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Literature Review Related to Spare Parts Demand Forecasting and Inventory Management

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Abstract

In the modern production and operation system, spare parts demand forecasting and inventory management play a crucial role in maintaining the continuity of enterprise production and controlling operation costs. This article reviews the methods of spare parts demand forecasting and inventory management in sup-ply chain management, sorts out the current theoretical and practical achieve-ments in the research fields of demand forecasting and inventory management in the supply chain, analyzes the current research status, and provides refer-ences for subsequent research and enterprise decision - making.

Keywords

Supply Chain Management; Demand Forecasting; Inventory Management; Machine Learning Methods; Time Series Methods

1. Introduction

Supply chain management refers to a management approach that effectively organizes suppliers, manufacturers, warehouses, distribution centers, and channel partners to carry out product manufacturing, transportation, distribution, and sales, aiming to minimize the cost of the entire supply chain system while meeting a certain level of customer service. Supply chain management includes five basic elements: planning, purchasing, manufacturing, distribution, and return. With the development of economic and manufacturing globalization, the core competitiveness of enterprises has gradually shifted to the competition of supply chain management. Many enterprises have focused on how to effectively organize and coordinate to improve the level of supply chain management. The 14th Five - Year Plan for Intelligent Manufacturing Development clearly states that "by 2025, 70% of manufacturing enterprises above a certain scale will basically achieve digitalization and networking, and the maturity of intelligent manufacturing capabilities will be significantly improved." With the continuous development of manufacturing enterprises, demand forecasting and inventory management play important roles in manufacturing enterprises. Accurate demand forecasting and appropriate inventory strategies can help manufacturing enterprises coordinate various production links, reduce warehousing costs, and better coordinate upstream and downstream suppliers as well as subsequent product distribution and scheduling. This article aims to review the theoretical and practical achievements of spare parts demand forecasting and inventory management, analyze the current research status, and look ahead to the future development direction, providing references for subsequent research and enterprise decision - making.

2. Spare Parts Demand Forecasting

2.1. Related Concepts of Demand Forecasting

Demand forecasting refers to the process of planning and predicting the demand for goods and materials, which helps enterprises maintain profitability as much as possible. Without strong demand forecasting capabilities, enterprises will face the risk of over - supply, wasting a large amount of costs and resources, or losing valuable business opportunities due to failure to predict customer demands, preferences, and purchase intentions.

When enterprises conduct demand forecasting, they generally combine qualitative forecasting with quantitative forecasting. Both require insights from different data sources in the supply chain. Qualitative data can be obtained from external data sources, such as news reports, cultural and social media trends, competitors, and market research. Internal enterprise data such as customer feedback and preferences can also help improve the accuracy of forecasting. Quantitative data is usually mainly obtained from within the enterprise, such as through sales data, peak shopping seasons, and web and search analysis.

2.2. Spare Parts Demand Forecasting

With the continuous improvement of the intelligent level of manufacturing enterprises, more complex demand patterns and large - scale data have made traditional statistical methods have obvious limitations. Deep learning and machine learning models have obvious advantages over traditional statistical methods.

Machine learning algorithms can capture non - linear relationships and time - dependent relationships in data, which are suitable for situations where there are complex relationships between demand and other factors. However, they require a large amount of historical demand data and high - quality data, as well as computing resources and time. Li et al (2024) used principal component analysis (PCA) to screen the influencing factors and then used the BP neural network algorithm for demand forecasting. Li and Ai (2024) further used singular spectrum analysis (SSA) and variational mode decomposition (VMD) on this basis to decompose the original data into trend signals and signals of multiple different cycles. Then, by introducing the echo state network (ESN), an SSA - VMD - ESN model was proposed to predict inventory demand. Fan et al (2024) separated the original data into a demand quantity sequence and an interval quantity sequence, divided the demand patterns of intermittent time series according to the similarity of each type of sequence, determined the demand pattern and matched the best prediction model, and finally combined the predicted values of the demand quantity and interval quantity to obtain the final prediction result. Compared with Fan, Dui et al (2024) decomposed the data into trend, seasonal, and irregular change parts based on the STL time - series decomposition algorithm, and then used an ensemble algorithm to predict the decomposed sequences separately. Finally, the prediction results of each part were added together to obtain the final demand prediction result. Rong et al (2024) first used Bayesian optimization to automatically adjust the hyperparameters of the model to obtain the best performance. Then, a convolutional neural network was used to extract spatio - temporal features from the demand data, and long - short - term memory was combined to capture the long - term dependencies in the demand sequence, so as to achieve accurate demand forecasting.

Time - series methods are particularly suitable for analyzing transient data, mainly including the autoregressive integrated moving average model (ARIMA), exponential smoothing methods, seasonal decomposition models, etc. However, due to their relatively simple and easy - to - use characteristics, they are more suitable for small and medium - sized enterprises or situations with limited data. An and He (2022) considered that the original data was a non - stationary time series, carried out differencing processing and parameter analysis, and constructed a seasonal differencing autoregressive integrated moving average model. The results showed that the data fitting of this model was good. Wang and Zhu (2022) used the linear regression method and the exponential smoothing method to predict the logistics demand in Shanghai. Through comparative analysis, the prediction result of the exponential smoothing method based on the time series was selected. Kumar et al (2024) divided the sales season into different intervals, each interval was related to different pricing strategies affected by random factors, and used the exponential smoothing method for demand forecasting. An algorithm was developed to optimize the inventory replenishment and dynamic pricing strategies. However, a single time - series method has demand inaccuracies. Therefore, combining machine learning algorithms with time - series methods can not only make up for the deficiencies of time - series methods but also improve efficiency. Yang et al (2024) used the K - means method to cluster the data and then used the ARIMA model for prediction. Dai et al (2024) selected the data with approximate fuzzy values in the original time series, processed it through the fuzzy entropy algorithm, introduced the grey system theory to eliminate the residuals in the demand time series, obtained the GM(1,1) model, and thus constructed the ARMA(p,q) model. The two models were combined to establish a GM(1,1)-ARMA(p,q) combined prediction model to complete the automatic demand prediction. Liang et al (2022) first used the seasonal adjustment model

(X12 - ARIMA) to decompose the original time series into a seasonal component sequence and a seasonally adjusted sequence. Then, the improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) method was used to decompose the seasonally adjusted sequence into a series of intrinsic mode functions (IMFs) and a residual sequence (Residue) of different time scales. After that, the FTS model based on the fuzzy C - means algorithm (FCM) to divide the domain interval was used to predict the seasonal component sequence, each IMF component, and the residual sequence respectively. Finally, the prediction results of each component sequence were integrated to reconstruct the predicted value of air passenger demand. Zheng et al (2019) applied the autoregressive moving average model based on the time series, constructed the time - series correlation function, used two order - determination methods, the Bayesian information criterion (BIC criterion for short) and the multi - population genetic algorithm, to determine the model parameters, and compared and analyzed the prediction results of the two models. The results showed that the time - series model based on the multi - population genetic algorithm had higher prediction accuracy.

Reviewing the research of the above scholars, it is found that a crucial part of demand forecasting is to reduce the dimensionality of the original data to improve data availability and reduce computational complexity. Classifying the processed data, using different methods for separate prediction, and then integrating the prediction results is a new research method at present.

3. Spare Parts Inventory Management

3.1. Related Concepts of Inventory Management

The goal of supply chain inventory management is subordinate to the goal of the entire supply chain. By planning, organizing, controlling, and coordinating the inventory on the entire supply chain, the inventory at each stage is controlled to a minimum, thus reducing inventory management costs, minimizing resource idleness and waste, and minimizing the overall inventory cost of the supply chain. Compared with traditional inventory management, supply chain inventory management is no longer a measure to maintain production and sales but a balance mechanism of the supply chain. Through supply chain management, the weak links in enterprise management are eliminated to achieve the overall balance of the supply chain (Ye,2024).

Accurate demand forecasting provides a solid foundation for subsequent enterprise inventory management. Different enterprises have different understandings of inventory management (Shao, et al, 2024) mainly including three types:

The first is to hold a large amount of inventory. In most cases, holding more inventory can bring a higher level of customer service. For enterprises that urgently need to win market share and have little financial pressure, inventory is undoubtedly the simplest and most effective measure to deal with abnormal situations in the supply chain. However, due to the high holding costs brought by inventory, enterprises usually only adopt such an inventory management method in specific periods.

The second is to control inventory reasonably. Enterprises use the relevant logic and methods of material requirements planning (MRP) and manufacturing resource planning (MRPII) to keep inventory within a reasonable range, neither generating sluggish inventory due to excessive amounts nor suffering shortages due to unexpected situations. Most manufacturing enterprises will control inventory within a range they consider reasonable.

The third is "zero inventory" or as little inventory as possible. The main representative is the just - in - time (JIT) inventory control method first proposed by Toyota in Japan. It advocates reducing various wastes in the production process through a series of improvement activities, while exposing and solving related problems, and finally achieving the effect of "zero inventory".

3.2. Spare Parts Inventory Management

Nowadays, demand uncertainty brings problems such as inventory backlogs, component damage, and failure to deliver on time to inventory management. Inventory management based on demand uncertainty has become a new popular research field.

Lu and Tang (2024) divided uncertain factors into four categories: demand uncertainty, lead - time uncertainty, supply uncertainty, and uncertainty of emergency supplies in response to emergencies. The commonly used solutions in different situations were discussed, including the EOQ model, fuzzy function, GSA method; multi - objective optimization model, dynamic response algorithm; Nash equilibrium model, game model; the combination of ABC and AHP method, and the EOQ model robust optimization model. And future possible research directions were proposed, such as comprehensively considering different uncertain factors and the risk preferences of various related parties. Guo and Ji (2023) classified inventory into dependent - demand inventory and independent - demand inventory according to the correlation of demand. Aiming at problems such as improper inventory management, low turnover rate, and serious inventory backlogs in dependent - demand inventory, a component readiness model was constructed, the component readiness level was defined, the calculation of component damage rate was introduced, a reasonable safety period was set to prevent delivery delays caused by external factors, and a dynamic management and control method for the product manufacturing cycle was established. Bo and Tian (2024) considered different random interferences, such as temperature changes, purchase prices, and holiday promotions, and proposed a parameter - based SLQ optimal control model. Simulations were carried out for inventory control problems of different dimensions. Francesco et al (2024) studied the supply chain inventory management problem in the context of a two - stage divergent supply chain. A SCIM software environment capable of modeling all the above - mentioned characteristics was designed and developed, and a new heuristic method combining the DRL algorithm and MS stochastic programming was proposed to calculate effective solutions for the proposed SCIM problem. The usefulness of the proposed heuristic method was demonstrated through a series of numerical experiment settings (for example, by changing the uncertainties related to demand and the number of distribution warehouses). Islam Md. Mohihul and Masahiro (2023) established a scenario - based stochastic rolling - planning three - stage logistics model. In this model, various risk factors such as customer demand, material quality, material price fluctuations, and delivery time were considered. The purpose of this model was to minimize the total logistics cost by controlling inventory, shortage, and backlog levels. Barto et al (2024) studied the challenges faced in inventory management by two warehouses operating under the "last - in, first - out" (LIFO) ordering strategy, including unpredictable demand patterns, Weibull - distributed decay, the need to adopt green technology to reduce carbon emissions, and various potential backlog scenarios.

Current inventory management considers different limiting factors, such as different scenarios of demand uncertainty and lead - time uncertainty, and combines corresponding model algorithms to set safety inventory, reduce storage costs, and improve inventory satisfaction. However, most research focuses on inventory control in different backgrounds and does not adjust and propose corresponding inventory management models based on actual cases and data.

4. Conclusion

Accurate demand forecasting enables enterprises to grasp market dynamics and trends, thus making relatively accurate production plans. Accurate inventory management can reduce inventory backlogs, capital occupation costs, and inventory risk costs. Through the review of existing literature, it is found that with the increasingly fierce market competition and the increase in customer - specific demands, accurate demand forecasting is affected by many factors. If the market cannot be accurately predicted, it will not only pose challenges to inventory management but also affect the coordination and initiative ability of the upstream and downstream of the supply chain management. This article starts from the methods of demand forecasting. Existing scholars use machine learning algorithms and time - series algorithms for demand forecasting. First, the data is pre - processed to improve data availability, and then, according to the characteristics of the data, appropriate machine learning algorithms or time - series algorithms are selected for demand forecasting. Regarding inventory management, due to the increase in uncontrollable factors such as customer - specific demands, seasonal fluctuations, delivery times, and market trends, it brings greater challenges to inventory management. This article starts from the perspective of demand uncertainty and explores the research of many scholars on demand uncertainty. Most scholars classify different demand types and select appropriate and accurate models or algorithms for solving according to different demand types.

Reviewing the above - mentioned research, it is found that there are relatively few articles considering the synergistic effect of demand forecasting and inventory management, and more research focuses on inventory management under demand uncertainty. Future research can explore the synergistic effect between the two and explore new forecasting methods to improve forecasting accuracy, so as to better reduce capital occupation costs, storage costs, inventory risk costs, and improve delivery time. Efficient demand forecasting and inventory management can also improve the level of supply chain management, coordinate the upstream and downstream of the supply chain, and enhance the core competitiveness of enterprises.

References

[1] An, Z.Y., He, E.Q. Regional Express Demand Forecasting Based on SARIMA Time - Series Model - Taking Jiangsu Province as an Example [J]. Logistics Sci-ence and Technology, 2022, 45 (20): 63 - 66 + 70.

[2] Barto, J., Eruguz, S. A., Spliet, R., et al. Reduced food waste through inventory control despite throwing out food before expiration: Online vs. offline re - tail [J]. Omega, 2024, 128.

[3] Bo, L., Tian, H. Stochastic optimal control and piecewise parameterization and optimization method for inventory control system improvement [J]. Chaos, Solitons and Fractals: the interdisciplinary journal of Nonlinear Science, and Nonequilib - rium and Complex Phenomena, 2024, 178.

[4] Dai, L.P., Shen, J.Y., Zhang, F.F. Automatic Prediction Model of Energy and Power Demand Based on Time - Series Algorithm [J]. Automation Technology and Applications, 2024, 43 (01): 49 - 51 + 65.

[5] Dui, H., Dong, X., Liu, M. A data - driven construction method of aggregated val - ue chain in three phases for manufacturing enterprises [J]. Computers & In-dustrial Engineering, 2024, 189.

[6] Fan, L.L., Cao, F.K., Wang, W.T., et al.Intermittent Demand Forecasting Method Based on Adaptive Matching of Demand Patterns [J]. Journal of Computer Applica - tions, 2024, 44 (09): 2747 - 2755.

[7] Francesco, S., Edoardo, F., Fabio, S. Combining deep reinforcement learning and multi - stage stochastic programming to address the supply chain inventory management problem [J]. International Journal of Production Economics, 2024.

[8] Guo, C.D., Ji, K. Research on Inventory Control Based on Component Readi-ness [J]. Journal of Hebei University of Science and Technology (Social Sciences Edition), 2023, 23 (04): 50 - 57.

[9] Kumar, L., Sharma, K., Khedlekar, U. Dynamic pricing strategies for efficient in - ventory management with auto - correlative stochastic demand forecasting using exponential smoothing method [J]. Results in Control and Optimization, 2024, 15.

[10] Li, W., Ai, X.Y. Manufacturer Inventory Demand Forecasting Based on ESN Mod - el [J]. Logistics Science and Technology, 2024, 47 (05): 35 - 39.

[11] Li, X.J., Zhang, F.Y., Yu, L. Wind Power Spare Parts Demand Forecasting Based on Principal Component Analysis - BP Neural Network [J]. Science Tech-nology and En - gineering, 2024, 24 (01): 281 - 288.

[12] Liang, X.Z., Wu, Z.K., Yang, M.G., et al. Research on Air Passenger Demand Forecasting Based on Quadratic Decomposition Strategy and Fuzzy Time - Series Model [J]. Chinese Journal of Management Science, 2020, 28 (12): 108 - 117.

[13] Lu, M.N., Tang, Q. Review of Supply Chain Inventory Management in Uncer-tain Environments [J]. Logistics Engineering and Management, 2024, 46 (02): 43 - 46 + 39.

[14] Mohibul, M. I., Masahiro, A. Development of an integrated scenario - based sto - chastic rolling - planning multistage logistics model considering various risks [J]. Heliyon, 2023, 9 (11): 28.

[15] Rong, L., Vinay, V. Optimizing Supply Chain Management Through BO - CNN - LSTM for Demand Forecasting and Inventory Management [J]. Journal of Or-ganiza - tional and End User Computing (JOEUC), 2024, 36 (1): 1 - 25.

[16] Shao, S.Q., Zhong, Y.G., Chen, Z., et al. Review of Data - Driven Inventory Man - agement Research Based on Demand Uncertainty [J]. Industrial Engineer-ing, 2024, 27 (03): 1 - 11.

[17] Wang, S.Y., Zhu, Z.T. Forecasting and Analysis of Logistics Demand in Shanghai Based on Time - Series [J]. Logistics Science and Technology, 2022, 45 (18): 50 - 54.

[18] Yang, M.J., Meng, Z.J., Li, C., et al. Intelligent Grid Demand Forecasting Based on Data Mining [J]. Microcomputer Applications, 2024, 40 (02): 101 - 105.

[19] Ye, Y.Q. Research on Inventory Management Problems and Countermeas-ures of Manufacturing Enterprises [J]. Modern Marketing (First Half of the Month), 2024, (06): 132 - 134.

[20] Zheng, Y., Huang, X., Xiao, Y.J. Research on Commodity Demand Forecasting Model Based on Time - Series [J]. Journal of Chongqing University of Technology (Natural Science), 2019, 33 (09): 217 - 222.