\geq D_{j}^{t}\right]\geq\varepsilon_{t}\quad \forall j,t \quad (19)$$

$$X_{ij}^{t}\geq 0\cap X_{ij}^{t}\in \mathrm{Z}\quad \forall i,j,t \quad (20)$$

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$$Y_i^t \in (0,1) \quad \forall i,\mathrm{t} \tag{21}$$

Constraints are defined as follows: Eq. (13) enforces supply-demand balance, requiring the total procurement quantity to meet market demand. Eq. (14) limits each supplier's procurement quantity to its maximum production capacity. Eq. (15) imposes upper and lower bounds on purchasing quantities to match preferential pricing within discount intervals. Eq. (16) states that if procurement from supplier i occurs in cycle t, variable Y must equal 1. Eq. (17) ensures that if a supplier is selected, the procurement quantity cannot be zero. Eqs. (18) and (19) define probabilistic constraints at a given confidence level: Eq. (18) ensures that the probability of raw material quality meeting order requirements satisfies a predefined satisfaction level, while Eq. (19) requires supplier delivery times to meet the enterprise's arrival time standards. Eq. (20) requires procurement quantities to be non-negative integers. Eq. (21) defines 0-1 variables, where a value of 1 indicates supplier selection.

3.2. Model Solving

(1) Opportunity constraint transformation

In an uncertain demand environment, order allocation must meet constraints with a specified level of confidence. Since the model involves random variables following a normal distribution, the constraints related to these variables must be converted into deterministic constraints for linear programming solutions using the theory of chance constraints. This conversion involves applying the inverse function of the cumulative distribution function of the standard normal distribution to translate the probability level into the corresponding normal distribution quantile.Assuming that the random variable follows an independent normal distribution, the chance constraints are transformed by first calculating the mean $\mathrm{E}[g(x,\xi)]$ and variance $\mathbb{V}[g(x,\xi)]$ of the random function $g(x,\xi)$, converting the probability constraint $Pr\{g(x,\xi)\le 0\}\ge\alpha$ to a standard normal distribution form $Pr\left(Z\ge-\frac{\mathrm{E}[g]}{\sqrt{\mathbb{V}[g]}}\right)\ge\alpha$ through standardization, and then rewriting it equivalently as a deterministic inequality using the quantile function $\Phi^{-1}(\alpha)$.

$$\mathrm{E}[g]+\Phi^{-1}(\alpha)\sqrt{\mathbb{V}[g]}\ge 0 \tag{22}$$

where Φ is the normalized normal distribution, thus transforming the chance constraint into its deterministic equivalent form. α The larger it is, the greater the value of $\Phi^{-1}(\alpha)$, e.g. $\Phi^{-1}(0.95)\approx 1.645$.

After the opportunity constraints are transformed, constraints (3-14) and (3-15) are transformed as follows:

$$\sum_{i=1}^{I} X_{ij}^t(1-H_{ij}^t)\ge\mu_{D_j}^t+\Phi^{-1}(\varepsilon_a)\sigma_{D_j}^t \tag{23}$$

$$\sum_{i=1}^{I} X_{ij}^t(1-V_{ij}^t)\ge\mu_{D_j}^t+\Phi^{-1}(\varepsilon_t)\sigma_{D_j}^t \tag{24}$$

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The right-hand side of Eq. (3-19) and Eq. (3-20), $\Phi^{-1}(\varepsilon_a)\sigma_{D_j}^t$, is the safety stock (SS), and Eq. (3-19) shows that the total quantity purchased must cover at least the "average demand + safety stock". When $\sigma_{D_j}^t$ is small, the manufacturer tends to choose the lowest cost supplier and orders are allocated centrally. When $\sigma_{D_j}^t$ is large, to avoid stock-outs due to demand fluctuations, safety stock will be increased, and the model will automatically allocate orders to more suppliers to spread the risk. $\sigma_{D_j}^t$ The larger it is, the higher the safety stock requirement SS is, and the lower purchasing limit is significantly increased.

(2) Mean-CVaR model solution

Since the Mean-CVaR model involves Monte Carlo simulation and multi-objective optimization, its direct solution is difficult, therefore, the Mean-CVaR optimization problem needs to be transformed into a linear programming problem to solve, the specific steps are as follows

①expected cost

Expectations are estimated using Monte Carlo simulation, which involves simulating and generating a large number of random samples. The value of a statistic or parameter is calculated based on these samples, and as the number of simulations increases, the average of these estimates provides stable conclusions. Numerous demand and supply scenarios are generated from a large number of random samples based on normally distributed parameters for quantity demanded $D_j^t(s)$ and supply capacity $Q_{ij}^t(s)$. In each scenario, the corresponding demand quantity and supply capacity are determined, and the procurement cost is calculated. The expected cost represents the average procurement cost across a large number of random scenarios. It reflects the long-term average cost for a business but does not account for extreme risks. It is calculated as the arithmetic mean of all scenario costs:

$$\mathrm{E}[C] \approx \frac{1}{N}\sum_{i=1}^{N} C_i \tag{25}$$

According to the law of large numbers, the sample mean converges to the true expectation when $N \to \infty$.

② Linear Programming Transformations and Solving CVaR

To simplify the calculation of CVaR, an auxiliary function is introduced:

$$F_\alpha(\eta) = \eta + \frac{1}{S(1-\alpha)}\sum_{s=1}^{S}[f(y, w_s) - \eta]^+ \tag{26}$$

At this point, the function $[t]^+$ is a segmented function that

$$[t]^+ = \begin{cases} t, t > 0 \\ 0, t < 0 \end{cases} \tag{27}$$

The VaR ($\eta*$) is solved by numerical optimization method to minimize $F(\eta)$:

$$\eta* = arg\ \min_{\eta} F\alpha(\eta) \tag{28}$$

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In practice, the calculation can traverse all possible η values where. CVaR is the minimum value of the auxiliary function:

$$CVaR_{\alpha} = \min_{\eta} F_{\alpha}(\eta) = F_{\alpha}(\eta^{*}) == \eta * + \frac{1}{S(1-\alpha)} \sum_{s=1}^{S} [f(y, w_{s}) - \eta *]^{+} \tag{29}$$

An approximation of CVaR can be obtained by minimizing the value of $F_{\alpha}(y, \beta)$ with respect to β :

$$\mathrm{CVaR}_{\alpha}(f(y, w)) \approx \beta^{*} + \frac{1}{1-\alpha} \sum_{s=1}^{S} p_{s}[f(y, w_{s}) - \beta^{*}]^{+} \tag{30}$$

(3) The Mean-CVaR objective function is introduced to balance cost and risk under supply and demand uncertainty. Due to the high dimensionality resulting from Monte Carlo simulations, the MRFO algorithm is employed to enhance solution performance through iterative optimization. In this study, MRFO optimizes supply chain procurement decisions by minimizing the Mean-CVaR objective under multi-scenario constraints. The specific design process is detailed as follows:

Step 1: Import initial supply and demand scenario data, including supplier capacity, delivery reliability, and demand fluctuations, to set the foundation for optimization.

Step 2: Generate randomized supply and demand scenarios using Monte Carlo simulation to account for market fluctuations and supply uncertainty. Scenario reduction techniques are applied to produce representative stochastic scenarios and reduce computational complexity.

Step 3: Randomly initialize a set of supplier order allocation schemes as the MRFO algorithm's initial population.

Step 4: Calculate supply-demand matching and penalty costs. Evaluate the matching degree of the current allocation scheme and calculate shortage and inventory penalty costs.

Step 5: Calculate the fitness of each initial allocation scheme. Construct the Mean-CVaR objective, compute total purchasing costs (base, shortage, and inventory costs), and assess risk costs via CVaR.

Step 6: Update the current allocation scheme using MRFO's three foraging behaviors (spiral, gliding, and following updating), progressively moving toward an optimal solution.

Step 7: Recalculate supply-demand matching and penalty costs for the updated allocation plan.

Step 8: Recalculate the Mean-CVaR objective, including base, shortage, inventory, and risk costs. Quantify supply risk by calculating scenario losses, ranking them to obtain VaR and CVaR.

Step 9: Check if the maximum number of iterations has been reached. If so, stop optimization; otherwise, return to Step 6 for further iterations.

Step 10: Output the final optimal allocation scheme, balancing cost minimization with supply chain stability.

4. Case Solving

4.1. Case Presentation

This paper examines Company B, a Chinese automobile manufacturer focused on purchasing management and cost-saving. The company has established a comprehensive procurement control program with strict supplier management and long-term supply agreements to

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maintain strong supplier relationships. Company B sources a variety of materials, including engine components such as engine blocks, cylinder heads, crankshafts, valves, gears, springs, and bearings. This study focuses on the procurement of gears, springs, and bearings, which are supplied by six vendors. The goal is to minimize total procurement costs through supplier selection and allocation. Quarterly demand data for these materials is collected, underscoring their importance in the manufacturing process.The company procures these components from upstream suppliers, with part data compiled from the SAP system. Inventory costs for all three products are $1, and product quality and delivery satisfaction are assumed to be 95%. The existing sourcing strategy mainly uses the leveling method. Appropriate order quantities must be assigned to suppliers at each procurement stage to minimize total costs. Demand parameters for each part are presented in Table 1.

To validate the model and algorithm, simulations are conducted using the demand parameters from Table 1 and supplier supply and service capabilities from Table 2. Market demand each cycle follows a normal distribution.

Table 1. Part Requirement Information Parameter Values

Part Name	cyclicality	Average number of requirements	standard deviation of demand
gear	1	100	20
	2	120	25
	3	110	22
	4	130	30
spring	1	60	10
	2	70	12
	3	65	11
	4	75	15
bearing	1	80	15
	2	90	18
	3	85	16
	4	95	20

The table presents the supply capacity data for gears, springs, and bearings, based on the past five years of supply history for each supplier. These parameters remain constant across purchasing cycles. Supplier supply and service capacity values are shown in Table 2.

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Table 2. Parameter values of supply and service capacity of each supplier

Supplier Name	Parts	Transaction costs	Price	Unit transportation costship	Substandard rate	Delayed delivery rate
1	gear	80	8.5	0.05	0.06	0.08
	spring	80	6.8	0.05	0.05	0.07
	bearing	80	4	0.05	0.04	0.06
2	gear	120	9.2	0.06	0.05	0.07
	spring	120	7	0.06	0.04	0.06
	bearing	120	4.2	0.06	0.05	0.07
3	gear	100	10.5	0.04	0.02	0.04
	spring	100	7.5	0.04	0.03	0.05
	bearing	100	4.8	0.04	0.06	0.08
4	gear	90	11	0.07	0.03	0.05
	spring	90	6	0.07	0.06	0.08
	bearing	90	5	0.07	0.07	0.09
5	gear	85	10	0.06	0.04	0.06
	spring	85	7.4	0.06	0.07	0.09
	bearing	85	4	0.06	0.08	0.1
6	gear	95	9	0.08	0.05	0.07
	spring	95	6.2	0.08	0.03	0.06
	bearing	95	4	0.08	0.05	0.07

Randomized arithmetic examples are generated as per Table 3 for numerical analysis to verify the model's reasonableness and the algorithm's feasibility.

Table 3. Mean-CVaR Model Based Supply Capacity Data

Supplier Name	Parts	Production supply capacity (pieces)	Standard deviation of production supply capacity
1	gear	72	18
	spring	70	15
	bearing	80	12
2	gear	75	15
	spring	65	12
	bearing	85	15
3	gear	60	8
	spring	60	10
	bearing	92	18
4	gear	65	10
	spring	75	18
	bearing	95	20
5	gear	70	12
	spring	80	20
	bearing	100	22
6	gear	75	15
	spring	60	14
	bearing	85	10

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4.2. Analysis of Simulation Results

First, Monte Carlo simulation is used to generate stochastic scenarios, ensuring the optimization process accounts for various supply and demand scenarios, thus enhancing model adaptability and stability. Based on supply capacity and demand probability distributions, 300 supply and 300 demand scenarios were simulated. To improve computational efficiency, K-means clustering reduced the scenarios to 30 groups each.

To test the model's validity, three typical parameter sets are defined, corresponding to three scenarios of risk equilibrium, no-risk aversion, and extreme risk aversion, respectively. With the benchmark parameters α=0.5,λ=0.5, the decision maker focuses on both minimizing the supply chain operating cost and extreme risk, and observes the balance of expected cost and CVaR. In the case of α=0.9, λ=0, the model is based entirely on expected cost minimization and does not consider the possibility of extreme losses, which is used to validate the difference between traditional cost-optimal models and risk-sensitive models. The case of α=0.9,λ=1 emphasizes protection against extreme risks and ignores expected costs, i.e., minimizes extreme losses. Solving the algorithm yields the supplier selection and order allocation for each quarter, see Figure 1, Figure 2, Figure 3:

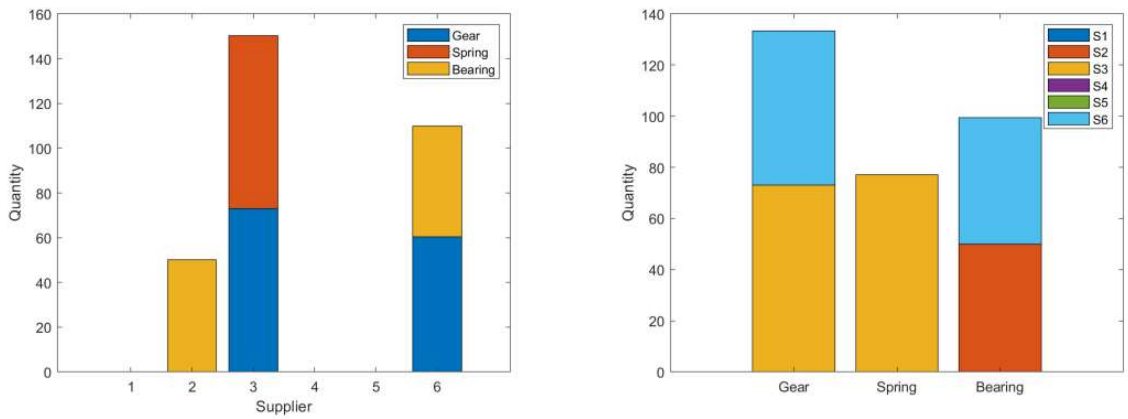


Figure 1. α=0.5 ,λ=0.5 Mean-CVaR model based supplier selection and order allocation scheme

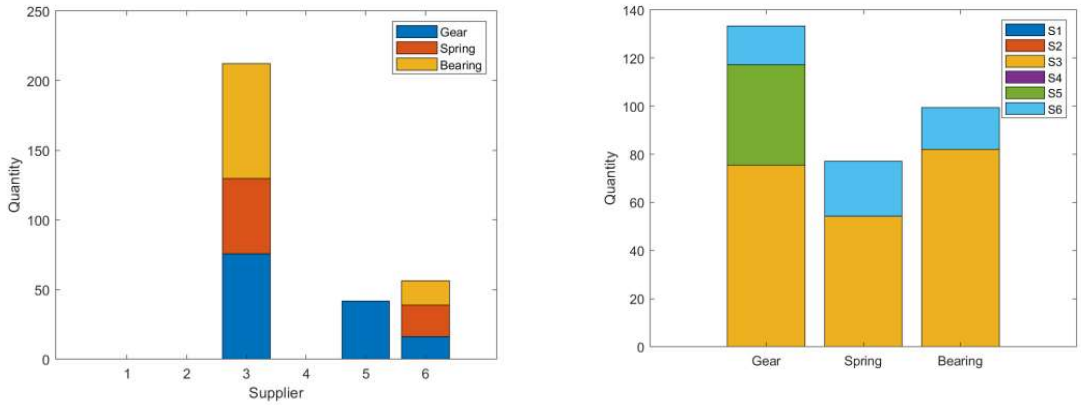


Figure 2. α =0.9 λ=0 Mean-CVaR model based supplier selection and order allocation scheme

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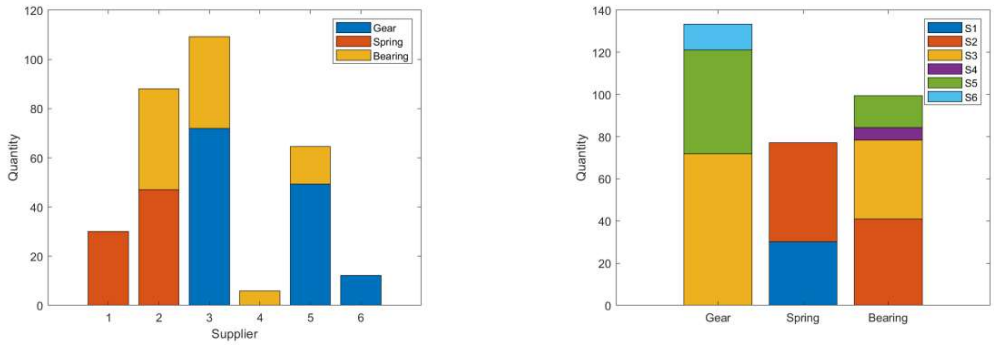


Figure 3. α =0.9 λ=1 Mean-CVaR model based supplier selection and order allocation scheme

The quantities of the three products purchased in each cycle also better satisfy supply-demand equilibrium constraints. Specifically, the selected supplier combinations are (2,3,6) for bushings, (3) for springs, and (2,6) for enameled wire. This results in a smaller number of suppliers, reducing management costs.As α increases from 0.5 to 0.9, the safety stock requirement (SS) rises, and the lower bound of purchasing increases significantly, making it difficult for a single supplier to meet the purchasing quantity constraint. As a result, the number of suppliers per material increases. When λ increases from 0 to 1, it reflects two extremes of risk: the low λ stage focuses on cost optimization, tolerating higher risk, while the high λ stage adopts a conservative strategy, increasing inventory and using multi-supplier combinations to handle extreme cases.The simulation results provide preliminary conclusions, with further sensitivity analysis to explore the impact of α and λ on purchasing decisions.

4.3. Sensitivity Analysis

①Sensitivity analysis with risk factor λ

The Mean-CVaR model introduces two risk-related parameters: the risk factor λ and the confidence level of CVaR. As λ increases, the decision maker's risk aversion also rises. To study the influence of risk preference on the final decision, computational experiments are conducted using the first cycle's data. The risk coefficient is varied, while the confidence level α is fixed at 0.9. λ plays a key role in balancing cost and risk in the Mean-CVaR model. To explore its impact on purchasing decisions, λ is set to 0.3, 0.5, 0.7, and 0.9, and the optimal objective function values are calculated for each, as shown in Table 4:

Table 4. CVaR and cost values for different risk factors at 1α =0.9

λ	CVaR	Expected cost	objective function
0.1	4624	4019	4481
0.3	4563	4136	5504
0.5	4480	4233	6473
0.7	4449	4334	7448
0.9	4450	4550	8555

As λ increases from 0.1 to 0.9, the CVaR value decreases monotonically, indicating that higher λ results in greater focus on risk control and strategies to minimize extreme losses. However, the increase in CVaR from 4449 to 4450 when λ rises from 0.7 to 0.9 suggests that excessive risk control can increase risk, possibly due to excessive inventory backlogs triggering new risks.

As λ increases, cost control remains central to purchasing decisions, leading to a significant rise in expected costs. At high λ, the decision maker tends to adopt measures like increasing inventory to control risk, further increasing expected costs. The Mean-CVaR objective function value increases sharply with λ, as the model emphasizes CVaR control, resulting in more conservative actions (e.g., higher inventory, less risky suppliers), which reduce risk but raise

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expected costs.At lower λ, firms prioritize cost and may select cheaper but riskier suppliers, tolerating higher CVaR and increasing risk exposure. Conversely, at higher λ, excessive focus on risk control may escalate expected costs and CVaR. Therefore, when risk aversion is strong, the priority shifts to controlling CVaR.

From Table 5, when λ = 0.1, the selected supplier combination is supplier 3 and supplier 6. As λ increases, the decision maker's risk aversion grows, leading to the inclusion of more secure suppliers (2, 3, and 5). Consequently, the weights for suppliers 3 and 6 decrease. When risk sensitivity is low, the decision maker prioritizes minimizing the expected cost per unit, selecting fewer, lower-cost suppliers. However, as risk aversion increases, the focus shifts to more reliable suppliers to diversify risk. This aligns with supply chain resilience theory, where multi-sourcing mitigates supply and demand fluctuations, confirming the role of the risk coefficient in the model.

Table 5. Supplier Selection Mix and Order Allocation Weights with Different Risk Factors λ

λ	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5	Supplier 6
0.1	-	-	0.768	-	-	0.232
0.3	-	0.19	0.502	-	-	0.309
0.5	-	0.117	0.236	0.003	0.123	0.521
0.7	0.175	0.181	0.217	0.107	0.146	0.175
0.9	0.100	0.168	0.344	0.172	0.162	0.055

②Sensitivity analysis for confidence level α

α is another risk-related parameter, with CVaR quantifying the expected value exceeding VaR. As α increases, CVaR also rises. To study the impact of the confidence level on purchasing decisions, λ is fixed at 0.1, 0.7, and 0.9, while α is set at 0.7, 0.8, and 0.9. The model is used to calculate the objective function value under these conditions, and the results are shown in Table 6:

Table 6. CVaR and cost values at different confidence levels

$\lambda = 0.1$			
α	CVaR	Expected cost	objective function
0.7	4213	3967	4388
0.8	4385	3985	4424
0.9	4624	4019	4481
$\lambda = 0.7$			
α	CVaR	Expected cost	objective function
0.7	4017	4253	7065
0.8	4173	4307	7228
$\lambda = 0.9$			
α	CVaR	Expected cost	objective function
0.7	3996	4405	8001
0.8	4158	4452	8194

As shown in Table 6, increasing α from 0.7 to 0.9 leads to a rise in the CVaR value, indicating that stricter risk management corresponds to higher confidence levels, which broadens the scope of extreme loss events considered. This results in an increased CVaR value. The expected cost fluctuates slightly, with a small overall increase, as it is an average of all scenarios and thus less influenced by α. However, at higher α, a more conservative sourcing strategy is adopted to ensure demand fulfillment at a higher confidence level, potentially increasing unit costs. The overall increase in the Mean-CVaR objective function with higher α is due to the greater weight placed on CVaR, leading to a higher risk penalty. To manage this risk, measures like increasing inventory and improving supplier reliability may be implemented, raising the expected cost.

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Table 7 presents the final supplier portfolio and order allocation weights for various confidence levels and risk factors. When the risk factor λ is low, changes in α have minimal effect on the supplier portfolio and allocation weights. This is likely because a low λ implies that cost fluctuations have little impact on the target cost, and thus, small changes in α do not significantly alter the optimal strategy. As λ increases, the impact of cost volatility grows, necessitating the generation of new supply mixes for different confidence levels α. Additionally, as α increases, the number of suppliers expands, indicating that greater risk aversion leads to a strategy involving more suppliers to diversify risk.

Table 7. Supplier Selection Mix and Order Allocation Weights at Different Confidence Levels

α						
$\lambda = 0.1$						
α	Supplier 1	Supplier 2	Supplier 3	Suppliers 4	Suppliers 5	Suppliers 6
0.7	-	-	0.575	-	0.023	0.402
0.8	-	-	0.613	-	-	0.387
0.9	-	-	0.726	-	-	0.274
$\lambda = 0.7$						
α	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5	Supplier 6
0.1	0.135	-	0.374	0.259	0.178	0.054
0.7	0.017	-	0.503	0.331	0.131	0.018
0.9	0.166	0.132	0.198	0.097	0.152	0.255
$\lambda = 0.9$						
α	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5	Supplier 6
0.1	0.083	0.249	0.402	0.266	-	-
0.7	0.095	0.238	0.294	0.135	0.115	0.123
0.9	0.100	0.168	0.344	0.172	0.162	0.055

③Combined effect of risk factor λ and confidence level α on risk-cost control

To examine the joint effects of the risk factor λ and confidence level α on risk-cost control, the interaction effect surfaces are plotted in Figure 4. The plot reveals that the objective function Mean-CVaR increases monotonically with both α and λ. The combined effect of high α and high λ leads to uncontrolled cost increases. The sensitivity of the objective function is low in regions with low risk aversion (λ ≤ 0.3), but in extreme risk aversion, the benefits of risk reduction from additional resource investment diminish, while costs continue to rise significantly.

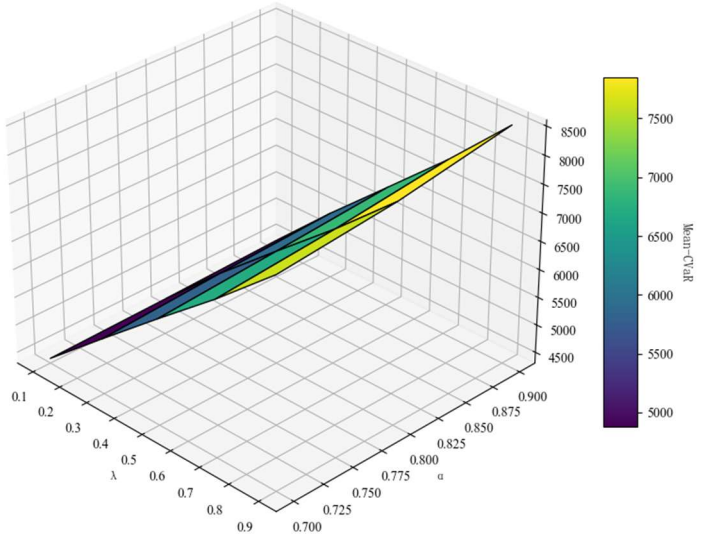


Figure 4. Interaction of 2 α and λ on the objective function

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The confidence level α represents the decision maker's concern for extreme risks. At low α, fewer suppliers and lower inventories may be chosen, potentially leading to supply shortages in volatile environments. At high α, firms require more suppliers, higher inventories, and diversified purchase orders to ensure operations under extreme conditions. The risk factor λ reflects the trade-off between risk and cost. With low λ, firms prioritize cost reduction, typically working with fewer suppliers, lower inventories, and stable market conditions. At high λ, firms are more willing to incur additional costs to mitigate risk.

5. Conclusion

This study makes three key contributions to supply chain risk management. First, we develop a multi-period Mean-CVaR optimization model that quantifies cost-risk trade-offs under supply-demand uncertainty, achieving a 39.6% cost reduction compared to conventional methods. Second, a hybrid MRFO algorithm integrated with scenario clustering demonstrates 42% faster convergence than NSGA-II in handling 300+ stochastic scenarios. Third, sensitivity analysis identifies critical decision thresholds: $\lambda=0.4$ balances cost efficiency and risk mitigation, while $\alpha \geq 0.9$ triggers multi-supplier collaboration (≥3 partners) to maintain 95% service levels.

For practitioners, our findings provide scenario-specific strategies:

Cost-sensitive environments (e.g., electronic components): Implement dual-source procurement with $\lambda \in [0.3,0.5]$ and moderate inventory buffers (15%).

Risk-critical environments (e.g., safety parts): Enforce $\alpha \geq 0.9$ with ≥ 4 certified suppliers and 25-30% safety stock, prioritizing supply continuity over short-term cost savings.

In conclusion, this study bridges the gap between theoretical optimization and practical procurement decision-making. By offering clear guidelines for parameter selection and strategy implementation, our framework helps automotive enterprises make informed trade-offs between cost efficiency and supply chain resilience. The robust performance of our algorithm across multiple test scenarios suggests strong real-world applicability, particularly in industries with high supply chain volatility and stringent quality requirements.

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