Research on the Application of Computer Technology in Multi-variety and Small-batch Material Production

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Abstract:
This paper employs the Autoregressive Integrated Moving Average Model (ARIMA) and regression analysis to examine the equilibrium relationship between inventory and service level. A survey questionnaire was used to study the data changes of inventory managers under different inventory conditions. This article adopts the Analytic Hierarchy Process (AHP) to accurately select 6 representative materials and establish an ARIMA model based on historical data for weekly prediction. Multiple predictions are made on interpolation data, interpolation data, and different parameters, and compared with historical data to provide the optimal prediction model. At the same time, this article combines historical data of manufacturing enterprises and uses regression analysis methods to explore the equilibrium state between inventory and service levels, providing more guidance for optimizing production arrangements. A regression model was established to analyze inventory data and the questionnaire on digital management of inventory. The optimal value of inventory was analyzed while ensuring the full utilization of computers to strengthen inventory management, providing production guidance for maximizing the interests of enterprises and consumers. By utilizing model predictions and conducting surveys and analyses on the application of computer technology in inventory management, the optimal inventory level can be determined, thereby assessing the extent to which computer technology plays a role in inventory management.

Keywords: digital application, inventory management, computer algorithm, small batch, multiple varieties

INTRODUCTION

With the diversified and personalized development of consumer demand, manufacturing enterprises are faced with the situation of multi-species and small-lot material production [1]. When visiting and researching many manufacturing enterprises, we found that such enterprises generally have a problem: in the dynamic production of small-lot materials, it is difficult to accurately predict the actual demand for materials, and it is difficult to determine the optimal level of material inventory, and then it is difficult to determine the balance between the inventory and the level of service.

Small-volume procurement is an essential feature of time-based procurement. An important difference between time-based procurement and traditional procurement models is that time-based production requires fewer production lots, and therefore supplies should be procured in small quantities [2]. Of course, supplying in small quantities increases the number and cost of shipments, especially when suppliers are located in remote situations, making it more difficult to implement just-in-time supply.

OBJECTIVES

In order to solve the enterprise pain point of "how to determine the reasonable inventory level of small quantities of materials"[3], this paper intends to use Excel data pivot charts to analyze the real historical data of the enterprise production based on statistical analysis and mathematical modelling to construct an ARIMA prediction model to determine the optimal level of material inventory, and then formulate the material production plan [4]. The aim is to explore the balance between inventory and service level, and maximize the interests of enterprises and customers.

The Autoregressive Integrated Moving Average Model (ARIMA) integrates the advantages of the Autoregressive Model (AR) and the Moving Average Model (MA) [5]. ARIMA can handle various types of time series data, including those with trends, seasonality, and cyclical patterns. The model's parameters (p, d, q) can be adjusted based on the data's characteristics, making it versatile for different data patterns. ARIMA uses differencing to transform non-stationary time series into stationary ones, which is crucial for satisfying the stationarity assumption required for modeling. Even if the data is non-stationary, ARIMA can stabilize it through appropriate differencing orders (d) and then proceed with modeling and forecasting. ARIMA parameters are typically estimated using least squares or maximum likelihood estimation, which are robust statistical methods. Model selection is aided by autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, and model validation is performed using residual tests (e.g., Ljung-Box test) to ensure the model's effectiveness. ARIMA performs well in short-term forecasting, especially for time series with clear trends and seasonality. It leverages historical data patterns to predict future values. The model provides confidence intervals for forecasts, helping users assess the uncertainty associated with predictions. ARIMA can be combined with other models to enhance forecasting accuracy. Although primarily used for univariate time series, ARIMA can be extended to handle multivariate time series through models like Vector Autoregression (VAR). ARIMA is more suited for short-term predictions. Its linear nature may not capture long-term trends effectively. ARIMA assumes linear relationships in data and may struggle with highly non-linear patterns. In such cases, combining it with non-linear models (e.g., neural networks) is recommended. ARIMA requires sufficient historical data to estimate parameters accurately. Insufficient data can lead to poor model fit. The model is sensitive to outliers in the data, which can affect model fitting and forecasting results. ARIMA is computationally efficient, making it suitable for quick modeling and forecasting, even in resource-constrained environments. Due to its efficiency, ARIMA can be used for real-time monitoring and forecasting. ARIMA is a powerful and flexible tool for time series analysis, particularly effective for short-term forecasting of univariate data with trends and seasonality. While it excels in handling linear patterns and non-stationarity, it may require enhancements or combinations with other methods to address non-linear relationships and long-term forecasting needs.[6]. It is influenced by external factors and has its own pattern of change. The model is that when the series is trending, it can be smoothed by differential treatment of some order[7].

Regarding the ARIMA time series forecasting model, scholars at home and abroad have commonly applied it to the research of macroeconomics, mathematics, infectious diseases and preventive medicine [8], and it is less common to apply it to the production problems of enterprises.

Behavioral theory is also used in this paper when making decisions. Behaviorism theory, which was founded by American psychologist John Watson on the basis of Pavlov's theory of conditioned reflex [9], advocated that psychology should abandon consciousness, imagery and other subjective things, and only study the stimulus and reaction that can be observed and measured objectively.

METHODS

The model is based on the following assumptions:(1) It is assumed that the data in the annexes are true, accurate and without error.(2) Assume that there is no inventory and no stock-outs at the end of the 100th and 101st week.(3) Assume that the product production time is 1 week.(4) Assume that if the product can be sold in 1 week, the inventory length is 0.

Based on statistical analysis, mathematical modelling, and based on the historical data of an enterprise, we tried to decompose the problem and solve it in four steps.

Step 1

First of all, 22,453 pieces of real historical data of the research enterprise were used to classify the material code, and the total demand, average unit price and demand frequency of 284 kinds of materials were calculated. Then, the three types of data were normalized and the weights of demand, unit price and demand frequency were calculated using the analytic hierarchy process. The comprehensive scores of 284 kinds of materials were weighted and sorted in descending order according to the scores. The top 15 kinds of materials were extracted and the trend of weekly number and demand was predicted. The 6 kinds of materials with the broadest weekly number coverage and stable development trend were selected for analysis. Then, the missing weeks of 6 kinds of materials were interpolated to obtain the complete demand data. ARIMA(p,d,q) model was used to predict the demand[10]. Finally, the historical data and predicted values were evaluated and analyzed according to the model statistics.

Step 2

Step 2 requires the use of historical data, demand characteristics, and forecast data for the six key materials selected in Step 1, but not the data for this week and beyond, to develop a reasonable production plan. And the requirements of the plan at the beginning of each week, this week's production can only be used in the next week and beyond, and to meet the beginning of the 101st week, until 177 weeks, to meet the service level of not less than 85%. When using the ARIMA (p, d, q) model for predictive modeling, it is necessary to utilize historical data and demand characteristics for demand forecasting. [11]. The second problem using the results of the demand forecast in problem one as a production plan for six materials, to build the inventory and stock-out solving model, to find out its average service level, inventory, stock-outs, service level, etc., and appropriately reduce the average level of service, to reduce inventory, to develop a more reasonable service level. Reduce the inventory and make a more reasonable production plan.

Step 3

Step 3 requires that some balance be struck between inventory levels and service levels in order to maximize revenue for the firm and good service for the consumer. In Step 2, the average service level of these six materials is around 95%, and the inventory levels are relatively high. Therefore, it is necessary to modify the production plan in Step 2 to reduce the inventory levels. The specific approach is to reduce the production plan by one unit per week and then recalculate the service level and average inventory using the calculation method in Step 2 [12]. Subsequently, reduce the production plan by another unit per week and perform the calculations again. This process is repeated multiple times for each material to obtain multiple sets of data on service level and average inventory [13]. Finally, regression analysis is conducted on these data to determine the relationship between the optimal service level and optimal inventory, identify a balanced relationship, and thereby formulate a better production plan.

Step 4

The difference between the calculation of Step 4 and that of Steps 2 and 3 is: firstly, the entire production plan of Steps 2 and 3 is advanced by one week, and secondly, there is one more week of inventory for each product than that in Steps 2 and 3, i.e., there is an increase in the average inventory level [14]. There is no change in the values of other quantities such as stock-outs, service levels, etc. This will lead to an increase in inventory funds, so a re-adjustment of the plan is explored, which is still adjusted according to the model in Steps 2 and 3 to develop a reasonable production plan.

ERSULTS

Build different types of material demand, and unit price of the average value, the frequency of demand model on the original data to establish a pivot table, according to the material code for classification, the demand for its summation and aggregation, the average unit price, the frequency of the material to count [15].

Construct a hierarchical analysis model to find the weights of each of the three factors: quantity demanded, average unit price, and frequency of demand [16]. For two-by-two comparisons of demand, unit price averages, and demand frequency importance, a comparison matrix is constructed based on the following scale, as shown in Table 1.

Table 1 Meaning of scales

Scale	Hidden Meaning
1	Indicates that the two factors are of equal importance compared to each other
3	Indicates that one factor is slightly more important than the other when compared to two factors
5	Indicates that one factor is significantly more important than the other when comparing two factors
7	Indicates that one factor is more strongly important than the other when comparing two factors
9	Indicates the extreme importance of one factor over the other when comparing two factors
2,4,6,8	The median of the two adjacent judgements above

Conduct a consistency test on the matrix to determine the weights of demand, the mean of unit price, and demand frequency. The results were obtained: the weights of demand, unit price, and frequency were 0.5455, 0.2727, and 0.1818, respectively.

Use the weighted average to calculate the composite score of various materials, the score for the descending order [17]. Take the top 15 materials and analyze the trend to make a line statistic of demand versus weeks. Based on the images according to the breadth of coverage of the weeks, the size of the demand, the frequency of occurrence, the code 6004020503, 6004010174, 6004010256, 6004010207, 6004020656, and 6004100008 are selected as the six key materials of concern. Linear interpolation and spline interpolation are carried out for these six materials.

Based on the collated weekly demand data of material 6004020503, observe its time series graph to find that the demand has a certain periodicity and growth trend, perform first-order differencing through SPSS, and make its time series.

The images were found to be periodically fluctuating up and down around a straight line, the data tend to be stable and have some autocorrelation, so the ARIMA (p,1, q) model was chosen for prediction [18].

By comparing the statistical results of the above six models, the smooth R-squared in ARIMA(3,1,12) model is 0.397, which is larger than other models, the root mean square of error RMSE=13.813, which is smaller than other five models, and the model significance test probability $p = 0.046 < 0.05$ According to the optimality test principle of the model: smooth R-square is large, root mean square of error RMSE is small, and the probability of $p = 0.046 < 0.05$ of the six predictions, the ARIMA(3,1,12) model has the best prediction effect. Table 2 shows some predicted data.

Table 2 Prediction data

weekly	Quantity demand	Projected value
1	45	
2	31	45
3	16	37
4	6	27
5	12	15
6	17	18
7	2	19
8	8	12
9	9	9
10	18	14
11	3	23
12	20	12
13	21	16
14	22	17
15	12	27

Similarly for the weekly demand data of material 6004010174, observe its time series graph to find that the demand has a certain periodicity and growth trend, first order difference through SPSS.

The images were found to be periodically fluctuating up and down around a straight line, the data tend to be stable and have some autocorrelation, so the ARIMA (p,1, q) model was chosen for prediction [19]. Six different p, q values were selected.

By comparing the six sets of predicted data above, the smooth R-squared in ARIMA(3,1,4) model is 0.432, which is larger than other models, the root mean square of error RMSE=13.013, which is smaller than other five models, and the probability of model significance test $p = 0.05 \leq 0.05$ According to the optimality test principle of the model: smooth R-square is large, root mean square of error RMSE is small, and the probability is small. $p = 0.05 \leq 0.05$ The ARIMA(3,1,4) model has the best prediction effect among the six predictions.

Similarly for the weekly demand data of material 6004010256, observing its time series graph found that the demand has a certain periodicity and growth trend, the first-order difference through SPSS.

In step 1, we used hierarchical analysis to precisely select six materials, and established an ARIMA model for weekly prediction of historical data, and made several predictions for uninterrogated data and interpolated data, and different choices of p, d, and q. The optimal prediction model was given by comparing it with the historical data.

In step 3, the equilibrium point between the average service level and the average inventory is calculated by fitting a quantitative function of the average service level and the average inventory using regression analysis.

Graphs were drawn using mathematical software such as SPSS and MATLAB to make the statistical and forecasting results more visual.

When the average service level is fitted to the average inventory, there is some deviation in the fitting function due to the limited data available, resulting in some error in the equilibrium point as well [20].

Multiple adjustments were made to the production schedule, using more data to explore the function between average service levels and average inventory levels to find a more precise balance.

DISCUSSIONS

For the six priority materials selected in step 1, the question asks for a reasonable production plan using historical data, demand characteristics, and forecast data, but not data for the current week and beyond, and assuming that the materials planned for production this week can only be used next week and beyond, and that the average level of service from week 101 to week 177 is not less than 85 per cent.

The model forecast in step 1 is the ARIMA(p,d,q) model, which is a demand forecast using historical data and demand characteristics, so step 2 uses the demand forecast results from step 1 to develop a production plan for the six materials and builds a model to find their average service level, inventory, stock-outs, and service level.

The materials planned to be produced this week can only be used in the next week and beyond. At the end of the 100th week, there is no inventory or stock-out, and the production plan quantity for the 100th week is exactly equal to the actual demand in the 101st week. Therefore, construct a model of inventory and stock-outs from week 101 to week 177.

Among the six materials selected in step 1, the material coded 6004020503 is selected, and its service level, production plan, actual demand, inventory, and out-of-stock for the 101st to 110th week are calculated. Find out all the data of the 6 materials from week 101 to week 177 The specific results are shown in the support material step 2 all the calculation results excel file.

Model and solve for average service levels, average production schedules, average actual demand, average stock levels, and average stock-outs. The average function in Excel was used to find the above mean values and the results.

From the results of step 2, it is found that the higher the average service level, the larger the inventory and the higher the funds on hand. Considering the price of the material, the inventory capital of the material. In order to achieve some equilibrium between inventory levels and service levels so that the firm maximizes revenue and the consumer receives good service. Now, by adjusting the existing weekly production plan, the mathematical relationship between the optimal service level and optimal inventory management is explored in order to find the equilibrium point between the inventory and the service, such that even when the average inventory reaches its minimum, the average service level can still achieve its maximum value and is not less than 85%.

The average service level of all 6 materials in step 2 is around 95% and the inventory is large, so the production plan in step 2 is now adjusted. Adjustment method is to reduce the production plan of step 2 by 1 piece per week, then calculate the optimal service level and optimal inventory according to the calculation method of step 2, and then reduce the new production plan by 1 piece per week and calculate again. Repeat the calculation 5 times for each type of material to get 5 sets of average service level and average inventory data.

Make a plot of average service level versus average inventory fit. For material 60040220503 found a curvilinear relationship between the two, the use of SPSS regression command under the curve fitting, selecting linear, quadratic and cubic for fitting, the results of the quadratic fit are the best. Using the fitted quadratic function, it can be calculated that the average service level is 86.5 per cent and the optimal inventory is the smallest, with a minimum value of 7.8, i.e., the minimum inventory is 8 and the average service level is 86.5 per cent, which achieves the equilibrium point between the optimal service level and optimal inventory.

From the forecast, it can be roughly seen that the inventory of material 2 reaches its lowest level when the average service level is 83 per cent, but considering that the average service level cannot be lower than 85 per cent, the optimal service level of 85 per cent is the equilibrium point of the optimal service level and optimal inventory; the equilibrium point of material 3, 4, 5 and 6 is reached when the optimal service level is 85%, 88%, 85% and 85%, respectively.

Among the production plans adjusted several times in the first step, the production plan with the average service level and average inventory closest to the balance point is selected as the optimal production plan. The number of weekly production plans, actual demand, inventory, out-of-stock and service level results for the material code 6004010207 and the combined results for the six materials.

Step 4 is the requirement that the materials planned for production this week can only be used two weeks and beyond, reconsidering Steps 2 and 3. After analysis, it is found that the operations that differentiate Step 4 from the calculations in Steps 2 and 3 are: firstly, the entire production plan of the original Steps 2 and 3 is advanced by one week; and secondly, there is one more week of inventory for each product than that of the products in Steps 2 and 3. There is no difference in the calculation of other quantities such as stock-outs, service levels, etc., except that it results in an increase in inventory and inventory capital. The fit is good and consistent with the results of step 3, so it is only necessary to advance the production schedule of step 3 by one week.

The model can be extended and applied to determine the optimal inventory level in manufacturing enterprises when producing multiple varieties and small quantities of materials, to the planning and scheduling of economic ordering lot sizes in retail enterprises and to dynamic production and inventory management in the field of logistics.

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