Application of multi-level inventory intelligent decision-making system in the automotive aftermarket

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Abstract. Automotive aftermarket spare parts supply chain related business gradually began to carry the core functions of customer service and profit growth, enterprises in the aftermarket spare parts business competition is fierce, after-sales business transformation has become a must for enterprises. This article examines the research on the multi-level inventory management method and the intelligent decision-making system for multi-level inventory of automotive aftermarket spare parts and analyzes its application in inventory planning and management in the automotive aftermarket. It aims to address the lack of scientific management methods and intelligent decision-making tools in inventory planning and management of automotive enterprises' aftermarket spare parts. The system is based on automotive data and supported by supply chain algorithm models. Its core modules include data management, spare parts classification, demand forecasting, inventory strategy, global optimization, inventory planning, and automatic suggestions. It supports enterprises in achieving accurate stocking, reducing inventory costs, decreasing manual calculation burden, improving accuracy and efficiency of calculations, enhancing information flow speed, and optimizing supply chain coordination efficiency.

Keywords: Automotive aftermarket, multi-level inventory, intelligent decision-making, demand forecasting, inventory planning

1 INTRODUCTION

As competition in the automotive industry intensifies, the core of competition for automotive companies is gradually shifting to the automotive aftermarket. By analyzing the characteristics of industrial composition, development trends, customer behavior, and service experiences in the Chinese automotive aftermarket, it can be concluded that there are great opportunities for the development of the Chinese automotive aftermarket [1].

For automotive companies, in order to gain a competitive advantage in an increasingly fierce market environment, it is necessary to strengthen supply chain collabora-

B. K. Kandel et al. (eds.), *Proceedings of the 2023 8th International Conference on Engineering Management (ICEM 2023)*, Atlantis Highlights in Engineering 23,
https://doi.org/10.2991/978-94-6463-308-5_8

tion [2]. With the demand for high-quality development, companies have higher management requirements in terms of supply chain efficiency, demand fulfillment, and inventory structure optimization to further enhance supply chain competitiveness.

The intelligent decision-making system for multi-level inventory of automotive aftermarket spare parts is based on automotive data and supported by supply chain algorithm models. It enables companies to achieve accurate stocking, reduce inventory costs, and improve the level of market demand fulfillment in inventory management.

2 Multi-level inventory management business process

To address the issues of high inventory costs, high obsolescence rates, and low initial service fulfillment rates in automotive aftermarket spare parts inventory management, businesses can employ various management approaches. These approaches include data cleansing, spare parts classification, demand forecasting, differentiated inventory strategies, inventory planning, automated replenishment suggestions, and global optimization. By utilizing scientific management methods and implementing intelligent decision-making for aftermarket spare parts, businesses can effectively reduce costs and improve efficiency.

3 System function module introduction

Multi-level inventory management system, in the context of automotive aftermarket spare parts supply chain management, utilizes modules such as data management, spare parts classification, demand forecasting, inventory strategy, global optimization, inventory planning, and automated suggestions. These modules help businesses improve management efficiency, optimize multi-level inventory resources, achieve scientific management of automotive aftermarket spare parts, and enhance overall supply chain competitiveness.

3.1 Data management

The system collects business data from the enterprise, including spare parts master data, warehouse information, distributor information, warehouse network structure, inventory data, supplier information, substitute part data, and spare parts procurement cycle data. After obtaining the data, data processing is performed. The data processing includes matching substitute part relationships and cleaning demand data, resulting in effective data for inventory management.

3.2 Spare parts classification

Based on the processed historical demand data within the past 6 months, the system calculates the spare parts classification matrix by applying configured rules for categorizing spare parts based on demand value and demand frequency. This allows for determining the classification type of each spare part at each warehouse node.

The demand value rule configuration follows these steps: (1) Calculate the demand value by multiplying the demand quantity by the unit price of the part. (2) Calculate the accumulated demand value for the parts within 6 months and sort them in descending order based on value. (3) Calculate the cumulative percentage of the demand value and divide it into ABC categories according to the specified criteria [3]. For example, the classification rules could be defined as follows: Class A represents the top 75% of the total demand value, Class B represents the next 20%, and Class C represents the remaining 5%.

The demand frequency rule configuration is as follows:

Using the past 6 months as the time range, each month's outbound transactions are denoted as n_1 to n_6. If the outbound quantity is greater than 0, n_i is assigned a value of 1; otherwise, n_i is assigned a value of 0.

Weighting coefficient: Calculate the weighted coefficient x as follows: $x = n_1\times6 + n_2\times5 + n_3\times4 + n_4\times3 + n_5\times2 + n_6\times1$.

Frequency digit: Calculate the frequency digit y as follows: y = MAX (1, 7 - ROUNDDOWN((x-1)/3, 0)). Each frequency digit corresponds to a specific frequency level, where a higher x value corresponds to a higher frequency level.

By applying these rules, the system determines the demand frequency for each spare part, which helps in classifying the spare parts effectively.

The weighted classification of demand frequency is shown in Table 1.

Table 1. Demand frequency weighted classification

Weighting coefficient(x)	**Weighted frequency classification**
$16\leq x$	X
$10\leq x < 16$	Y
$0\leq x < 10$	Z

3.3 Demand forecasting

Based on the processed demand data and spare parts replenishment cycle, the system performs demand forecasting for spare parts. Insufficient demand forecasting can lead to inadequate inventory, affecting the stability of market supply. On the other hand, excessive demand forecasting can result in excess inventory and increased inventory management costs [4]. Accurate demand forecasting methods can mitigate the bullwhip effect, improve supply chain efficiency, and enhance inventory management accuracy [5].

The algorithm for demand forecasting includes the following steps:

Demand Data Processing and Feature Analysis: Process the demand data and analyze the features of the processed demand data, extracting demand distribution characteristics. Demand features include holiday patterns, seasonal patterns, weather patterns, promotional patterns, vehicle ownership patterns, price patterns, and demand frequency patterns.

Model Development: Use the obtained influencing factors and processed demand data as inputs, organize the features and demand data in mathematical forms, and build a library of forecasting algorithm models. The algorithm model library includes fitting models, time-series models [6], machine learning models [7], and multi-factor hybrid models.

Algorithm Matching: Select the optimal forecasting model for each spare part from the numerous models. The evaluation criteria for the optimal forecasting model are forecast accuracy and stability. Forecast accuracy is evaluated using the Mean Absolute Percentage Error (MAPE), and forecast stability requires that the model's accuracy deviation is not too large and does not exceed the lower limit of forecast accuracy over multiple forecasting periods. The matching results determine the forecasting model for each spare part.

Demand Forecasting: Output the forecasted demand data for each warehouse node, based on the specified frequency and cycle, for each spare part.

By following these steps, the system provides demand forecasting data for spare parts at various warehouse nodes.

3.4 Inventory strategy

Compared to fixed inventory control methods, flexible inventory strategies can achieve better inventory management results [8]. Differentiated inventory strategies encompass safety stock rules, delivery cycle rules, and stocking days rules. These strategies can be customized based on various dimensions such as spare part codes, spare part classification types, spare part types, vehicle models, and warehouse nodes, according to the specific business requirements.

3.5 Multi-level inventory optimization

Automotive aftermarket inventory management often involves a multi-tiered inventory network [9]. By constructing a multi-tiered inventory management model within the supply chain, optimizing inventory management parameters, the goal of effective inventory management can be achieved.

The configuration of multi-tiered inventory optimization rules includes the optimization objectives of the multi-tiered inventory and the range for optimizing service fulfillment rates. The optimization objectives of the multi-tiered inventory refer to the overall service fulfillment rate targets that need to be achieved for the entire inventory, which can be set based on actual management requirements. In this case, the 10 global optimization goals for service completion rate are set within the range of 90% - 99%, with 10 goals set in 1% steps.

The optimization range for service fulfillment rate can be flexibly set based on multiple dimensions such as spare part classification types, spare part codes, and warehouse scopes. In this article, the service fulfillment rate calculation for multi-tier inventory optimization is conducted based on spare part classification and the effective warehouse scope. The specific rule configuration is provided in Table 2:

Table 2. Multi-level inventory optimization rules

Serial number	Rule name	Rule scope	Rule condition	Rule description
1	AX rule	Global Effective	Spare parts classification, AX	95% ~ 99%
2	BX rule	Global Effective	Spare parts classification, BX	92% ~ 97%
3	CX rule	Global Effective	Spare parts classification, CX	90% ~ 95%
4	AY rule	Global Effective	Spare parts classification, AY	90% ~ 95%
5	BY rule	Global Effective	Spare parts classification, BY	88% ~ 93%
6	CY rule	Global Effective	Spare parts classification, CY	85% ~ 90%
7	No reserve	Global Effective	Spare parts classification, AZ, BZ, CZ	50% ~ 50%

In the optimization calculation of multi-level inventory management, the first step is to calculate the spare part importance ranking of each warehouse based on the frequency of demand, demand amount, and spare part price over the past six months. The three factors have equal weight and are arranged in descending order. The final output is the ranking of spare part importance for each warehouse.

Next, the greedy algorithm is used to calculate the service level settings for each warehouse and each spare part at each optimization point. For optimization point 1, with a global optimization target of 90%, the specific parameters are calculated as follows: (1) Calculate whether the overall service level of each warehouse meets the target value of 90% for each spare part at the lower limit of the optimization range. If the requirement is met, determine the parameter results, calculate the corresponding inventory cost and inventory turnover rate, and output the calculated parameter settings and inventory-related results. If the requirement is not met, continue with the calculation. (2) If the results from the previous step do not meet the requirements, adjust the service level value of the spare part ranked first in terms of importance to the upper limit of the optimization range, and recalculate whether the overall service level of each warehouse meets the target value. If it is not reached, continue adjusting the service level value of the spare part ranked second in terms of importance to the upper limit of the optimization range, until the overall service level of each warehouse meets the target value. Determine the parameter results, calculate the corresponding inventory cost and inventory turnover rate, and output the calculated parameter settings and inventory-related results. (3) If the overall service level of a certain warehouse exceeds the target value after adjusting the service level value of the spare part ranked second in terms of importance to the upper limit of the optimization range, decrease it in increments of 0.5% and calculate whether the adjusted overall service level meets the target value. If it still exceeds the target value, continue to decrease it until the lowest service level parameter is calculated for this spare part, which satisfies the overall service level target at the warehouse level. Stop the calculation, determine the parameter results, calculate the corresponding inventory cost and inventory turnover rate, and output the calculated parameter settings and inventory-related results. (4) After completing the calculation of service level parameters for each warehouse, output the service level parameter values and overall inventory cost and inventory turnover rate results for each warehouse and each spare part for optimization point 1. Repeat this process for optimization points 2 to 10. For point 10, firstly calculate whether the overall service level of each warehouse meets the target value of 99% for each spare part at the lower limit of the optimization range. If the results from the previous step do not meet the requirements, adjust the service level value of the spare part according to the calculation steps of point 1.

After completing the calculation for the 10 optimization points, the service fulfillment rate is compared and analyzed against inventory cost and inventory turnover indicators as shown in Table 3. Taking into account the calculation results and the operational requirements of the enterprise, a parameter scheme can be selected under the corresponding global fulfillment rate target to be implemented in the subsequent formal inventory planning calculation environment.

Table 3. Multi-level inventory optimization indicator calculation results

Serial number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Optimization target	90%	91%	92%	93%	94%	95%	96%	97%	98%	99%
Inventory cost (Mio CNY)	371	373	377	385	407	484	802	2331	10399	55928
Inventory turnover	6.08	6.06	6	5.87	5.55	4.67	2.82	0.97	0.22	0.04

3.6 Inventory planning

Based on the inventory parameter settings, demand forecast results, and details of special management parts, the calculation of safety stock, standard stock, and maximum stock is performed for each warehouse node within a certain future period. Parts on the blacklist are excluded from the calculation and the results are not output.

Maximum Stock = Safety Stock + (Planning Period + Lead Time) * Forecasted Average Daily Sales

Standard Stock = Safety Stock + Planning Period * Forecasted Average Daily Sales

Safety Stock = NORMINV (Service Level) * SQRT (Historical Demand Variance * Lead Time + Average Daily Demand^2 * Lead Time Variance)

There are many factors that influence the setting of safety stock, including service level, lead time, demand volatility, and others [10].

The calculation example process is as follows:

For a certain part, the current demand forecast value at the central warehouse is 14, and the historical demand for the past 6 months is as follows: 10, 25, 9, 12, 37, 14.

The calculated average daily demand is 0.467, with a historical demand standard deviation of 2.011. The optimization results in a service level set at 0.975, corresponding to a safety stock coefficient (Z-value) of 1.96. The inventory parameters include a planning period of 30 days and a delivery period of 50 days, with no fluctuations in the lead time and a lead time standard deviation of 0. The inventory parameters are shown in Table 4.

Table 4. Inventory parameter example

Category	**Average daily demand**	**Historical demand standard deviation**	**Service level**	**Safety stock coefficient**	**Planning period**	**Delivery period**	**Lead time standard deviation**
Data	0.467	2.011	0.975	1.96	30	50	0

According to the inventory planning calculation rules, the safety stock value is 35, the standard stock value is 49, and the maximum stock value is 72. Based on this, we can calculate the monthly inventory plan for the next 6 months.

Safety Stock = 1.960 * SQRT (2.011^2 * 80 + 0.467^2 * 0^2) ≈ 35

Standard Stock = 35 + (30 * 0.467) ≈ 49

Maximum Stock = 35 + (30 + 50) * (0.467) ≈ 72

These calculations provide the inventory plan for each month based on the given parameters and formulas.

3.7 Automatic suggestion

According to the calculated inventory plans for each warehouse node, combined with the inventory data and demand forecast data, the replenishment plan suggestions and medium to long-term replenishment plans can be calculated.

The calculation process is as follows:

Current Replenishment Suggestion = Current Maximum Stock - On-hand Stock - In-transit + Backorders (If the suggestion is negative, adjust it to 0 as no procurement/replenishment is needed)

N-month Replenishment Plan = Current Month Standard Stock - Initial On-hand Stock - In-transit + Backorders + Current Demand Forecast (If the suggestion is negative, adjust it to 0 as no procurement/replenishment is needed)

4 Conclusions

The research in this paper focuses on the multi-level inventory management of automotive aftermarket spare parts, aiming to address the lack of scientific management methods and intelligent decision-making tools in inventory planning for automotive enterprises.

In the field of multi-level inventory management for automotive aftermarket spare parts, various advanced algorithm models and management concepts are applied to solidify scientific planning processes and methods, thereby enhancing inventory management capabilities. Differentiated inventory management strategies and flexible spare parts management methods are employed to meet the operational requirements of different types of spare parts, thereby improving management accuracy. To address the scenarios of multi-level inventory networks, a multi-level inventory global optimization method is designed to achieve overall optimization and control of inventory. Through an intelligent decision-making system, the burden of manual calculations can be reduced, while improving accuracy and efficiency. Additionally, it enhances the speed of information flow and optimizes the efficiency of supply chain coordination.

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