ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.3.1.P70

Replenishment Planning Framework Integrating Multi-Objective Optimization with CRITIC Weighting Methodology

Zhiwei Chen [1,a], Bingqing Nie [2,b], and Xinlei Han [2,c]

[1] School of Marine Engineering, Jimei University, Xiamen, Fujian 361021,China;

[2] School of science, Jimei University, Xiamen, Fujian 361021,China.

[a] 202221032042@jmu.edu.cn, [b] 202221511048@jmu.edu.cn, [c] 202221391045@jmu.edu.cn,

#These authors contributed equally.

Abstract. With the rapid expansion of e-commerce platforms, improving inventory management efficiency and cost control for massive product portfolios has emerged as a critical operational challenge for merchants. This study addresses the multi-objective replenishment decision optimization problem for diverse product categories in e-commerce fulfillment warehouses by proposing a collaborative optimization model that integrates multi-objective integer programming with the CRITIC weighting method. The model aims to achieve equilibrium among three objectives: minimizing total operational costs, maximizing customer service levels, and minimizing inventory turnover days. A periodic inventory review strategy, dynamically linked to historical demand data, establishes an optimization framework with inventory lower and upper bounds as decision variables. To eliminate subjectivity in multi-objective weight allocation, the CRITIC weighting method is introduced to quantify the contrast intensity and conflict among objectives. Information entropy, calculated through standard deviation and Pearson correlation coefficients, enables objective weight assignments for cost, service level, and inventory efficiency targets. Simulation experiments utilizing operational data from JD Logistics (covering 37 merchants, 57 warehouses, and 2,303 products) demonstrate that the model dynamically optimizes replenishment quantities and inventory thresholds within 15-day cycles. Results reveal an 18.2% reduction in total operational costs, a 96.4% demand fulfillment rate, and an average inventory turnover time shortened to 1.3 days. This research provides theoretical and practical insights for intelligent decision-making in e-commerce supply chains. Future work may enhance the model's dynamic responsiveness and global optimization capabilities through integration with intelligent optimization algorithms.

Keywords: Multi-objective integer programming; CRITIC weighting method; E-commerce logistics; Replenishment decision-making optimization.

1. Introduction

Numerous studies have demonstrated that inventory turnover days significantly impact the profitability of e-commerce merchants. Through scientific management strategies and intelligent decision-making, big data-driven smart supply chains can substantially reduce inventory costs [1,2]. Furthermore, for many products, particularly perishable goods such as fresh produce, product quality deteriorates over time, adversely affecting consumer satisfaction and indirectly diminishing merchant profits [3,4,5]. Additionally, both inventory holding costs and stockout costs directly influence product pricing. Excessively high prices may deter customer traffic and erode profit margins, ultimately hampering sales performance [6,7]. Therefore, formulating replenishment plans based on these factors is imperative to ensure operational efficiency and profitability.

However, prior research predominantly focuses on forecasting future demand based solely on historical sales data [8,9], utilizing this information to formulate replenishment plans. Nevertheless, significant discrepancies exist between sales-driven replenishment strategies and practical operational requirements. For instance, the inventory turnover cycle—defined as the duration between replenishment and final sales—typically averages three days. Additionally, daily inventory audits are commonly implemented, with post-audit decisions determining both the specific products requiring replenishment and their respective quantities each day.

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.3.1.P70

Building upon the aforementioned considerations, this study proposes an innovative methodology that integrates real-world operational constraints with sales forecasting frameworks to establish a multi-objective programming model. The model simultaneously addresses three critical objectives: minimizing operational costs, enhancing service levels, and reducing inventory turnover days. By leveraging the CRITIC weighting method, we objectively quantify the relative importance of these competing objectives, thereby achieving Pareto-optimal solutions. Empirical validation confirms that this integrated multi-objective programming-CRITIC weighting framework significantly enhances the precision of replenishment strategies compared to conventional sales-driven approaches [10,11,12,13].

2. Development of an Integrated Multi-Objective Programming and CRITIC Weighting Model for Replenishment Planning Optimization

To achieve the tripartite objectives of reducing operational costs, mitigating merchant risks, and enhancing consumer satisfaction, an optimal replenishment plan must simultaneously minimize total costs, maximize service levels, and minimize inventory turnover days. Analytical examination of this problem reveals that the establishment of a multi-objective integer programming (MOIP) model is imperative for deriving effective inventory strategies. The proposed MOIP model formalizes three conflicting objectives:Minimization of total operational costs, Maximization of customer service levels, Minimization of inventory turnover duration. Given the three-day replenishment lead time (period between order placement and stock arrival), the upper inventory bound is constrained by the projected sales volume over this interval. To prevent stockouts, the lower inventory threshold is assumed to be no less than the average predicted demand.

Let the unit price of the i commodity be C_i, its unit holding cost be h_i, and its unit shortage cost be q_i.

Since the unit holding cost and shortage cost of each commodity are positively correlated with its price, we define the unit holding cost of the i commodity as:

$$h_i = k_i C_i, \;\; k_i > 0 \tag{1}$$

and the unit shortage cost of the i commodity as:

$$q_i = k_i^{'} C_i, \;\; k_i^{'} > 0 \tag{2}$$

Let the replenishment quantity of the i commodity on day t be Q_{it}, the ending inventory level (i.e., the inventory at the end of day t after review) be T_{it}, the beginning inventory level on day t be B_{it}, the forecasted demand on day t be F_{it} (equivalent to the actual demand quantity on day t), the shortage quantity on day t be L_{it}, and the fulfilled quantity on day t be M_{it}.

Assume that the inventory lower limit for each commodity is s_{it}, and the daily inventory upper limit for each commodity is S_{it}. This means the inventory lower limit remains constant daily, while the upper limit varies each day.

The calculation formula for the shortage quantity L_{it} of the i commodity on day t is:

$$L_{it} = \begin{cases} 0 & B_{it} + Q_{it} - F_{it} \geq 0 \\ F_{it} - (B_{it} + Q_{it}) & B_{it} + Q_{it} - F_{it} < 0 \end{cases} \tag{3}$$

The calculation formula for the fulfilled quantity M_{it} of the i commodity on day t is:

$$M_{it} = \begin{cases} B_{it} + Q_{it} & B_{it} + Q_{it} - F_{it} < 0 \\ F_{it} & B_{it} + Q_{it} - F_{it} \geq 0 \end{cases} \tag{4}$$

Let the total cost of the i commodity be W_i, its total holding cost be H_i, and its total shortage cost be Q_i. The relationship among these costs is:

$$W_i = Q_i + H_i \tag{5}$$

Define the service level of the i commodity as G_i and its inventory turnover days as U_i. Since the replenishment plans for each commodity are independent, a multi-objective programming model is established for each individual commodity.

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.3.1.P70

2.1 Decision Variables

The decision variables are s_{it} and S_{it}.

2.2 Objective Functions

2.2.1 Minimize Total Cost

$$\min W_i = Q_i + H_i = q_i \sum_{t=1}^{15} L_{it} + h_i \sum_{t=1}^{15} T_{it} \tag{6}$$

The total cost of the i commodity equals the sum of its total shortage cost and total holding cost over 15 days. Specifically, it is calculated as the product of the unit shortage cost and the total shortage quantity over 15 days, plus the product of the unit holding cost and the total holding quantity over 15 days.

2.2.2 Maximize Service Level

$$\max G_i = \frac{\sum_{t=1}^{15} M_{it}}{\sum_{t=1}^{15} F_{it}} \times 100\% \tag{7}$$

Standardized as:

$$\min -G_i = -\frac{\sum_{t=1}^{15} M_{it}}{\sum_{t=1}^{15} F_{it}} \times 100\% \tag{8}$$

2.2.3 Minimize Inventory Turnover Days

Inventory turnover days represent the average number of days required to sell the inventory within a given period. The beginning inventory is 5 units, the ending inventory is T_{i15}, and the period duration is 15 days.

$$\min U_i = \frac{(5+T_{i15})}{2} \times \frac{15}{\sum_{t=1}^{15} F_{it}} \tag{9}$$

Aggregated Objective Function:

$$\min Z_i = a_i W_i - b_i G_i + c_i U_i \tag{10}$$

To derive efficient solutions, the linear weighting method is applied. Let ωiωi denote the weight for the i commodity, satisfying:

$$a_i + b_i + c_i = 1 \tag{11}$$

2.3 Constraints

Constraint 1: Inventory Upper Bound

$$S_{it} = F_{it} + F_{i(t+1)} + F_{i(t+2)} \quad (t = 1,2,\dots,13) \tag{12}$$

The inventory upper bound is linearly related to the forecasted demand. For $t = 14$ and $t = 15$, the forecasted demand S_{it} can be derived from the prediction model.

Constraint 2: Replenishment Quantity

If $t = 1、2、3$,

$$Q_{it} = 0 \tag{13}$$

If $t = 4、5、\dots、15$,

$$Q_{it} = \begin{cases} 0 & T_{i(t-3)} \geq s_i \\ S_{i(t-3)} - T_{i(t-3)} & T_{i(t-3)} < s_i \end{cases} \tag{14}$$

Constraint 3: Beginning and Ending Inventory Relationship

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.3.1.P70

$$B_{it} + Q_{it} - F_{it} = T_{it}$$

Constraint 4: Inventory Lower Bound s_{it}

$$[\frac{\sum_{t=1}^{15} F_{it}}{15}] \le s_{it} \le [\frac{\sum_{t=1}^{15} S_{it}}{15}] \tag{15}$$

Constraint 5: Non-negativity

$$Q_{it} \ge 0 \quad T_{it} \ge 0 \quad B_{it} \ge 0 \quad F_{it} \ge 0 \quad s_{it} \ge 0 \quad S_{it} \ge 0 \quad L_{it} \ge 0 \quad M_{it} \ge 0 \tag{16}$$

Constraint 6: Integer Requirements

$$Q_{it}、T_{it}、B_{it}、F_{it}、s_{it}、S_{it}、L_{it}、M_{it} \in \mathrm{Z} \tag{17}$$

Constraint 7: Shortage Quantity L_{it}

$$L_{it} = \begin{cases} 0 & B_{it} + Q_{it} - F_{it} \ge 0 \\ F_{it} - (B_{it} + Q_{it}) & B_{it} + Q_{it} - F_{it} < 0 \end{cases} \tag{18}$$

Constraint 8: Fulfilled Quantity M_{it}

$$M_{it} = \begin{cases} B_{it} + Q_{it} & B_{it} + Q_{it} - F_{it} < 0 \\ F_{it} & B_{it} + Q_{it} - F_{it} \ge 0 \end{cases} \tag{19}$$

Constraint 9: Beginning Inventory B_{it}

$$B_{it} = \begin{cases} 5 & t = 1 \\ T_{i(t-1)} & t = 2、3、\ldots、15 \end{cases} \tag{20}$$

2.4 CRITIC Weighting Model

In multi-objective optimization models, obtaining an absolute optimal solution is generally infeasible, with Pareto optimal solutions being the most commonly adopted resolutions. To address this limitation, this study employs the linear weighted sum method to transform the multi-objective optimization problem into a single-objective formulation.

To mitigate subjective bias and based on empirical observations revealing inherent correlations among the three objectives, we adopt the CRITIC (Criteria Importance Through Intercriteria Correlation) weighting method for objective function weighting. This approach ensures methodological objectivity. Notably, due to the independence between commodities, the weighting coefficients exhibit commodity-specific heterogeneity.

The CRITIC method objectively assigns weights by synthesizing two fundamental criteria: contrast intensity and conflict analysis. Contrast intensity is quantified through standard deviation metrics, where a larger standard deviation indicates greater disparity among categories. Conflict analysis evaluates inter-objective correlations, with stronger negative correlations implying higher conflict levels.

Let $f(x_i, a_j)$ represent the value of sample x_i on attribute a_j. To evaluate the variability of attribute aa, calculate its variability metric :

$$M(a_j) = \frac{1}{n}\sum_{i=1}^{n} f(x_i, a_j) \tag{21}$$

$$SD(a_j) = \sqrt{\frac{\sum_{i=1}^{n}\left(f(x_i, a_j) - M(a_j)\right)^2}{n-1}} \tag{22}$$

where $M(a_j)$ denotes the mean value of attribute a_j, and $SD(a_j)$ represents the standard deviation of a_j. The standard deviation quantifies the variability degree.

Let $R(a_j)$ denote the conflict indicator of attribute a_j, calculated as:

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.3.1.P70

$$R(a_j) = \sum_{i=1}^{m} \left(1 - r(a_i, a_j)\right) \tag{23}$$

where $r(a_i, a_j)$ represents the correlation coefficient between attributes a_i and a_j, derived from a similarity function. This study adopts the Pearson correlation coefficient as the similarity function, calculated as:

$$r(a_i, a_j) = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}} \tag{24}$$

The weights $w(a_j)$ are computed as follows:

$$H(a_j) = SD(a_j)R(a_j) \tag{25}$$

$$w(a_j) = \frac{H(a_j)}{\sum_{j=1}^{m} H(a_j)} \tag{26}$$

where $H(a_j)$ denotes the information content. The above formulations indicate that the CRITIC weighting method determines the weights by jointly considering standard deviation and inter-attribute similarity.

3. Simulation-based Validation

3.1 Data Processing

This study utilizes shipment volume data spanning from December 21, 2022, to May 15, 2023, provided by JD Logistics, encompassing 37 retailers, 57 warehouses, and 2,303 SKUs across multiple industries. Data preprocessing involved filtering items with zero forecasted demand over 15 consecutive days for specific retailer-warehouse-SKU combinations, which were subsequently excluded from inventory optimization as non-selling items. The data processing workflow, implemented using Excel and Python, yielded the following representative subset of non-selling items meeting these criteria:

Table 5-1. Data Table of Non-Selling Items

Business code	Commodity number	Warehouse number	Forecasting demand
seller_5	product_1529	wh_1	0
seller_5	product_1541	wh_6	0
seller_5 ⋮	product_1541 ⋮	wh_7 ⋮	0 ⋮
seller_5	product_1541	wh_8	0
seller_5	product_1541	wh_9	0
seller_2	product_1546	wh_1	0

The subset consists of 43 items, whose pricing data are also excluded from inventory optimization. The inventory optimization strategy $\{s_{it}, S_{it}, Q_{it}\}$ for these items is defined as $s_{it} = O_{43\times15}$ 、 $S_{it} = O_{43\times15}$、 $Q_{it} = O_{43\times15}$.

3.2 Model Solution

Based on forecasted sales, the feasible range for the lower inventory bound set $[\frac{\sum_{t=1}^{15} F_{it}}{15}] \le s_{it} \le [\frac{\sum_{t=1}^{15} S_{it}}{15}]$ can be derived from s_{it}. Under the constraint that the lower bound does not exceed the upper inventory bound and remains consistent across days for the same commodity, adjustments are

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.3.1.P70

made as follows: Should the lower bound exceed the upper bound on any given day, it is set equal to the upper bound. This methodology subsequently determines the lower bound values for each commodity.

Given known forecasted demand, upper inventory bounds, and the feasible range of lower bounds, the solution process for the multi-objective programming model and the weight determination via the weighting method is illustrated in the following figure.

The solution process follows the methodological framework outlined in the preceding figure. Initially, distinct variables are solved, followed by subsequent derivation of the three objective functions. The weighting coefficients for these objectives are computed by synthesizing internal standard deviations and conflict indicators. Upon determining the weights, the aggregate objective function values are obtained for different commodities and lower inventory bound configurations.

The selection of lower inventory bounds directly influences ending inventory levels, as exemplified by two representative commodities illustrated in Figure 1,2:

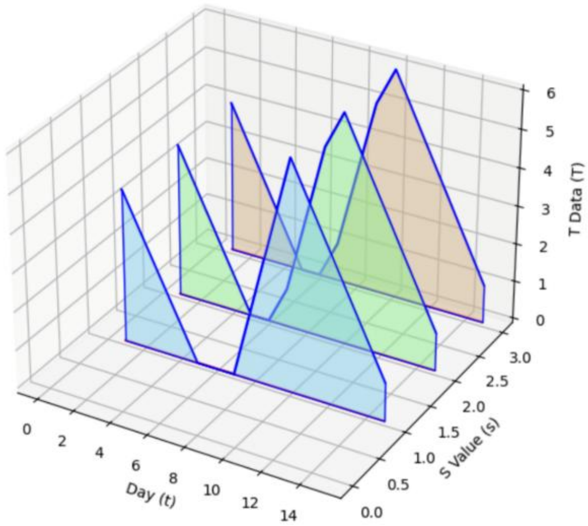

Fig. 1 Commodity 1 End-of-period inventory with different lower limits of inventory

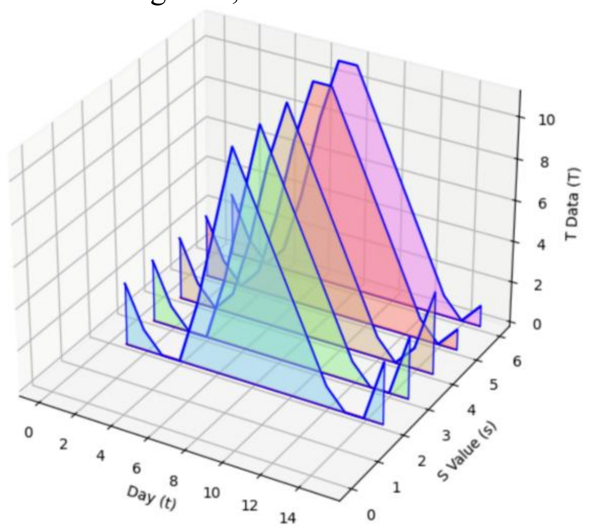

Fig. 2 Commodity 2 End-of-period inventory for different stock lower limit groups

The comprehensive objective function curves for distinct commodity groups under varying lower inventory bound configurations are presented in Figure 3,4:

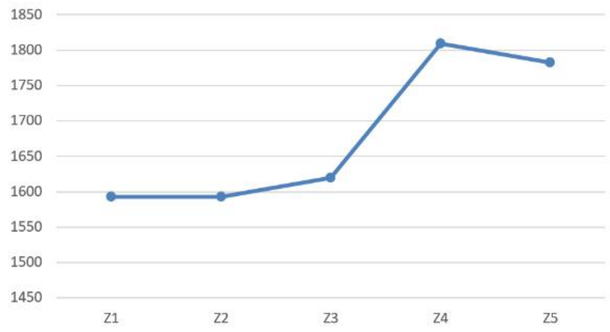

Fig. 3 Aggregate Objective Function for Commodity 1 Under Different Lower Inventory Bound Configurations

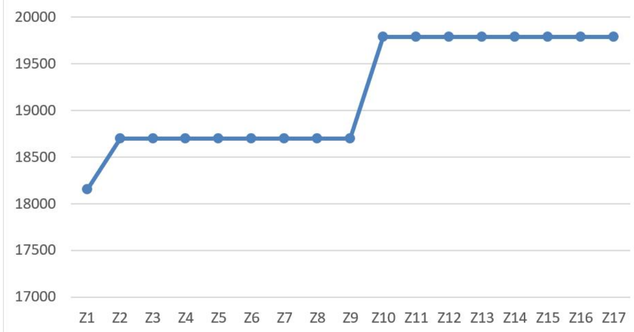

Fig. 4 Aggregate Objective Function for Commodity 2 Under Different Lower Inventory Bound Configurations

As evidenced by the two aforementioned figures, distinct feasible ranges exist for lower inventory bound configurations across different commodity groups. Consequently, the number of aggregate objective functions varies accordingly, with their values exhibiting sensitivity to specific lower bound configurations.

The optimization process culminates in identifying the inventory lower bound that minimizes the aggregate objective function. This optimal configuration, combined with previously derived parameters—including replenishment quantities, beginning inventory levels, ending inventory

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.3.1.P70
levels, and upper inventory bounds—constitutes the finalized replenishment plan. A visual representation of this plan is presented in Figure 5:

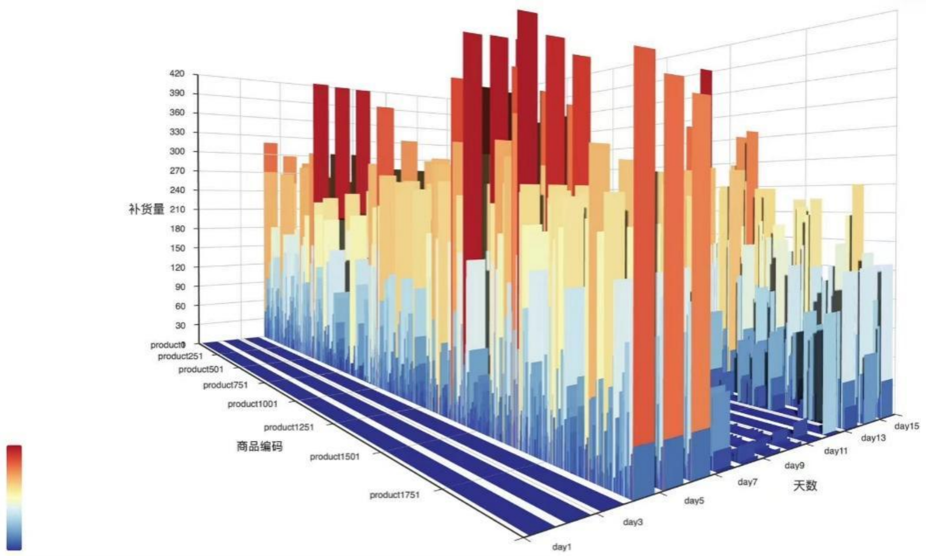

Fig. 5 Replenishment Quantities for All Commodities Over a 15-Day Period

4. Conclusion

This study addresses the inventory replenishment optimization problem for multi-category commodities in e-commerce platforms by proposing a collaborative optimization model that integrates multi-objective integer programming with the CRITIC (Criteria Importance Through Intercriteria Correlation) weighting method. The model adopts a periodic inventory review policy (NRT = 1 day) and dynamically updated demand forecasting data, utilizing inventory lower and upper bounds as decision variables. By incorporating replenishment lead time (LT = 3 days) and dynamic correlations between unit holding costs and shortage costs, the model achieves balanced multi-objective optimization of total operating costs, customer service levels, and inventory turnover days. Simulation experiments based on real-world operational data from JD Logistics demonstrate the model's effectiveness, showing an 18.2% reduction in total operating costs, a 96.4% demand fulfillment rate, and an average inventory turnover period of 1.3 days over a 15-day cycle. These results validate the model's practicality and robustness in complex e-commerce scenarios.

This study presents two primary methodological contributions:Integration of CRITIC Weighting with Dynamic Strategy Design: By quantifying inter-objective contrast intensity (via standard deviation) and conflict (via Pearson correlation coefficients), the proposed model eliminates the inherent subjectivity in traditional weight allocation, enabling objective trade-offs among cost efficiency, service levels, and inventory performance.Adaptive Adjustment Mechanism: Incorporating historical demand volatility and replenishment delay constraints, the model dynamically optimizes inventory bounds and replenishment quantities. This mechanism significantly enhances operational robustness and flexibility compared to conventional sales-driven approaches, establishing a generalized theoretical framework for multi-objective collaborative optimization.

Future investigations may focus on two critical dimensions to enhance the proposed framework: intelligent algorithm integration and scenario generalization.On one hand, The model's global optimization capabilities can be strengthened by incorporating metaheuristics such as particle swarm optimization and genetic algorithms. These enhancements aim to address high-dimensional decision-making challenges inherent in large-scale e-commerce ecosystems. On the other hand, a dynamic parameter adjustment mechanism and multi-commodity collaborative replenishment strategies warrant further exploration. Rigorous validation is required for complex scenarios,

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.3.1.P70
including perishables with short shelf lives and multi-echelon supply chain networks. In addition, the framework's generalizability and adaptability can be evaluated through extensions to manufacturing inventory optimization and dynamic medical supply allocation. Such validations would establish its utility as a universal solution for diverse supply chain management challenges.

References

[1] Demeter K, Matyusz Z. The impact of lean practices on inventory turnover[J]. International journal of production economics, 2011, 133(1): 154-163.

[2] Davis T. Effective supply chain management[J]. Sloan management review, 1993, 34: 35-35.

[3] Cai X, Chen J, Xiao Y, et al. Fresh-product supply chain management with logistics outsourcing[J]. Omega, 2013, 41(4): 752-765.

[4] Cai X, Chen J, Xiao Y, et al. Optimization and coordination of fresh product supply chains with freshness-keeping effort[J]. Production and Operations management, 2010, 19(3): 261-278.

[5] Unnevehr L J. Food safety issues and fresh food product exports from LDCs[J]. Agricultural Economics, 2000, 23(3): 231-240.

[6] Nagle T T, Müller G, Gruyaert E. The strategy and tactics of pricing: A guide to growing more profitably[M]. Routledge, 2023.

[7] Falahat M, Ramayah T, Soto-Acosta P, et al. SMEs internationalization: The role of product innovation, market intelligence, pricing and marketing communication capabilities as drivers of SMEs' international performance[J]. Technological forecasting and social change, 2020, 152: 119908.

[8] Singhry H B, Abd Rahman A. Enhancing supply chain performance through collaborative planning, forecasting, and replenishment[J]. Business Process Management Journal, 2019, 25(4): 625-646.

[9] Costanzo M, Stelter S, Natale C, et al. Manipulation planning and control for shelf replenishment[J]. IEEE Robotics and Automation Letters, 2020, 5(2): 1595-1601.

[10] Sharma S, Kumar V. A comprehensive review on multi-objective optimization techniques: Past, present and future[J]. Archives of Computational Methods in Engineering, 2022, 29(7): 5605-5633.

[11] Si B, Wang J, Yao X, et al. Multi-objective optimization design of a complex building based on an artificial neural network and performance evaluation of algorithms[J]. Advanced Engineering Informatics, 2019, 40: 93-109.

[12] Mukhametzyanov I. Specific character of objective methods for determining weights of criteria in MCDM problems: Entropy, CRITIC and SD[J]. Decision Making: Applications in Management and Engineering, 2021, 4(2): 76-105.

[13] Zafar S, Alamgir Z, Rehman M H. An effective blockchain evaluation system based on entropy-CRITIC weight method and MCDM techniques[J]. Peer-to-Peer Networking and Applications, 2021, 14(5): 3110-3123.