

The Construction of a Newsvendor Model Based on Conditional Value at Risk (CVaR) and the Determination of Optimal Order Quantity

Meijia Wang¹ Adisak Sangsongfa² Noppadol Amdee^{3*}

^{1,2,3*}*Department of Industrial Technology Management, Faculty of Industrial Technology,
Muban Chom Bueng Rajabhat University, Ratchaburi, Thailand*

*Corresponding author e-mail: noppadolamd@mcru.ac.th

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Abstract

To address the growing uncertainty in demand for electric vehicles in the market, this article develops an extended CVaR Newsvendor model. Compared to existing Newsvendors, there are two contributions: (i) embedding both risk aversion and loss aversion in utility-oriented objectives; (ii) handling limited additions using the “three scenarios” (no stockouts/no additions, no stockouts/limited additions, and stockouts/limited additions). Based on 12 months of data from a single retailer, the model was calibrated under a normal distribution demand and fixed cost structure, and evaluated using a Monte Carlo simulation. The model had a high fitting degree (98.08%) and a low root mean square absolute error (0.8 vehicles). This study assumes a single cycle and a single project, with parameters considered stable during the sample period, and does not explicitly incorporate exogenous factors such as policies and input prices. These assumptions limit the research's generality, but clarify how to adjust the framework in practice through scenario-based parameter tuning.

Keywords: Conditional Value at Risk (CVaR), Electric vehicle supply chain, Inventory management, Newsvendor model, Risk management

INTRODUCTION

In the context of rapid global economic development, supply chain management has become a key factor for enterprises in various industries to maintain competitiveness. [1]. Inventory optimization, as the core link in supply chain management, aims to improve the efficiency of the supply chain and minimize total operating costs through effective inventory control strategies [2]. However, due to the increasing instability of market demand, traditional inventory management methods are facing severe challenges, especially in industries such as electric vehicles [3], information technology, communication, and artificial intelligence, where technology updates quickly and policies have a significant impact.

The electric vehicle business is a new and rapidly growing sector fueled by technological advancements and government policy support, which causes market demand to fluctuate significantly [4]. Empirical studies have shown that macroeconomic policy uncertainty significantly disrupts the inventory behavior and replenishment pace of enterprises, increasing the decision-making pressure on inventory management [5]. To preserve supply chain continuity and market competitiveness in a highly volatile market, businesses must make more informed inventory decisions [6]. Therefore, it becomes especially crucial to find an efficient way to handle market unpredictability and optimize inventory management in the supply chain for electric vehicles [7].

Conventional methods for managing inventory, which include well-known models such as the Newsvendor model and the Economic Order Quantity (EOQ) model, often rely on static assumptions about market demand, meaning they do not account for changes over time. These models primarily focus on maximizing profits or minimizing costs, which sounds good in theory. However, these approaches often fall short when it comes to addressing the actual high-demand volatility that is prevalent in the electric car industry. This is particularly true in highly volatile markets, where businesses may be exposed to substantial financial risks. This situation creates a challenge that the conventional models do not adequately address, leaving many businesses to struggle with uncertainty and unpredictability in their inventory management practices. New decision models must be implemented to enhance the resilience and effectiveness of inventory management, enabling better handling of uncertainty and the need for risk management. To handle demand fluctuations and market uncertainty, Garvey and Carnovale suggested a novel “Rippled Newsvendor Model” to optimize inventory management methods in the face of risk propagation along the supply chain [8].

Due to its emphasis on tail risk, the Conditional Value at Risk (CVaR) model has been widely adopted in financial risk management as a sophisticated risk management tool. A fresh viewpoint and analytical justification for inventory decisions in supply chain management are offered by incorporating the CVaR model into the Newsvendor model. When faced with high risks, the CVaR-based Newsvendor model can help businesses make more robust inventory decisions and better manage market demand unpredictability [5]. Consequently, there is substantial theoretical and practical benefit in researching the development of a CVaR-based Newsvendor model [9].

This study aims to construct an extended newsvendor model under the CVaR decision criterion, focusing on inventory optimization in the electric vehicle supply chain. Based on this core objective, this article implements the following testable sub-objectives:

Theoretical objective: To derive an analytical expression for utility type CVaR and provide its calculation criteria given a cost structure and demand setting; Provide an analytical solution for the optimal order quantity and the



first-order optimality conditions, explaining the existence, uniqueness (under the given conditions), and applicable scenarios.

Solution objective: Based on the above analytical results, form an achievable solution process for calculating Q^* monthly and output ordering decisions that are consistent with maximizing utility CVaR.

Verification objective: Based on the actual sales data of a specific electric vehicle retailer for 12 consecutive months, conduct numerical verification of the model, report Root Mean Squared Absolute Error (RMSAE) and fitting degree, to test the accuracy and robustness during the sample period.

Management significance: Based on empirical evidence, combined with model output, provide ordering strategy recommendations that match business constraints, and provide actionable support for inventory optimization decisions in the electric vehicle supply chain under demand uncertainty.

LITERATURE REVIEW

1. Basic Theories of Risk Aversion and Loss Aversion

In the realms of behavioral economics and decision theory, risk aversion and loss aversion stand as two principal concepts. In the face of uncertainty, the tendency of a decision-maker to opt for safer choices, despite lower expected returns, is termed risk aversion. Often used in the fields of management, economics, and finance, this idea elucidates why people and organizations tend to choose more prudent strategies over choices with higher risks and possible benefits. To forecast how individuals or organizations will behave in unpredictable situations, the traditional Expected Utility Theory employs a risk aversion coefficient to quantify this propensity.

A fundamental idea in behavioral economics, loss aversion, was first proposed by Kahneman and Tversky in Prospect Theory [10]. It explains how people tend to avoid losses rather than seek profits when making decisions because they are more sensitive to losses than to similar benefits. Numerous economic activities, including business risk management, consumer choices, and investment decisions, have empirical support for this phenomenon. Loss aversion in management explains why businesses use cautious tactics when things are unclear, to prevent possible financial losses, even if doing so would restrict profit growth.

Risk and loss aversion have a significant influence on businesses' inventory choices in supply chain management [3]. When faced with supply chain disruption threats and market demand uncertainties, firms frequently display strong inclinations toward risk and loss aversion [11]. Despite the possibility of stockouts and lost sales, this practice encourages companies to reduce order quantities to minimize the risk of unsold inventory and potential holding expenses.

2. Risk Management and Supply Chain Inventory Optimization

In supply chain management, risk management is crucial, especially considering the increasing volatility and unpredictability of market demand. Determining the ideal inventory levels in an unpredictable market situation to satisfy customer demand while lowering associated costs is known as inventory optimization, and it is a crucial problem in supply chain management. In traditional inventory optimization frameworks, EOQ [12] is typically solved based on deterministic or stable demand rates and fixed replenishment parameters to minimize long-term average costs; The classic newsvendor model, on the other hand, is specifically designed for single cycle/short lifecycle

scenarios with uncertain (random) demand, balancing excess costs and out of stock costs based on a given demand distribution. The limitations of the newsvendor model are mainly due to the simplification of the distribution form and parameter stability, single-period setting, and the handling of extreme tail situations and additional constraints. Therefore, when facing intensified demand fluctuations and rising tail risks, the traditional approach of relying solely on minimizing expected costs may underestimate downside risks, and there is an urgent need to introduce tail risk measures such as CVaR to enhance the robustness of decision-making.

The integration of risk management into supply chain inventory optimization has been the subject of a growing amount of research in recent years [5]. These models have gradually included risk and loss aversion as essential determinants of decision-making. In their study of supply chain inventory optimization under demand uncertainty, for instance, Taghizadeh and Venkatachalam suggested the best inventory techniques for varying degrees of risk aversion [13]. A study by Venkataraman and Asfaw [14] examined how manufacturers create contracts to address retailers' loss aversion in a supply chain with risk-neutral manufacturers and loss-aversion retailers.

According to these findings, conventional models that aim to maximize profits or costs might not be applicable in unpredictable situations [15]. More robust inventory management techniques can be designed by considering the decision-maker's risk preferences and loss aversion behavior, which can help prevent financial losses in severe situations. However, these models continue to be complex and challenging to handle when dealing with many risk factors (including price volatility, supply disruptions, and demand variations), and successfully incorporating these risk factors into the models is still a crucial area of ongoing research [9].

3. The Application and Challenges of CVaR Models in Supply Chain Management

To quantify and control tail risk in investment portfolios, the CVaR model was first introduced in the field of financial risk management. Two risk indicators utilized in the Newsvendor Model, Value at Risk (VaR) and CVaR, were thoroughly compared by Jammerneegg and Kischka. They noted that CVaR offers a more thorough risk assessment than traditional VaR, especially when it comes to handling potentially high losses. The application of CVaR in supply chain management was further examined by Jammerneegg and Kischka, who emphasized its increasing acceptance and extensive use in tackling risks, including supply chain interruptions and market demand uncertainty, due to its benefits in managing extreme risks [16].

In the literature on supply chain management, the CVaR model has been extensively applied in various fields, including supply chain contract design, supply chain financing, and inventory management. For instance, to maximize ordering choices in the face of demand uncertainty, Taghizadeh and Venkatachalam included CVaR into the Newsvendor Model. They discovered that the CVaR-based Newsvendor Model provided more reliable inventory management techniques, particularly when demand volatility was significant, as the CVaR model outperformed conventional approaches [17].

Although the CVaR model has considerable potential for supply chain management, certain obstacles still hinder its practical application [5]. Firstly, the CVaR model exhibits comparatively high computational complexity, particularly in supply chains with multiple products and tiers, where it requires a substantial amount of computing power to solve [17]. Another crucial problem is precisely estimating the model's parameters, such as the risk aversion and demand distribution coefficients [18]. The efficacy of inventory decisions may be impacted by biased



model predictions resulting from inaccurate parameter estimation [19]. Furthermore, the suitability of the CVaR model for dynamic situations has not yet been thoroughly confirmed. Further study is needed to determine the robustness of the model in scenarios where supply chain and demand factors are continuously changing [20].

There have been studies introducing CVaR into the newsvendor model, indicating the necessity of using tail risk measurement under stochastic demand; However, there are still three shortcomings in this context as a whole: (1) it mainly focuses on minimizing CVaR in a single stage, and rarely depicts both risk avoidance and loss avoidance in utility oriented objectives, making it difficult to distinguish the policy effects of “tail exposure suppression” and “average loss control”; (2) The handling of the additional ordering mechanism mostly assumes infinite or implicit availability, with less explicit modeling of the three scenario differences caused by the finite additional upper limit M: no shortage/limited addition/shortage and limited addition, resulting in a weakened behavior of tail shortage after the “Q+M” truncation; (3) Less monthly indicator validation is conducted on industry data. Based on this, this article proposes in the context of electric vehicle retail: (i) introducing both risk avoidance and loss avoidance into the utility type CVaR objective; (ii) Characterization of the three scenarios surrounding M and their corresponding existence and first-order conditions; (iii) Validation and implementation details description of indicators based on 12 months of real data to fill the gap mentioned above.

METHODS

The average loss that surpasses the VaR at a specific confidence level is known as the CVaR. One risk measurement technique that works well for determining the average loss in extreme situations is CVaR. A more thorough risk assessment is provided by CVaR, which considers the average loss exceeding this threshold, in contrast to VaR, which only considers the loss at the threshold. Businesses can more precisely measure and control supply chain risks by integrating CVaR into electric vehicle supply chain management.

The CVaR formula is expressed as (Equation 1) [21]:

$$CVaR_{\alpha} = \frac{1}{1 - \alpha} \int_{\alpha}^1 VaR_u du \quad (1)$$

Where α is the confidence level, and VaR_u is the VaR at different confidence levels u . At the confidence level α , VaR_{α} is the threshold at which the ‘worst-case scenario’ begins; $CVaR_{\alpha}$ is the average loss of all worse results after crossing this threshold. Therefore, compared to only looking at the VaR of quantiles, CVaR focuses more on the severity of tail conditions and is used to measure the cost exposure caused by “extreme but possible” stockouts or excesses.

CVaR can be calculated by following the steps:

- Determining the VaR value: Calculate the VaR value for a given confidence level α .
- Identify losses that exceed VaR: Find all loss values that exceed VaR.
- Calculate CVaR: Average all loss values that exceed VaR to get the CVaR value.

A traditional inventory management strategy for deciding what to stock when demand is unknown is the newsvendor model. This work develops an extended CVaR-based newsvendor model by incorporating CVaR, risk

aversion, and loss aversion into the conventional newsvendor model, thereby enhancing risk management in the electric vehicle supply chain.

Confidence level and loss aversion coefficient are used to quantify risk aversion and loss aversion, respectively. Businesses can optimize their inventory management strategy to ensure the stability and dependability of the supply chain by adjusting the confidence level and loss aversion coefficient in the supply chain management of electric vehicles.

For the extended CVaR-based newsvendor model, we have the following assumptions [22]:

- I. The market demand obeys a normal distribution.
- II. Initial ordering costs are lower than additional ordering costs.
- III. Retailers may place additional orders during the sales cycle, subject to a maximum number of further orders.
- IV. Commodity sales and recovery prices are known and fixed.
- V. Retailers are risk-averse and loss-averse.

This article approximates the demand using a normal distribution as a working hypothesis for parametric calibration and simulation evaluation. This approximation facilitates the derivation of clear first-order optimality conditions and reduces the complexity of the solution. At the same time, the evaluation and conclusions of the model are given within this assumption framework, and the scope of application is limited based on this premise. Simultaneously setting the initial ordering cost lower than the additional cost reflects an everyday business reality: initial ordering usually enjoys scale and planning advantages, while mid-term additions often come with urgency, small batches, and transportation premiums; From a model perspective, the initial ordering cost being lower than the additional cost avoids the degenerate solution of “all dependence on additional”, making the “beginning mid period” have identifiable cost trade-offs. The above two items only serve as modeling prerequisites for solving and verifying; Therefore, the generalizability of this article is interpreted based on this boundary condition, and other distribution forms or different cost relative relationships are not within the scope of this study.

The objective of expanding the Newsvendor model to consider CVaR is to optimize the usefulness of the CVaR function, which accounts for both risk and loss aversion. The following is the definition of the utility CVaR function (Equation 2):

$$U_{\lambda}^{\mu}(Q) = E[R(Q)] - \lambda \cdot CVaR_{\alpha}(Q) - \mu \cdot L(Q) \quad (2)$$

Where Q is the order quantity (assuming that the order quantity is the retailer's target sales volume), and $E[R(Q)]$ is the subscription volume Q corresponding to the expected revenue, which reflects the revenue that the firm is likely to earn under the order quantity Q which reflects the revenue that the firm is expected to get under the order quantity. The risk aversion coefficient measures the degree of risk aversion of the firm. The loss aversion coefficient measures a firm's loss aversion and represents the CVaR at the confidence level, which is the average loss over the VaR.

$L(Q)$ is a loss function to quantify the loss due to demand uncertainty and can be expressed as (Equation 3):

$$L(Q) = E[\max(0, D - Q)] \quad (3)$$

The objective of maximizing utility CVaR is to determine the optimal ordering quantity and construct the corresponding objective function. The specific formula is (Equation 4):

$$\max U_{\lambda}^{\mu}(Q) = \max\{E[R(Q)] - \lambda \cdot CVaR_{\alpha}(Q) - \mu \cdot L(Q)\} \quad (4)$$

Suppose that p is the selling price of the goods, c is the initial ordering cost, r is the out-of-stock penalty cost, and D is the random demand. Then $E[R(Q)]$ can be expressed as (Equation 5):

$$E[R(Q)] = pQ - cQ - rE[\max(0, D - Q)] - hE[\max(0, Q - D)] \quad (5)$$

Theorem 1: In the extended newsvendor model based on CVaR and loss aversion criterion, the optimal ordering quantity of the risk-aversion retailer Q^* should satisfy the following conditions (Equation 6):

$$Q^* = \operatorname{argmax}\{E[R(Q)] - \lambda \cdot CVaR_{\alpha}(Q) - \mu \cdot L(Q)\} \quad (6)$$

Proof: Assume that the market demand D distribution function of F , CVaR is defined as when loss aversion and non-zero stock-out costs are also considered (Equation 7):

$$CVaR_{\alpha}(Q) = \max\left\{v + \frac{1}{1-\alpha} E[U(pQ - cQ - r \cdot (D - Q)^+ - h \cdot (Q - D)^+ - v)^+]\right\} \quad (7)$$

Where v is the utility threshold, and h is the inventory holding or depreciation cost, $(\cdot)^+ = \max\{0, \cdot\}$. $U = u(\pi)$ is the loss aversion utility function, denoted as (Equation 8):

$$U(\pi) = \begin{cases} \pi - \pi_0, & \pi \geq \pi_0 \\ \mu(\pi - \pi_0), & \pi < \pi_0 \end{cases} \quad (8)$$

Where π_0 denotes the target return.

Combining the gain function, loss function, and CVaR function, the objective function is constructed as (Equation 9):

$$\max U_{\lambda}^{\mu}(Q) = \max\left\{E[R(Q)] - \lambda \cdot \max\left\{v + \frac{1}{1-\alpha} E[U(pQ - cQ - r \cdot (D - Q)^+ - h \cdot (Q - D)^+ - v)^+]\right\} - \mu \cdot L(Q)\right\} \quad (9)$$

In order to analyze in detail the performance of the extended newsvendor model under different demand conditions, it is divided into three scenarios based on the relationship between demand D , initial order quantity Q , and the upper limit M that can be added (this article sets the upper limit M as the constraint for adding orders). In each scenario, the price p , initial ordering cost c , additional cost s , out of stock penalty r , risk parameters α , λ , μ and upper limit M remain unchanged from the demand distribution parameters, and only the random demand D and the induced additional quantity X and the resulting costs change. The division of the three paragraphs allows us to see clearly which type of cost dominates when adjusting Q and M , and thus understand the marginal impact of “adding one point ordering” in the first-order optimal condition.

Through a detailed examination of each scenario, a more accurate objective function can be constructed to determine the optimal order quantity Q^* . The following is a detailed discussion of the three scenarios. The details are as follows:

1) $D \leq Q$: In this case, no stock-outs will occur, and only the inventory cost and utility function need to be considered $U(\pi)$.

This is obtained:

The expected return function (Equation 10),

$$E[R(Q)] = pQ - cQ - hE(Q - D) \quad (10)$$

The loss function (Equation 11),

$$L(Q) = hE(Q - D) \quad (11)$$

The CVaR function (Equation 12),

$$CVaR_{\alpha}(Q) = \max \left\{ v + \frac{1}{1-\alpha} E[U(pQ - cQ - h \cdot (Q - D) - v)^+] \right\} \quad (12)$$

Since the utility function is assumed $U(\pi)$ to be linear, it is known from the utility function.

$$CVaR_{\alpha}(Q) = \max \left\{ v + \frac{1}{1-\alpha} E[(pQ - cQ - h(Q - D) - v)^+] \right\} \quad (13)$$

The objective function is obtained as

$$\max_Q U_{\lambda}^{\mu}(Q) = \max_Q \left\{ pQ - cQ - hE[Q - D] - \lambda \cdot \max_{v \in R} \left\{ v + \frac{1}{1-\alpha} E[(pQ - cQ - h(Q - D) - v)^+] \right\} - h\mu(Q - D) \right\} \quad (14)$$

Because

$$U_{\lambda}^{\mu n}(Q) = pQ - cQ - hE[Q - D] - \lambda \cdot \max_v \left\{ v + \frac{1}{1-\alpha} \cdot E[(pQ - cQ - h(Q - D) - v)^+] \right\} - h\mu(Q - D) \quad (15)$$

$$\therefore \frac{dU_{\lambda}^{\mu}(Q)}{dQ} = p - c - h \cdot \frac{dE[Q-D]}{dQ} - \lambda \cdot \frac{d}{dQ} \max_{v \in R} \left(v + \frac{1}{1-\alpha} \cdot E[(pQ - cQ - h(Q - D) - v)^+] \right) - h\mu$$

included among these: $\frac{dE[Q-D]}{dQ} = \frac{d}{dQ} \int_0^Q (Q - D)f(D) dD = F(Q)$

Suppose: $\max_{v \in R} \left(v + \frac{1}{1-\alpha} \cdot E[(pQ - cQ - h(Q - D) - v)^+] \right)$ is used in $v = v^*$ take the maximum value.

v^* is the optimal threshold for calculating CVaR. For a given Q , the v^* following conditions are satisfied (Equation 16):

$$v^* = \max_{v \in R} \left\{ v + \frac{1}{1-\alpha} E[(pQ - cQ - h(Q - D) - v)^+] \right\} \quad (16)$$

Again: $\frac{d}{dQ} (pQ - cQ - h(Q - D) + v) = p - c - h$

we get

$$\frac{dU_{\lambda}^{\mu}(Q)}{dQ} = p - c - h \cdot F(Q) - \frac{\lambda}{1-\alpha} E[p - c - h] - h\mu \quad (17)$$

Let $\frac{dU_{\lambda}^{\mu}(Q)}{dQ} = 0$, i.e.

$$\frac{dU_{\lambda}^{\mu}(Q)}{dQ} = p - c - h \cdot F(Q) - \frac{\lambda}{1-\alpha} E[p - c - h] - h\mu = 0$$

Further simplification and collation give,

$$F(Q) = \frac{(p - c)(1 - \alpha - \lambda) - \lambda h}{h(\alpha - 1)} - \mu \quad (18)$$

Principle

$$Q^* = F^{-1} \left[\frac{(p - c)(1 - \alpha - \lambda) + \lambda h}{h(1 - \alpha)} - \mu \right] \quad (19)$$

2) $Q < D \leq Q + M$: In this case, the cost of additional order quantities and out-of-stock penalties need to be considered.

From this, it is obtained:

The expected return function (Equation 20)

$$E[R(Q)] = pQ - cQ - rE(D - Q) - sE(D - Q) \quad (20)$$

where s is the unit cost of the additional order quantity.

Loss function (Equation 21)

$$L(Q) = E(D - Q) \quad (21)$$

CVaR function (Equation 22)

$$\begin{aligned} CVaR_{\alpha}(Q) &= \max_Q \left\{ v + \frac{1}{1-\alpha} E[(U(pQ - cQ - r \cdot (D - Q)^+ - h \cdot (Q - D)^+) - v)^+] \right\} \\ &= \max_{v \in R} \left\{ v + \frac{1}{1-\alpha} E[(U(pQ - cQ - r(D - Q) - s(D - Q) - v))^+] \right\} \end{aligned} \quad (22)$$

Thus, the objective function is obtained as (Equation 23)

$$\max_Q U_{\lambda}^{\mu}(Q) = \max_Q \left\{ pQ - cQ - rE(D - Q) - sE(D - Q) - \lambda \cdot \max_Q \left(v + \frac{1}{1-\alpha} E[(U(pQ - cQ - r(D - Q) - s(D - Q) - v))^+] \right) - \mu \cdot E(D - Q) \right\} \quad (23)$$

because

$$U_{\lambda}^{\mu}(Q) = pQ - cQ - rE(D - Q) - sE(D - Q) - \lambda \cdot \max_{v \in R} \left\{ v + \frac{1}{1-\alpha} E[pQ - cQ - r(D - Q) - s(D - Q) - v]^+ \right\} - \mu \cdot E(D - Q) \quad (24)$$

$$\therefore \frac{dU_{\lambda}^{\mu}(Q)}{dQ} = p - c - r \cdot \frac{dE(D-Q)}{dQ} - s \cdot \frac{dE(D-Q)}{dQ} - \lambda \cdot \frac{d}{dQ} \max_{v \in R} \left\{ v + \frac{1}{1-\alpha} E[pQ - cQ - r(D - Q) - s(D - Q) - v]^+ \right\} - \mu \cdot \frac{dE(D-Q)}{dQ}$$

included among these

$$\frac{dE[D-Q]}{dQ} = \frac{d}{dQ} \int_Q^{Q+M} (D - Q)f(D) dD = f(Q + M) \cdot M - \int_Q^{Q+M} f(D) dD = f(Q + M) \cdot M - F(Q + M) + F(Q)$$

$$\therefore \frac{dU_{\lambda}^{\mu}(Q)}{dQ} = p - c - (r + s + \mu)[f(Q + M) \cdot M - F(Q + M) + F(Q)] - \lambda \cdot \frac{d}{dQ} \max_{v \in R} \left\{ v + \frac{1}{1-\alpha} \cdot E[pQ - cQ - r(D - Q) - s(D - Q) - v] \right\} \quad (25)$$

Assuming that

$$\max_{v \in R} \left\{ v + \frac{1}{1-\alpha} \cdot E[pQ - cQ - r(D - Q) - s(D - Q) - v] \right\}$$

is at the optimal point, the maximum value is taken. For a given Q, the following condition is satisfied (Equation 26):

$$v^* = \max_{v \in R} \left\{ v + \frac{1}{1-\alpha} \cdot E[pQ - cQ - r(D - Q) - s(D - Q) - v] \right\} \quad (26)$$

Let $\frac{dU_{\lambda}^{\mu}(Q)}{dQ} = 0$, and $\frac{d}{dQ} E[pQ - cQ - r(D - Q) - s(D - Q) - v^*] = p - c + r + s$

We get

$$\frac{dU_{\lambda}^{\mu}(Q)}{dQ} = p - c - (r + s + \mu)[f(Q + M) \cdot M - F(Q + M) + F(Q)] - \frac{\lambda}{1-\alpha} (p - c + r + s) = 0 \quad (27)$$

$$\therefore \frac{(p - c)(1 - \alpha - \lambda) - \lambda(r + s)}{(r + s + \mu)(1 - \alpha)} = f(Q + M) \cdot M - F(Q + M) + F(Q)$$

In the limiting case, the product of the retailer's utility and loss aversion coefficients is considered to converge to some constant, and one can continue to simplify the above equation to get,

$$\therefore \frac{(p - c)(1 - \alpha - \lambda) - \lambda(r + s)}{(r + s + \mu)(1 - \alpha)} = F(Q) - F(Q + M)$$

When $Q < D \leq Q + M$ order quantity Q and additional quantity M are sufficient to satisfy all the potential demand, it is assumed here that $F(Q + M) = 1$, then

$$F(Q) = 1 + \frac{(p - c)(1 - \alpha - \lambda) - \lambda(r + s)}{(r + s + \mu)(1 - \alpha)} \quad (28)$$

$$\therefore Q^* = F^{-1} \left[1 + \frac{(p - c)(1 - \alpha - \lambda) - \lambda(r + s)}{(r + s + \mu)(1 - \alpha)} \right] \quad (29)$$

3) $D > Q + M$: In this case, it is still necessary to consider the cost of the additional order quantity and the stock-out penalty. Still, in this case, there is an upper limit on the additional order quantity, denoted as M.

This is obtained:

The expected return function (Equation 30),

$$E[R(Q)] = pQ - cQ - sM - rE[D - (Q + M)] \quad (30)$$

The loss function (Equation 31),

$$L(Q) = E[D - (Q + M)] \quad (31)$$

The CVaR function (Equation 32)

$$CVaR_{\alpha}(Q) = \max_{v \in \mathbb{R}} \left\{ v + \frac{1}{1-\alpha} \cdot E[(U(pQ - cQ - sM - rE[D - (Q + M)] - v))^+] \right\} \quad (32)$$

Thus, the objective function is obtained as (Equation 33)

$$\max_Q U_{\lambda}^{\mu}(Q) = \max_Q \left\{ pQ - cQ - sM - rE[D - (Q + M)] - \lambda \cdot \max_Q \left\{ v + \frac{1}{1-\alpha} \cdot E[U(pQ - cQ - sM - r \cdot E[D - (Q + M)] - v))^+] \right\} - \mu \cdot E[D - (Q + M)] \right\} \quad (33)$$

$$\therefore U_{\lambda}^{\mu}(Q) = pQ - cQ - sM - rE[D - (Q + M)] - \lambda \cdot \max_Q \left\{ v + \frac{1}{1-\alpha} \cdot E[(U(pQ - cQ - sM - r \cdot E[D - (Q + M)] - v))^+] \right\} - \mu \cdot E[D - (Q + M)] \quad (34)$$

included among these

$$\frac{dE[D - (Q + M)]}{dQ} = \frac{d}{dQ} \int_{Q+M}^{+\infty} (D - (Q + M))f(D) dD = F(Q + M) - 1$$

$$\therefore \frac{dU_{\lambda}^{\mu}(Q)}{dQ} = p - c - (r + \mu)(F(Q + M) - 1) - \lambda \cdot \frac{d}{dQ} \max_Q \left\{ v + \frac{1}{1-\alpha} E[U(pQ - cQ - sM - r \cdot E[D - (Q + M)] - v)] \right\}$$

Assuming that

$$\max_Q \left\{ v + \frac{1}{1-\alpha} E[U(pQ - cQ - sM - r \cdot E[D - (Q + M)] - v)] \right\}$$

takes the maximum value at.

For a given Q, the following conditions are satisfied (Equation 35):

$$v^* = \max_Q \left\{ v + \frac{1}{1-\alpha} E[U(pQ - cQ - sM - r \cdot E[D - (Q + M)] - v)] \right\} \quad (35)$$

Let $\frac{dU_{\lambda}^{\mu}(Q)}{dQ} = 0$, and $\frac{d}{dQ} E[U(pQ - cQ - sM - r \cdot E[D - (Q + M)] - v)] = p - c - r(F(Q + M) - 1)$

We got (Equation 36)

$$\frac{dU_{\lambda}^{\mu}(Q)}{dQ} = p - c - (r + \mu)(F(Q + M) - 1) - \frac{\lambda}{1-\alpha} (p - c - r(F(Q + M) - 1)) = 0 \quad (36)$$

Further simplification and collation give,

$$F(Q + M) = 1 + \frac{(p - c)(1 - \alpha - \lambda)}{(r + \mu)(1 - \alpha) + \lambda r} \quad (37)$$

get

$$Q^* = F^{-1} \left[1 + \frac{(p - c)(1 - \alpha - \lambda)}{(r + \mu)(1 - \alpha) + \lambda r} \right] - M \quad (38)$$

In the extended newsvendor model based on $CVaR_{\alpha}$ and the loss aversion criterion, the optimal order quantity Q^* for a risk-aversion retailer should satisfy the following conditions (Equation 6):

By optimizing the objective function, the optimal ordering quantity Q^* calculated by combining the above three scenarios, respectively, is as follows:

$$Q^* = \begin{cases} F^{-1} \left[\frac{(p-c)(1-\alpha-\lambda) + \lambda h}{h(1-\alpha)} \right] - \mu, & D \leq Q \\ F^{-1} \left[1 + \frac{(p-c)(1-\alpha-\lambda) - \lambda(r+s)}{(r+s+\mu)(1-\alpha)} \right], & Q < D \leq Q+M \\ F^{-1} \left[1 + \frac{(p-c)(1-\alpha-\lambda)}{(r+\mu)(1-\alpha) + \lambda r} \right] - M, & D > Q+M \end{cases} \quad (39)$$

Under various demand scenarios, this composite expression illustrates the best ordering approach the store should use to maximize predicted revenue and reduce CVaR. We can effectively ascertain the ideal order amount under various demand scenarios by combining the outcomes of the three scenarios, thereby striking a balance between risk aversion and revenue maximization.

$$U_{\lambda}^{\mu}(Q) = \begin{cases} pQ - cQ - hE[Q-D] - \lambda \cdot \max_{v \in \mathbb{R}} \left\{ v + \frac{1}{1-\alpha} E[(pQ - cQ - h(Q-D) - v)^+] \right\} - h\mu(Q-D), & D \leq Q \\ pQ - cQ - rE(D-Q) - sE(D-Q) - \lambda \cdot \max_{v \in \mathbb{R}} \left\{ v + \frac{1}{1-\alpha} E[(pQ - cQ - r(D-Q) - s(D-Q) - v)^+] \right\} - \mu \cdot E(D-Q), & Q < D \leq Q+M \\ pQ - cQ - sM - rE[D-(Q+M)] - \lambda \cdot \max_{v \in \mathbb{R}} \left\{ v + \frac{1}{1-\alpha} E[(pQ - cQ - sM - r \cdot E(D-(Q+M)) - v)^+] \right\} - \mu \cdot E[D-(Q+M)], & D > Q+M \end{cases} \quad (40)$$

Testify to the end.

Theorem 1 shows how to solve for the optimal ordering quantity of the risk-aversion retailer given the risk-aversion coefficient λ and the loss-aversion coefficient μ and how to solve for the optimal ordering quantity of the risk-aversion retailer given the risk-aversion factor λ and Q^* .

Next, we aim to prove the uniqueness of the optimal ordering quantity for a given utility function, thereby ensuring the robustness of the model's decisions.

Theorem 2: In the utility function (Equation 2),

Assuming the demand distribution function is continuous, the utility function is a concave function of the order quantity Q , and a unique optimal order quantity Q^* exists.

Proof: Based on Theorem 1, the utility function (Equation 2),

1) $D \leq Q$

In this case, no stock-outs occur, and the entire order quantity meets the demand. From this, we get:

Utility function (Equation 15),

By the proof of Theorem 1, it follows that the first-order derivative (Equation 17).

Then the second-order derivative (Equation 41),

$$\frac{d^2 U_{\lambda}^{\mu}(Q)}{dQ^2} = -h \cdot f(Q) \quad (41)$$

$$\because f(Q) > 0$$

$$\therefore \frac{d^2 U_{\lambda}^{\mu}(Q)}{dQ^2} = -h \cdot f(Q) < 0 \quad (42)$$

Then the utility function $U_{\lambda}^{\mu}(Q)$, when $D \leq Q$ is a concave function when and there always exists a unique optimal ordering quantity Q^* , the optimal ordering quantity (Equation 19).

2) $Q < D \leq Q + M$: A partial stock-out occurs in this case, and additional orders must be considered.

This is obtained:

utility function (Equation 24),

From the proof of Theorem 1, it follows that the first-order derivative (Equation 27).

In the limit, the product of the retailer's utility and loss aversion coefficients is considered to converge to some constant, and the second-order derivative is solved as (Equation 43),

$$\frac{d^2 U_{\lambda}^{\mu}(Q)}{dQ^2} = -(r + s + \mu)[f(Q) - f(Q + M)] \quad (43)$$

It has been assumed that the market demand faced by a product retailer follows a normal distribution, where the normal distribution function $f(x)$ is continuous and symmetric, and both sides of the distribution of $f(x)$ are monotonically increasing and take their maximum value at the peak.

The normal distribution function (Equation 44),

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\gamma)^2}{2\sigma^2}} \quad (44)$$

Where γ denotes the mean and σ denotes the standard deviation of the normal distribution.

$$\therefore f(Q) > f(Q + M)$$

$$\therefore \frac{d^2 U_{\lambda}^{\mu}(Q)}{dQ^2} = -(r + s + \mu)[f(Q) - f(Q + M)] < 0$$

Then the utility function $U_{\lambda}^{\mu}(Q)$, when is a concave function when $Q < D \leq Q + M$ and there always exists a unique optimal ordering quantity Q^* , the optimal ordering quantity (Equation 29)

3) $D > Q + M$: In this case, the additional order quantity limit M . is thus obtained:

Utility function (Equation 34)

From the proof of Theorem 1, it follows that the first-order derivative.

Then the second-order derivative (Equation 45)

$$\frac{d^2 U_{\lambda}^{\mu}(Q)}{dQ^2} = -\left(r + \mu - \frac{\lambda r}{1 - \alpha}\right) F(Q + M) = \left[\left(\frac{\lambda}{1 - \alpha} - 1\right)r - \mu\right] F(Q + M) \quad (45)$$

According to the practical significance of each parameter, it can be seen that $\left(\frac{\lambda}{1 - \alpha} - 1\right)r - \mu < 0$, and $F(Q + M) > 0$, there are $\frac{d^2 U_{\lambda}^{\mu}(Q)}{dQ^2} < 0$.

Then the utility function $U_{\lambda}^{\mu}(Q)$, when $D > Q + M$ is a concave function when and there always exists a unique optimal ordering quantity Q^* , the optimal ordering quantity (Equation 38)

In summary, the utility function $U_{\lambda}^{\mu}(Q)$ is concave concerning the ordering quantity Q , and a unique optimal ordering quantity Q^* exists.

Under this setting, as the order quantity increases, the weight of out of stock related losses decreases and the holding/additional related costs increase. The objective function exhibits a unimodal shape of “first rising and then falling” (or quasi concave/concave under common distributions), therefore there exists a unique inflection point Q^* , which is not as good as this point in balancing “normal returns” and “tail safety” no matter how many or few it is.

Testify to the end.

By Theorem 1 and Theorem 2, it can be seen that for a risk-aversion and loss-aversion retailer, assuming that the out-of-stock cost is non-zero when its risk aversion, loss aversion coefficients, and other relevant parameters are given, then its unique optimal order quantity Q^* can be obtained by Theorem 1(formula (39), and the objective function can also be obtained by formula (40).

This model not only helps companies make more informed decisions in the face of fluctuating market demand and supply chain disruptions but also enables optimal supply chain management by optimizing inventory management strategies and reducing inventory holding costs and out-of-stock costs.

RESULTS AND DISCUSSION

1. Data Source and Model Background

To validate the extended Newsvendor model based on CVaR proposed in this article, we selected 12 consecutive months of store sales data from a single brand electric vehicle retailer in Heilongjiang, China, as the validation sample. This data encompasses the entire one-year sales cycle of the region and reflects the typical seasonal fluctuations and sources of uncertainty in the electric vehicle market. On the one hand, factors such as quarterly promotion pace, holidays, and model launches lead to systematic fluctuations in demand in different months; On the other hand, external shocks such as subsidies/policy adjustments, progress of charging facility deployment, supply chain arrival rhythm, and price changes will amplify the asymmetric losses of demand tail risks and stockouts/unsold products in local months. Therefore, the 12-month data includes both regular seasonal patterns and random fluctuations driven by policy and supply and demand disturbances, which aligns with the research objective of measuring tail loss and evaluating order decision robustness using CVaR in this paper.

Table 1: Monthly number of EV units sold by the retailer

Month	Volume of sales
1	27
2	30
3	37
4	34
5	41
6	44
7	37
8	41

Table 1: Monthly number of EV units sold by the retailer (Cont.)

Month	Volume of sales
9	34
10	30
11	27
12	34

Based on the above empirical data, we optimized and validated the monthly order quantity using Python: Pandas was used for data organization and result output, NumPy/SciPy was used for random sampling and distribution fitting, and Matplotlib was used for visualization. Under the Rockafellar Uryasev (R-U) formulation (also known as expected shortage), numerical approximation of $CVaR_\alpha$ is performed based on discrete samples. Based on historical sales data, characterize the demand distribution monthly and establish a sampling scale. Conduct approximately 5000 Monte Carlo samplings per month to evaluate the target value of candidate order quantities. Subsequently, a “grid+local” joint search is employed within a bounded interval proportional to the average monthly demand to determine the optimal order quantity Q^* . The RMSAE and Accuracy, as defined in the article, are then calculated based on this result. This implementation does not have a random seed set, so there may be slight differences in the sampling sequence between different runs. However, the conclusion remains stable within the scale of our problem.

2. RMSAE and Accuracy Validation Method

This paper employs Accuracy and RMSAE as the primary evaluation metrics to assess the fit between the model’s predicted values and the actual sales data. Accuracy measures the relative error between the predicted and actual values, and its formula is as follows (Equation 46):

$$\text{Accuracy} = \frac{1}{n} \sum_{i=1}^n \left(1 - \frac{|y_i - \hat{y}_i|}{y_i} \right) \times 100\% \quad (46)$$

Where y_i represents the actual sales data and $\hat{y}_i$ is the model’s predicted optimal order quantity. The closer Accuracy is to 1, the smaller the gap between the expected and actual values.

RMSAE measures the error between the predicted and actual sales values, and its formula is (Equation 47):

$$\text{RMSAE} = \sqrt{\frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|} \quad (47)$$

A lower RMSAE indicates a higher predictive accuracy of the model.

3. Model Validation Process

We generated the optimal order quantity for 12 months of the year using optimized code implemented in Python. This study conducted 5,000 Monte Carlo samplings per month for the evaluation of target values and indicators. The code does not have a fixed random state, so there may be slight sampling differences in the results between repeated runs; however, the overall conclusion is not affected.

The following formulas were used in the code to calculate the utility function and CVaR in the extended newsvendor model (Equation 1).

Based on a confidence level of $\alpha = 0.05$ (i.e., the retailer is 95% confident in meeting the sales target), we calculated the CVaR for each ordering strategy, optimizing it using actual sales data and stockout penalties.

To enhance the model's sensitivity to risk aversion, loss aversion, and predictive accuracy, we adjusted the penalty terms for risk aversion and loss aversion to reflect the dynamic intensity of these factors. Specifically, the following adjustments were made (Equation 48 and Equation 49):

$$\lambda_{\text{adjusted}} = \lambda \times 80 \times \left(\frac{\text{mean_sales}}{40} \right) \quad (48)$$

$$\mu_{\text{adjusted}} = \mu \times 60 \times \left(\frac{\text{mean_sales}}{40} \right) \quad (49)$$

Based on average sales volume, this adjustment method ensures that as sales increase, the model's requirements for risk aversion and loss aversion also increase, making it better suited to dynamic market demands. By increasing the weight of the penalty terms, the model is guided to select more robust ordering strategies.

Additionally, to improve the model's sensitivity to prediction errors, the RMSE penalty term was magnified (Equation 50):

$$\text{RMSE}_{\text{adjusted}} = 150 \times \text{RMSE}(Q, \text{actual_sales}) \quad (50)$$

This adjustment enables the model to emphasize the deviations from actual sales data in the ordering quantity predictions, thereby improving forecast accuracy.

The determination of core behavioral parameters (λ, μ) in this article follows the process of "baseline coefficient $\rightarrow$ sales scaling $\rightarrow$ small-scale selection": first, set a baseline (λ, μ) that does not change with the month, and then use the average sales scaling formula given in the previous text (while using a consistent amplification factor caliber for the RMSE penalty term) to obtain the effective coefficient for the current month. It should be emphasized that the multiplier is not manually specified, but obtained through sensitivity testing of small-scale discrete grids and symmetric disturbances: under the premise of fixed (p, c, s, h, r, M) and confidence level α , the baseline coefficient combination is repeated month by month, and Monte Carlo evaluation is used to solve Q^* to calculate the indicators, with the overall utility of the sample period as the main factor and RMSE/fitting degree as the auxiliary factor for selection; The final adoption is the minimum multiplier that can smooth Q^* fluctuations without compromising the error index, without reducing overall utility.

4. Model Validation Results

The validation results calculated using the above formulas show that the model's average accuracy is 98.08%, indicating a high level of precision in predicting market demand in most cases. (Figure 1)

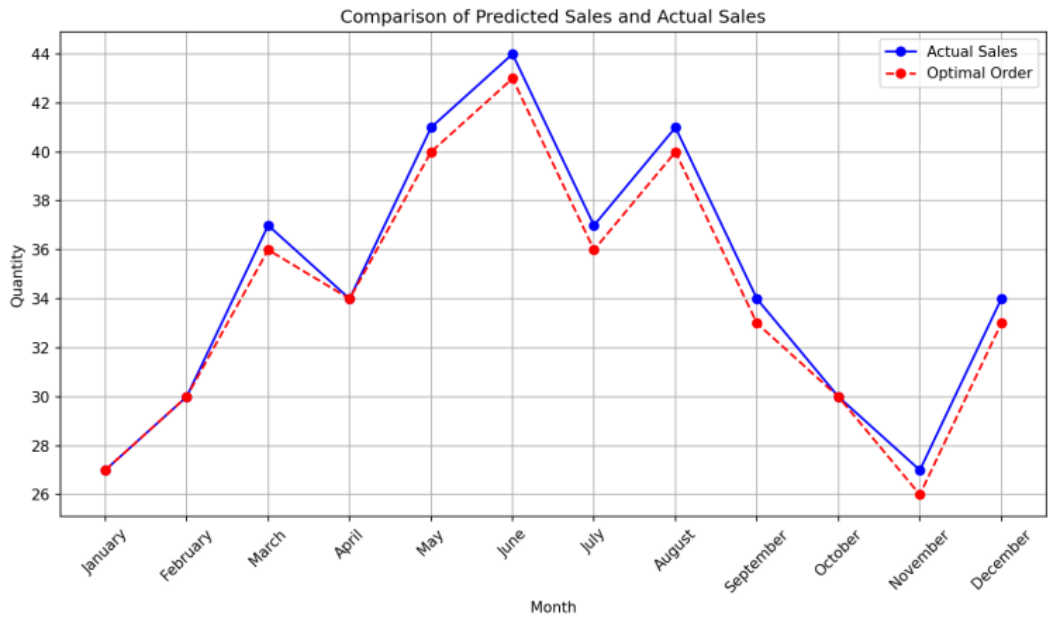


Figure 1: Comparison of predicted sales and actual sales

The calculated RMSAE is 0.8 units, meaning the average difference between the model's predicted optimal ordering quantity and the actual sales data is 0.8 units per month. (See Figure 2) This error demonstrates the model's practical value in solving inventory optimization problems in the electric vehicle supply chain.

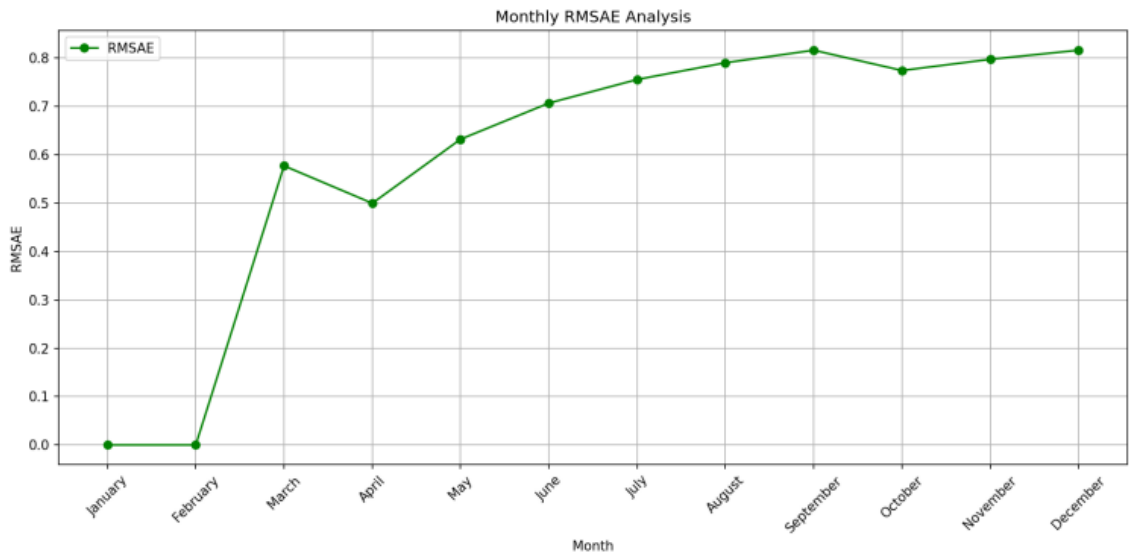


Figure 2: Error analysis chart

According to the validation results, the extended newsvendor model based on CVaR developed in this paper demonstrates substantial value and accuracy in demand forecasting and inventory management for the electric vehicle market. However, parameter weight adjustments based on input data are necessary to enhance its effectiveness.

CONCLUSION

This study developed an extended Newsvendor model within the CVaR framework to characterize tail risks associated with demand uncertainty in the electric vehicle supply chain and optimize ordering decisions accordingly. Based on the actual sales data of a specific retailer for 12 consecutive months, the results showed that the model had good fitting and robustness during the sample period, with an average prediction accuracy of approximately 98.08% and an RMSAE of approximately 0.8 vehicles per month. This indicates that the introduction of the CVaR ordering strategy can effectively mitigate downside risks while maintaining service levels, considering extreme losses.

From the perspective of parameter sensitivity, an increase in the risk aversion coefficient λ will strengthen the focus on tail losses, making the overall ordering strategy tend towards conservatism. The improvement of the loss aversion coefficient focuses on reducing the average loss exposure, which, in most cases, aligns with the direction of risk aversion and jointly promotes a reduction in the order quantity. Its effect is more significantly affected by the relative relationship between holding/discount costs (h) and additional costs (s). Relatively speaking, the confidence level (α) mainly plays a role in “amplifying or converging tail weights”: at higher α values, the above coefficient adjustments have a more significant impact on the order quantity; When the additional upper limit (M) is small, the tail of stockouts exceeding $Q+M$ becomes heavier, and the conservative effect is also more substantial; At the same time, increasing the out of stock penalty (r) will push up the target service level, offsetting the aforementioned downward trend to some extent.

At the practical level, this model provides a quantifiable basis for enterprises to develop ordering plans in uncertain demand and policy environments. On the one hand, it can differentiate risk aversion and loss aversion based on risk tolerance; On the other hand, by combining operational constraints such as additional upper limit M , out-of-stock penalty r , and holding/additional costs, a parameter combination consistent with service commitments is formed to achieve more robust stocking decisions at different market stages.

Compared to previous studies that directly embedded CVaR into newsvendor targets, the difference in this paper lies in: firstly, using a utility based expression, risk avoidance and loss avoidance are hierarchically weighted within the objective function, and the mechanism is used to distinguish the effects of tail and expected losses on order quantity; The second is to propose three scenario divisions around the limited addition upper limit M (no shortage/no addition; no shortage/limited addition; with shortage and limited addition) and provide first-order conditions and existence explanations based on them; The third is to conduct monthly evaluations on real business data and disclose the Monte Carlo scale and evaluation indicators.

Of course, the conclusions of this study are still subject to several premises. Firstly, monthly demand is approximated by a normal distribution, and a sampling scale is set based on historical sales. If the actual distribution is skewed or has a fat tail, the estimation of CVaR and optimal order quantity may deviate; Secondly, the empirical sample comes from a single retailer and a single year (12 months), and the heterogeneity of regions and channels needs further testing; Thirdly, the study did not incorporate exogenous factors such as raw material prices, subsidies/policy adjustments, investment in charging infrastructure, and the pace of vehicle launches into a structured explanation, making it more suitable for periods when prices and policies are relatively stable; Fourthly,



the numerical implementation does not have a fixed random seed, and there may be slight differences in the sampling sequences of different runs (which does not affect the main conclusion of this article).

LIMITATIONS AND RECOMMENDATIONS

This study shows that the extended newsvendor model based on CVaR significantly improves the model's flexibility in handling uncertainty by dynamically adjusting the risk aversion and loss aversion coefficients. To enhance the model's robustness and predictive accuracy in varying market demand situations, it's essential to carefully adjust its parameter weights according to the characteristics of the input data. In practical terms, the model may be prone to overfitting or underfitting, but these issues can be effectively addressed through appropriate parameter adjustments. Practically, adjustments to dynamic parameters ought to rely on a thorough examination of past sales figures, encompassing seasonal variations, shifts in policies, and uncertainties in market demand. Through these evaluations, crucial factors such as risk aversion and loss aversion coefficients can be suitably adjusted in the model to ensure effective forecasting of future demand. The method of dynamic adjustment reduces the model's reliance on datasets and enhances its ability to generalize in complex and volatile market conditions.

Future research can further explore cross-subject and multi-cycle scenario extensions, as well as how to incorporate more external variables (such as policy changes, competitor strategies, etc.) into the model to achieve dynamic optimization of parameters, thereby enhancing the adaptability and prediction accuracy of the model under extreme market conditions.

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