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MODELLING AND SIMULATION OF PURCHASING DECISION BY DATA-DRIVEN DEMAND

Fang, X.*,**,# & Wang, Y.***
* Collaborative Innovation Center for Chongqing's Modern Trade Logistics & Supply Chain, Chongqing Technology and Business University, Chongqing 400067, China
** International College, Krirk University, Bangkok 10220, Thailand
*** School of Business Administration, Chongqing Technology and Business University, Chongqing 400067, China
E-Mail: xin_f@ctbu.edu.cn, wangyu43@ctbu.edu.cn (# Corresponding author)

Abstract
This paper constructs a data-driven demand purchasing confidence rule-based model based on the theory of evidential reasoning to address the problem of purchasing decision bias in which the decision maker anchors the prior demand. First, we apply a synthetic algorithm to reason about the confidence structure distribution of the purchasing decision and then iteratively optimize the purchasing quantity according to the confidence structure distribution to minimize the cost loss function. Finally, we choose the average cost loss and service level value as the evaluation indexes to explore the purchasing confidence rule model. The simulation shows that compared with the expected purchasing decision based on the stochastic cumulative distribution function, the decision based on the confidence structure distribution can reduce the purchasing decision bias, manifested in the lower mean cost loss and a higher mean value of service level. Sensitivity analyses of the number of rules, product shelf life, and critical values show that the purchasing confidence rule base is highly adaptable.
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Key Words: Purchasing, Confidence Rule Base Modelling, Data-Driven Demand, Simulation

1. INTRODUCTION

Purchasing is an important issue in business operations management, and reasonable purchasing levels can help firms control inventory, improve service levels, and contribute to the overall performance of themselves and their supply chains [1, 2]. Fisher and Raman, working on a survey based on purchasing by mid- to high-end skiwear firms, found that increasing the precision of purchases would add sixty percent of new profits [3]. A case study by Katok on map purchasing decisions of a firm revealed that optimal purchasing decisions could help firms save more than USD 8 hundred thousand per year [4]. Correspondingly, there are numerous cases of companies losing profits due to poor purchasing decisions. For example, a surgical supply company in the United States suffered a 25 percent drop in sales in the second quarter of the year due to an underestimation of inventory levels on hospital shelves, which amounted to a loss of USD 22 million [5].

Therefore, mathematical modelling and simulation optimization of purchasing decisions have become the focus of attention in academia and industry [6], and the challenge is the uncertainty of market demand [7-11]. Most of the literature recommends that the uncertain demand be converted to a stochastic probability distribution and that the expected optimal procurement be explored based on the quantile of the cumulative distribution of the stochastic demand or the kth order moments of the stochastic demand [12-17]. For example, the classical newsvendor problem is based on the random probability theory of determining the ordering quantity to minimize the expected total cost caused by over-ordering versus under-ordering [7]. Zhang et al. investigate the mean-variance-skewness-kurtosis-based model of the newsvendor problem based on the probability distribution model [18]. However, an empirical study by Schweitzer and Cachon [19] reveals that decision makers' actual purchases systematically deviate from the theoretical optimum by showing that firms' purchasing decisions are anchored to the purchases made in the previous cycle, i.e., the current purchasing decisions chase the value of the prior demand. Indeed, the negative socio-economic impacts of this supply-demand imbalance have received much attention in various fields. In particular, China's fourteenth five-year plan for national economic and social development emphasizes the formation of a higher level of dynamic equilibrium in which demand leads to supply and supply creates demand. This is a new trend in the relationship between supply and demand, which requires it to permeate all aspects of product production, consumption, and distribution.

The knowledge and experience of firm managers affect purchasing decision-making behaviour, and integrating their knowledge and experience can effectively improve the accuracy of purchasing decisions [20]. A purchasing confidence rule base synthesized iteratively from evidential reasoning theory provides a solution to mitigate purchasing decision bias [21]. A confidence rule base is an information representation that can deal with uncertain information, integrating qualitative and quantitative knowledge [22]. It can transform the uncertainty of the information into a certain confidence probability through rules and express it utilizing a confidence distribution, as well as transferring it without loss in the process of combining the rules until the synthesis of the final result [23]. Confidence rule bases have been applied in several fields, such as bridge risk assessment [24], cyber security posture prediction [25], fault detection [26], and cold logistics service quality assessment [27]. These applying cases reveal that the confidence rule based on evidential reasoning theory is superior to traditional prediction methods.

With practical need, this paper concentrates on the problem of reducing the purchasing decision bias of decision-makers anchored to up-front demand. The phenomenon of anchoring purchasing decisions to prior sales demonstrates the importance of historical demand data, which provides an entry point for the research in this paper. First of all, based on the historical product sales data and its mean and variance, the purchasing decision bias and the market demand trend are used as the input and output of the purchasing confidence rule base. Next, the numerical characteristics of inputs and outputs are statistically analysed to design the arithmetic rules of the purchasing confidence rule base, and the decision maker's empirical knowledge is integrated to construct the initialized purchasing confidence rule base. Third, the theory of evidential reasoning and the iterative synthesis algorithm are used to reason about the confidence structure distribution of the purchasing decision, and the premise attribute values, rule weights, and the resultant confidence distribution are trained with the help of the minimize function in the Python Scientific Computing Optimization Library. Finally, the performance of the purchasing confidence rule base is calculated by the normal distribution cumulative distribution function with the mean value of cost loss and the mean value of service level as the evaluation indexes, and the confidence purchasing decision of the enterprise is elaborated through the sensitivity analyses of the number of rules, the shelf life, and the critical value.

The innovations of this paper are, firstly, to provide a new decision-making method for purchasing in firms in uncertain demand environments. This paper constructs a purchasing confidence rule base based on demand data. It iteratively synthesizes the confidence structure distribution of purchasing decisions using evidential reasoning theory, in which the purchasing decision-making method differs from the decision-making paradigm based on expectation optimality. Secondly, the demand data-driven procurement confidence rule base has better performance and adaptability. This paper's purchasing decision based on confidence structure distribution inference reduces the purchasing decision bias and has lower mean cost loss and higher mean service level. Meanwhile, the simulation optimization reveals that the mean cost loss and the mean service level improve with the number of rules, the shelf life, or the critical value, demonstrating the excellent adaptability of the purchasing confidence rule base.

2. PROBLEM DESCRIPTION

To solve the product sourcing problem in demand uncertainty environments, the literature in supply chain management usually converts such uncertainty into random probability distributions. It relieves it with the help of the expected effect theory [1]. In particular, under the assumption that the demand D obeys a cumulative distribution function of F, the decision maker calculates the expected ordering Q based on the expected utility theory to minimize the loss function $\boldsymbol{L}$ as Eq. (1). Namely:

$$Q^* = argmin_{Q\in\mathcal{R}^+}\boldsymbol{L} = argmin_{Q\in\mathcal{R}^+}\{s\cdot(Q-D)^+ + g\cdot(D-Q)^+\} \tag{1}$$

where s is the loss incurred per unit of surplus product, and g is the loss incurred per unit of out-of-stock product. From the first-order optimality condition, the firm's expected optimal ordering Q^* satisfies $F(Q^*) = \frac{g}{S+g}$, especially when $s = c - v, g = p - c$, we can get: $Q^* = F^{-1}\left(\frac{p-c}{p-v}\right)$.

The cumulative distribution function F has a profound effect on the expected ordering Q^*. This requires the decision maker to have sufficient knowledge to describe the analytical form of the function and ensure that the function portrays actual demand to the greatest extent possible. This paper proceeds from the analysis of historical sales data, establishes a purchasing confidence rule base based on evidential reasoning theory to replace the cumulative distribution function F, minimizes the loss function on a parameter-optimized confidence structure distribution, and then calculates the confidence purchasing Q^* that reduces the cost loss's mean value and improves the service level's value.

The historical sales data of the product is decomposed into a training set and a test set. The role of the training set is to construct and optimize the purchasing confidence rule base, based on which the unitized inputs in the test set are computed to reason about the confidence purchasing. At the same time, the expected purchasing is calculated based on the assumption of the cumulative distribution function of the normal distribution. Then, the cost loss of the two is computed by comparing the confidence purchasing, expected purchasing, and actual purchasing in the test set. Compare the confidence procurement, expectation procurement, and actual procurement in the test set sequentially and calculate the cost loss and service level mean of the two to evaluate the performance and adaptability of the procurement confidence rule base.

3. MODELLING

3.1 Procurement model

A initialize the procurement confidence rule base $R(\bar{X}_1, \bar{Y}_1, D)$ can be constructed with a given prerequisite attribute $\bar{X}_1$, output $\bar{Y}_1$, and confidence structure D. The k^{th} rule can be shown as Eq. (2).

$$R_k \mapsto IF\ x\ is\ \bar{x}_i, THEN\left\{\left(D_1, \beta_{1,k}\right), \cdots, \left(D_N, \beta_{N,k}\right)\right\} \tag{2}$$

with a weight θ_k, activation weights ω_k, for all $k \in \{1, \cdots, K\}$.

Where, $\omega_k = \theta_k\alpha_k / \sum_{i=1}^{K}\theta_i\alpha_i$ according to literature [28], and α_k denotes the confidence probability that the input x is subordinate to the value of the premise attribute in the k^{th} rule. The value of α_k is calculated as Eq. (3).

$$\begin{cases} \alpha_{l+1} = \frac{x_k - \bar{x}_l}{\bar{x}_{l+1} - \bar{x}_l}, \bar{x}_l \le x_k \le \bar{x}_{l+1} \\ \alpha_l = 1 - \alpha_{l+1}, \bar{x}_l \le x_k \le \bar{x}_{l+1} \\ \alpha_s = 0, s \ne l, l+1 \end{cases}, k = 1, 2, \cdots, K; x \in X_1, \bar{x}_l \in \bar{X}_1 \tag{3}$$

Combining the above K rules then constitutes the initialized procurement confidence rule base $R(\bar{X}_1, \bar{Y}_1, D)$, and the distribution of confidence structures β_n reasoned by the iterative synthetic algorithm based on evidential reasoning is shown as Eq. (4).

$$\beta_n = \frac{\mu\times\left[\prod_{k=1}^{K}\left(\omega_k\beta_{n,k}+1-\omega_k\sum_{i=1}^{N}\beta_{i,k}\right)-\prod_{k=1}^{K}\left(1-\omega_k\sum_{i=1}^{N}\beta_{i,k}\right)\right]}{1-\mu\times\prod_{k=1}^{K}(1-\omega_k)}, n = 1, 2, \cdots, N \tag{4}$$

where: $\mu = \left[\sum_{n=1}^{N}\prod_{k=1}^{K}\left(\omega_k\beta_{n,k} + 1 - \omega_k\sum_{i=1}^{N}\beta_{i,k}\right) - (N-1)\prod_{k=1}^{K}\left(1 - \omega_k\sum_{i=1}^{N}\beta_{i,k}\right)\right]^{-1}$.

Given any unitary input, one can compute the confidence structure $S = \{(D_n, \beta_n)\}_{n=1}^{N}$ of the iterative synthesis. The resulting confidence purchase $\tilde{Y}$ for the next period based on the current period's sales volume decision is as Eq. (5),

$$\tilde{Y} = \sum_{n=1}^{N}(D_n\beta_n)\,[\max(\Delta Y_1) - \min(\Delta Y_1)] + \min(\Delta Y_1) + D_t \tag{5}$$

3.2 Parameter optimization model

The parameter optimization model is given as Eq. (6):

$$Min_Q\ L = mean\{(p-c)(D-Q)^+ + (c-v)(Q-D)^+\} \tag{6}$$

$$s.t.\ \begin{cases} \beta_{n,k} \in [0,1]; n = 1,\cdots,N; k = 1,\cdots,K \\ \sum_{n=1}^{N}\beta_{n,k} = 1; k = 1,\cdots,K \\ \theta_k \in [0,1]; k = 1,\cdots,K \\ x_i - x_{i+1} \le \delta_i; x_i, x_{i+1} \in \bar{X}_1 \end{cases}$$

The optimization objective is the minimum cost loss means, which is subject to the following four constraints: (1) confidence structure distribution constraint, which requires that the distribution of the confidence structure under each rule lies in the interval [0, 1]; (2) a unitization constraint, i.e., the sum of the confidence structure distributions under each rule is equal to 1; and (3) a rule weight constraint, i.e., the importance assigned to each rule lies between the intervals [0, 1]; (4) prerequisite attribute reference value constraints, which require any input reference value to have an increasing ordering. The optimization of the model is done through the minimize function in the Python Scientific Computing Optimization Library, which passes a one-dimensional array to the objective function and its gradient and iterates based on the optimization method to return the optimized parameters and objective values from the sourcing confidence rule base.

4. SIMULATION

4.1 Demand data

The simulation dataset is derived from the Kaggle database, which records the sales information of a product retailed by a retailer in Brazil for 935 days. The time series distribution of these data is shown by the dots in Fig. 1, which shows that the retail data of this product is highly stochastic and nonlinear, which poses a challenge to the purchasing decision of the firm. There are three modes: first, the first 25 % of the demand dataset is selected as the training data, and the remaining data is the test data (Q1); second, the first 50 % of the demand dataset is selected as the training data and the remaining data is the test data (Q2); and third, the first 75 % of the demand dataset is selected as the training data and the remaining data is the test data (Q3). Each Q1, Q2, and Q3 rule base contains seven arithmetic rules, as shown in Table I.

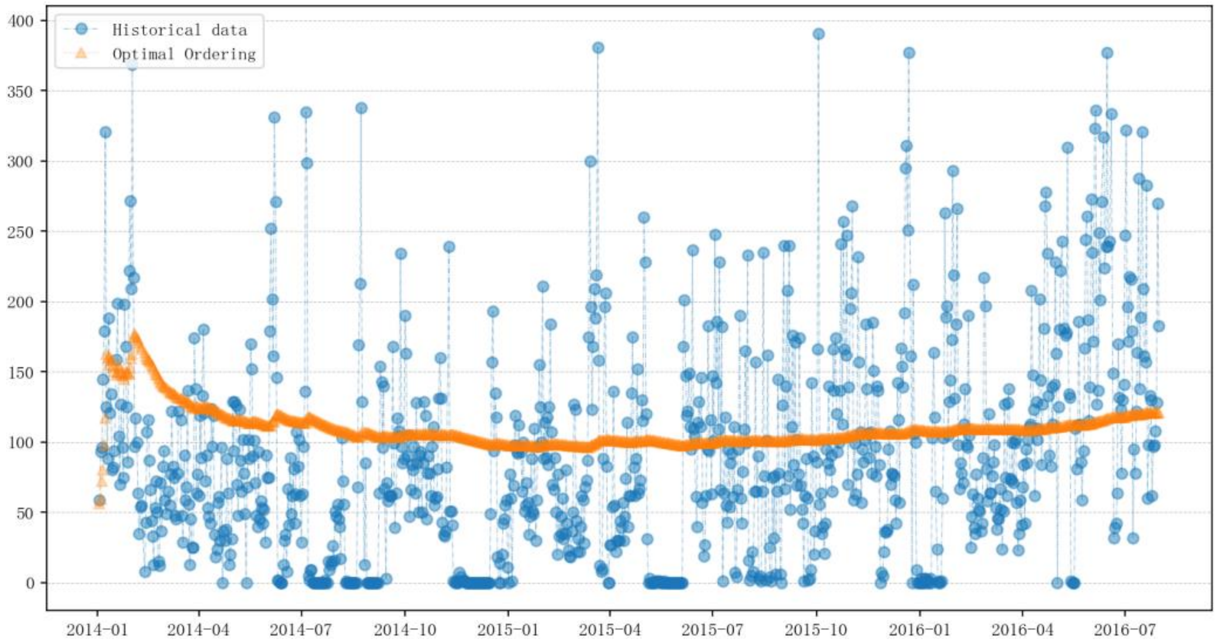

Figure 1: Time-series distribution of simulated simulation data and training data.

Table I: Initializing the procurement belief rule base of simulation.

Mode	Num	Weight	Input	Output	Results				
					0.0000	0.2500	0.5000	0.7500	1.0000
Q1	1	1.0000	0.0000	0.1724	0.3104	0.6896	0.0000	0.0000	0.0000
	2	1.0000	0.1292	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
	3	1.0000	0.5414	1.0000	0.0000	0.0000	0.0000	0.0000	1.0000
	4	1.0000	0.7621	0.5862	0.0000	0.0000	0.6552	0.3448	0.0000
	5	1.0000	0.7685	0.4969	0.0000	0.0124	0.9876	0.0000	0.0000
	6	1.0000	0.8562	0.8986	0.0000	0.0000	0.0000	0.4056	0.5944
	7	1.0000	1.0000	0.6673	0.0000	0.0000	0.3308	0.6692	0.0000
Q2	1	1.0000	0.0000	0.1440	0.4240	0.8560	0.0000	0.0000	0.0000
	2	1.0000	0.2253	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
	3	1.0000	0.5920	1.0000	0.0000	0.0000	0.0000	0.0000	1.0000
	4	1.0000	0.7651	0.6349	0.0000	0.0000	0.4604	0.5396	0.0000
	5	1.0000	0.7651	0.4929	0.0000	0.0284	0.9716	0.0000	0.0000
	6	1.0000	0.8721	0.8986	0.0000	0.0000	0.0000	0.4056	0.5944
	7	1.0000	1.0000	0.6673	0.0000	0.0000	0.3308	0.6692	0.0000
Q3	1	1.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
	2	1.0000	0.2394	0.0732	0.7072	0.2928	0.0000	0.0000	0.0000
	3	1.0000	0.5049	1.0000	0.0000	0.0000	0.0000	0.0000	1.0000
	4	1.0000	0.7456	0.5464	0.0000	0.0000	0.8144	0.1856	0.0000
	5	1.0000	0.7657	0.4982	0.0000	0.0072	0.9928	0.0000	0.0000
	6	1.0000	0.8689	0.8982	0.0000	0.0000	0.0000	0.4072	0.5928
	7	1.0000	1.0000	0.6607	0.0000	0.0000	0.3572	0.6428	0.0000

4.2 Simulation analysis

Simulation results of the purchasing confidence rule base are explored from two perspectives: cost loss and service level. Define the mean cost loss as $loss = mean_{D \in \Phi_2}[(p-c) \cdot (D-Q)^+ + (c-v) \cdot (Q-D)^+]$, and the mean values of cost loss for the corresponding test sets in the Q1 to Q3 models are shown in Fig. 2. The results show that the mean value of cost loss (confidence loss) generated by the ordering decision (R) based on the reasoning of the purchasing confidence rule base is lower than the value (expectation loss) based on the expected optimal ordering decision (E), with the lowest confidence loss of 215.40 in the Q2 model. This value corresponds to a reduction in the expectation loss of 23.78 percent.

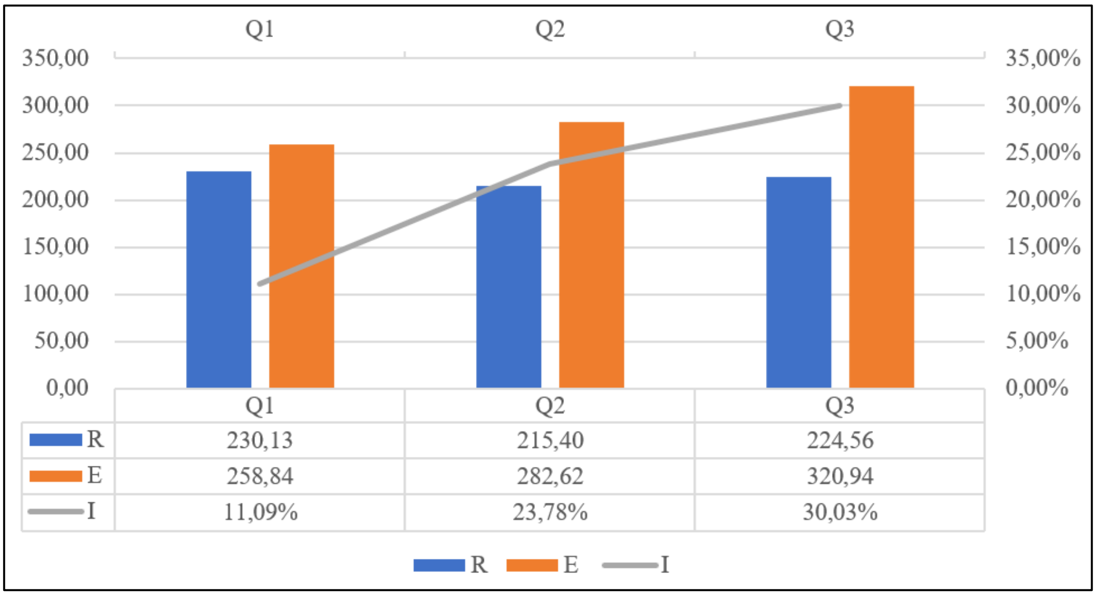

Figure 2: Comparison between the believed cost loss means, and the expected cost loss means.

Second, the purchasing decision based on the reasoning of the purchasing confidence rule base has a more satisfactory service level and outperforms the value corresponding to the optimal ordering decision based on expectations. Define the ordering level to be $\Delta = \frac{Q}{D} \times 100\%$, and Fig. 3 shows the average single-cycle service level values for different ordering strategies for the three groups of models. The results show that the ordering inferred by the purchasing confidence rule base under the advantage of cost leadership still has a high service level; in particular, when weighing both cost and service level, choosing the Q2 model not only reduces the mean cost loss by 23.78 % but also improves the average service level value to 86.38 %, which is superior to that of the expectation-optimal ordering decision. It is worth noting that the expected optimal ordering generates high inventories, with ordering level averages of 509.22 %, 592.26 %, and 486.05 % for the three models, respectively, which are much higher than the ordering levels under the purchasing confidence rule base (corresponding to 280.96 %, 324.67 %, and 226.62 %).

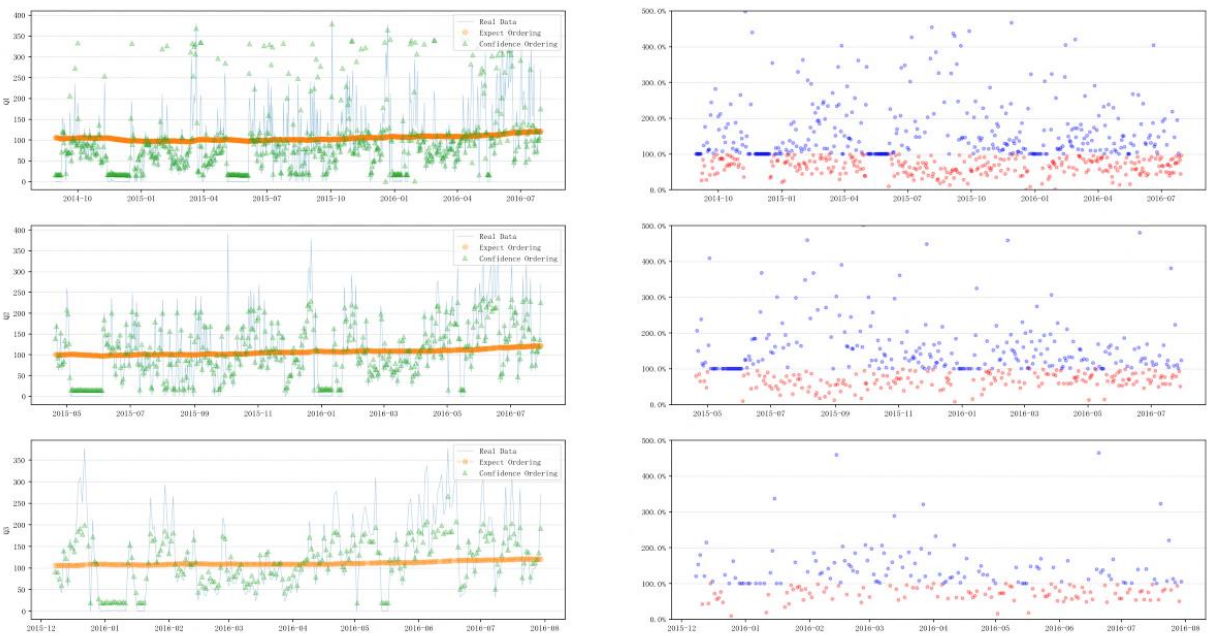

Figure 3: Time-series distribution of belief purchases versus expectation purchases.

4.3 Sensitivity analysis of rule numbers

Rules are the basis for constructing a purchasing confidence rule base, and if the rules can reveal the functional relationship between inputs and outputs, the constructed purchasing confidence rule base will have strong inference ability. However, when the inputs and outputs are strongly stochastic and nonlinear, the design of reasonable rule contents and the number of rules are concerned with the inference results. Literature shows that statistical analysis of data and expert experience are the standard methods for constructing rules, and this paper focuses on creating rules in the purchasing confidence rule base with the help of the extensive and minimal value features of the training set data. The sensitivity analysis of the rule numbers to the mean value of cost loss and the mean value of service level for the three models described in the previous section for setting parameters (p, c, v) = (10, 4, 1) is shown in Fig. 4.

The results show that rule count changes impact the procurement ordering decisions inferred by the procurement confidence rule base. The impact indicates that the confidence loss is superior to the expected loss regardless of the rule number, and the corresponding average value of the service level needs to be discussed in a case-by-case manner. To be specific, (1) when the number of rules is small (or large), the Q2 mode (or the Q3 mode) is the best choice for the decision maker because the lowest confidence loss and the highest confidence level are generated under this mode; (2) when the number of rules is moderate, the choice of mode needs to be weighed against the confidence cost and the confidence level because at this time, the Q2 mode generates the lowest confidence cost, but the best confidence level is obtained under the Q3 mode is obtained under the Q3 mode.

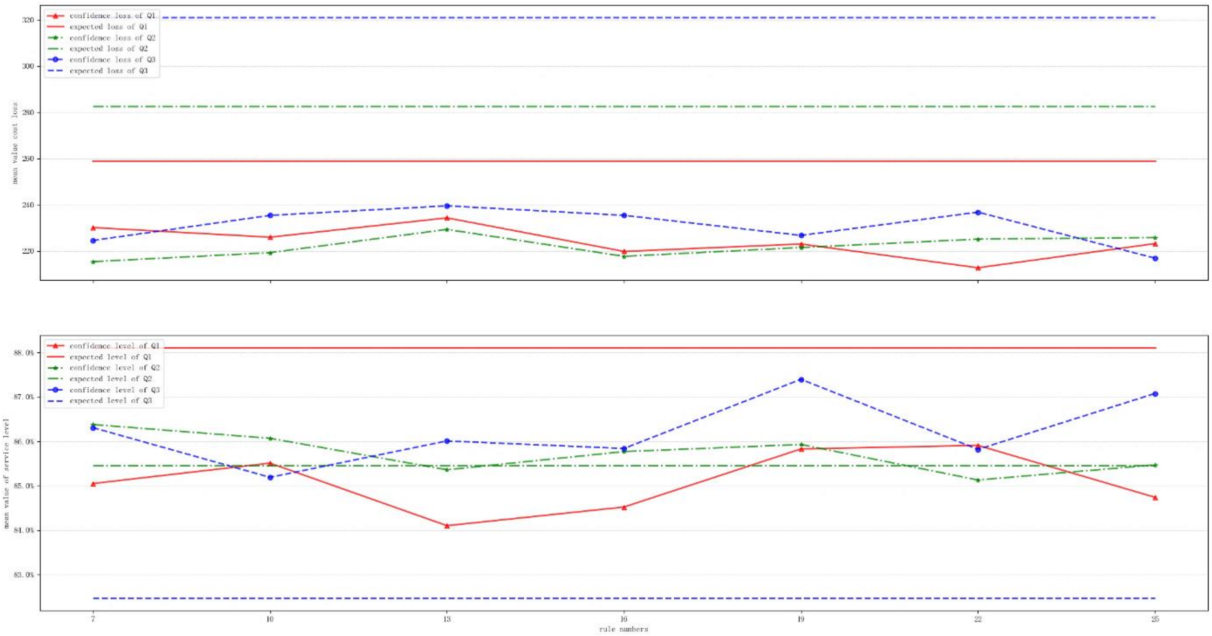

Figure 4: Sensitivity analysis of the rule number.

4.4 Sensitivity analysis of shelf cycles

Shelf life in this context refers to the period between when a product is stocked on the shelf and when it is withdrawn from the market, and in practice, many products have a limited shelf life. For example, the shelf life of instant cooked food or fresh milk in bags is usually one day, and the shelf life of seasonal vegetables, fish, and flowers is generally less than one week. Shelf life sensitivity analysis facilitates product inventory management, cost savings, and service level control. The purchasing confidence rule base has been explored previously to reason about single-cycle purchasing decisions, and based on the results of this reasoning, the impact of shelf-life changes on the mean cost loss and the mean service level value is shown in Fig. 5.

The results show that both the mean cost loss and the mean service level increase with increasing shelf life, but both are better than their counterparts generated by expected ordering. (1) Both confidence loss and expectation loss increase with increasing shelf life, and both confidence loss and its increase are lower than expectation loss and its increase. (2) Both confidence level and expectation level increase with increasing shelf life, and confidence level is higher than the corresponding expectation level. (3) In terms of the overall movement of shelf life, the Q2 model is the best choice for decision makers because in this model the confidence loss is the lowest and the confidence level is the highest; however, in the case where shelf life is equal to six, the Q2 model is the best choice for decision makers because the confidence loss is the lowest and the confidence level is the highest. However, when the shelf life is equal to six, the Q1 model, which has not been favoured, performs the best. Therefore, the decision maker must specify the product category before constructing an appropriate purchasing confidence rule base.

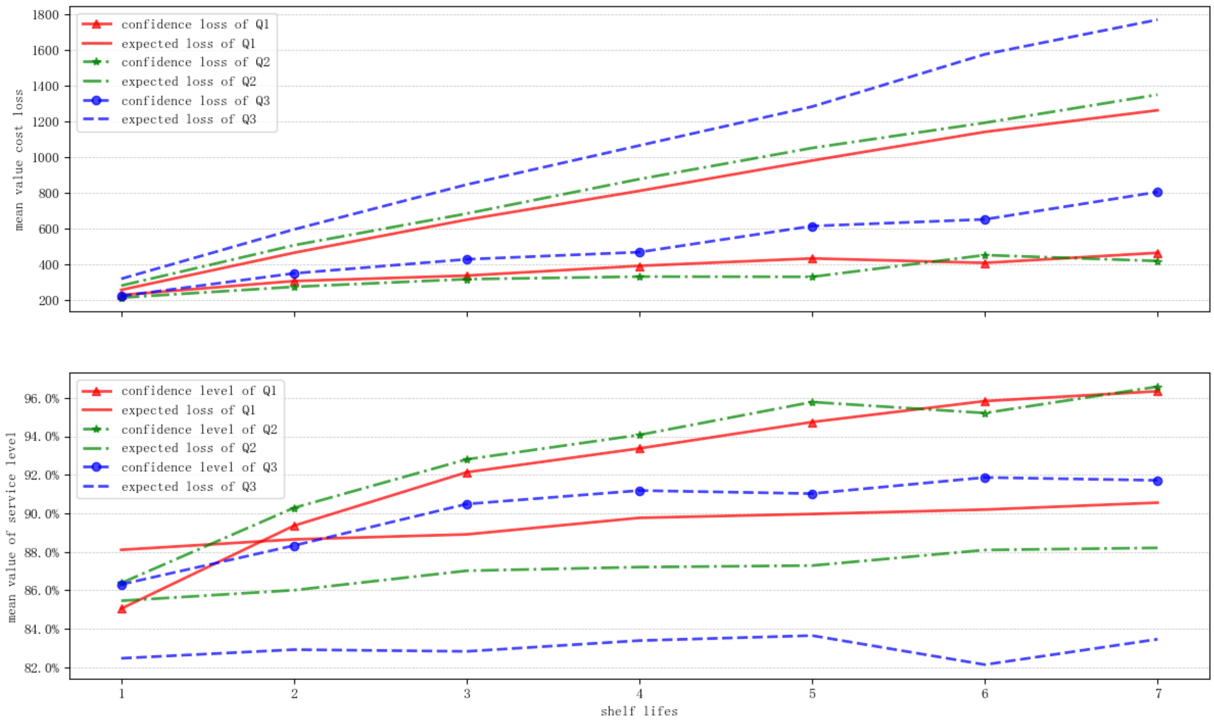

Figure 5: Sensitivity analysis of shelf life.

4.5 Sensitivity analysis of critical values

The critical value plays an essential role in the ordering decision, and its value is equal to $(p - c) / (p - v)$. In the expected optimal ordering decision, the decision maker calculates the expected ordering based on the quantile of the cumulative function determined by the critical value; in the inference process of the purchasing confidence rule base, the critical value not only determines the calculation of the input values but also is a component of the objective function in the parametric optimization model. Without loss of generality, only the change in the critical value brought about by a change in the price of the product p is explored, i.e., the setting of $(c, v) = (4, 1)$.

The results shown in Fig. 6 show that the critical value has an impact on both cost loss and service level, as evidenced by (1) whether it is based on the expected optimal ordering decision or the ordering decision based on the procurement of the confidence rule base, the average value of the cost loss and the average value of the service level produced by both of them increase with the increase of the critical value. The confidence loss is lower than the expected loss. This indicates that the decision-maker who seeks to minimize the cost loss tends to choose the procurement confidence rule base; (2), with the gradual increase of the critical value, the trend of the average value of the service level in the Q1, Q2, and Q3 modes is not the same. Fig. 6 shows that the confidence levels under Q2 and Q3 modes are higher than the desired level, in which when the critical value is high (i.e., high price), the Q3 mode is the optimal choice for decision makers pursuing the maximization of the service level; on the contrary, in the category of low critical value, it is preferred to recommend decision makers to select the purchasing confidence rule base constructed based on the Q2 mode, where the cost loss and the service level are taken into account at the same time.

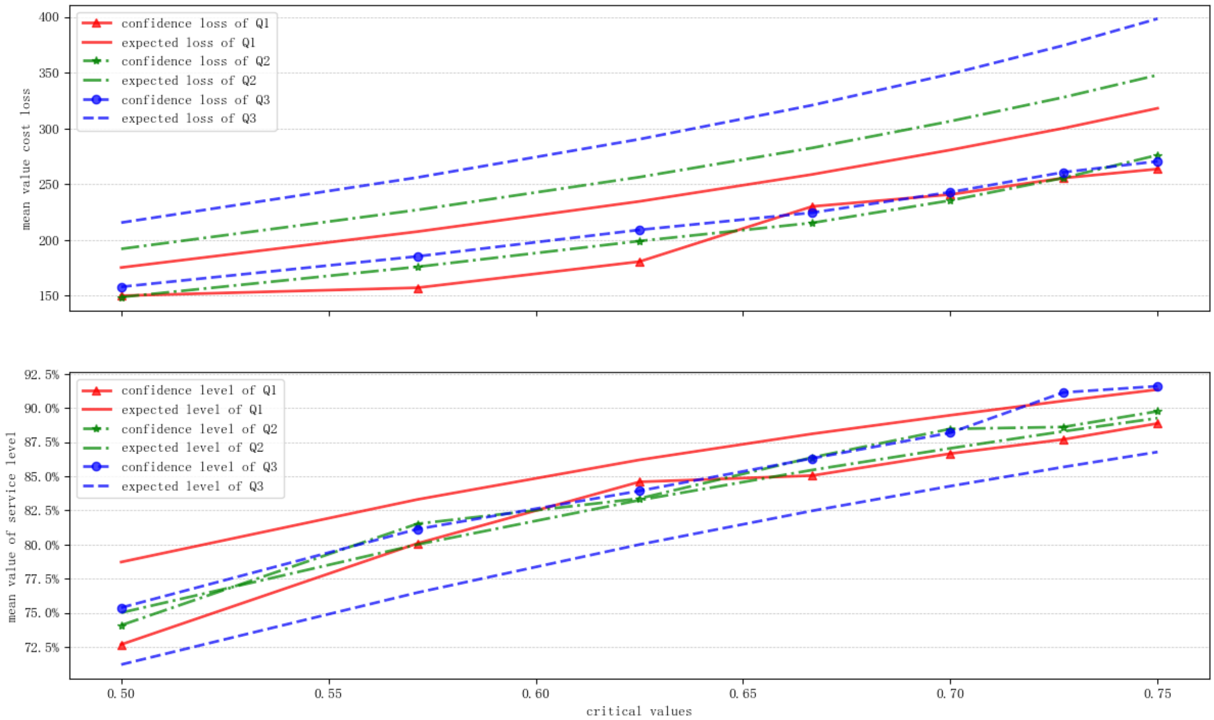

Figure 6: Sensitivity analysis of the critical values.

5. CONCLUSION

This paper establishes a purchasing confidence rule base based on demand data, iteratively synthesizes the enterprise's purchasing confidence structure distribution based on the theory of evidential reasoning, and trains and optimizes the enterprise's confidence purchasing with the help of the minimize function in the optimization library of Python Scientific Computing. The research conclusions are as follows:

Firstly, a demand data-driven purchasing confidence rule base can help enterprises improve their performance. Compared with the expected purchasing based on the random cumulative distribution function, the purchasing decision based on the confidence structure distribution can reduce the purchasing decision bias, lower the mean cost loss of the firm, and increase the mean value of service level. Demand-driven simulations show that the ordering decision inferred from the purchasing confidence rule base produces a mean cost loss of about three-quarters of the mean cost loss of the expected optimal ordering decision, and the corresponding service level is improved by almost one percentage point.

Second, the demand data-driven purchasing confidence rule base is highly adaptive. On the one hand, the mean cost loss resulting from the ordering decision inferred from the purchasing confidence rule base is better than the mean cost loss resulting from the expected optimal ordering, regardless of the number of rules in the purchasing confidence rule base; however, the magnitude of the number of rules affects the mean service level value. On the other hand, the mean value of cost loss and the mean value of service level increase with increasing shelf life, but both are better than their counterparts under the desired ordering decision. Sensitivity analysis reveals that the purchasing confidence rule base outperforms the expectation ordering decision over a moderate range.

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