Research on the demand prediction of parts inventory for auto customer service

Rong Zeng

College of mechanical and electrical engineering JING HAN University, Wuhan, 430056, China

Abstract: In order to optimize the inventory of auto aftermarket parts, the second weighted moving average method is used to forecast the demand of auto aftermarket parts. Compared with the traditional weighted moving average method, the results show that the improved method is better than the traditional method.

1. Introduction
The prediction of auto parts inventory demand is the premise of determining reasonable parts inventory, and the prediction method directly affects the accuracy of the prediction.

The methods of demand forecasting mainly include qualitative forecasting and quantitative forecasting. Qualitative methods include regression analysis and time series method, etc. [1]. Regression analysis mainly considers influencing factors, and the selection of future values of independent variables and dependent variables is predictive to a certain extent, which will interfere with the predicted values. However, the time series method does not consider the factors that affect the demand, including the moving average method, exponential smoothing method, etc.

Automobile aftermarket parts demand is affected by many factors, the degree of influence is difficult to predict, so this paper adopts the improved moving average method to predict it.

2. Influence factors of automobile aftermarket parts
The influencing factors of automobile after-sales parts are very complex, which are not only affected by supply lead time, inventory cycle, cost and other factors, but also affected by seasonal factors, political factors, economic level and so on [2]. Therefore, its demand forecasting is not large, forecasting accuracy is not high. Combined with the above characteristics, this paper proposes an improved forecasting method to predict the demand for auto aftersales parts, which can solve the problem of inventory control, reduce enterprise cost, improve management efficiency and improve customer relationship to a certain extent.

3. Improved forecasting methods

3.1 The traditional weighted moving average method
Taking the actual sales data of a company's product M-H-VVT from 2010 to 2013 [3] as an example, the effectiveness of the improved weighted moving average method is illustrated.

| month | 2011  | 2012  | 2013  |
|-------|-------|-------|-------|
| January | 13612 | 10100 | 13313 |
Through the traditional weighted moving average method, it is found that the results still have a certain lag, the curve variance is smaller than the actual value, the curve is more gentle, but the accuracy is obviously better than the simple moving average method. The error of the weighted moving average method is large, and there is room for improvement in the selection of weight. The better weight can be selected by empirical method and trial method.

3.2 Improved weighted moving average forecasting method

The weighted moving average method is a very typical short-term prediction, which is used to predict the parameter values in a period of time in the future through the past historical data. This method needs enough data to calculate the prediction result, otherwise, the calculation error may be too large due to the lack of data. From the data in Table 1, it can be seen that the storage demand of auto parts is obviously affected by the seasonality. From January to May of each year, the demand of this product is more than 10000. In June August, the demand obviously drops to about 7000, and then it increases obviously from September to December. In this paper, considering the seasonal periodic change of automobile parts storage demand, the corresponding parameters are added to the weighted moving average method to improve the prediction accuracy of the method.

The model is modified by the difference value to reduce the influence of lag. Based on the influence of seasonal periodicity of auto parts storage, $W$ is set as the percentage of the average value of seasonal periodic months to the overall average value, and $M$ is the demand forecast month. Then:

| time       | Actual sales Xn | Periodic mean | $W$  |
|------------|-----------------|---------------|------|
| 2011.1     | 13612           |               |      |
| 2011.2     | 12665           |               |      |
| 2011.3     | 14515           |               |      |
| 2011.4     | 10539           |               |      |
| 2011.5     | 11730           | 12612         | 98.4%|
| ...        | ...             | ...           | ...  |
| 2013.8     | 9036            | 9328          | 72.8%|
| 2013.9     | 15793           |               |      |
| 2013.1     | 15600           |               |      |
| 2013.11    | 23179           |               |      |
| 2013.12    | 24936           | 19877         | 155.1%|
| Average    | 12816           | 12431         |      |

Because multiple calculation of weight will lead to over fitting of predicted data and tend to be stable, the improved formula is as follows:
\[ \bar{x} = w_1x_1 + w_2x_2 + \cdots + w_nx_n \]

where: \( f_1 + f_2 + \cdots + f_n = 1 \)

If \( M \) is January, \( W_i = W_1 \);
If \( M \) is June, \( W_i = W_2 \);
If \( M \) is September, \( W_i = W_3 \);
If \( M \) is other months, \( W_i = 1 \).

Then, by adding seasonal and cyclical factors into the forecast of automobile parts storage demand, the calculation results are as follows:

| time    | Actual sales Xn | Cyclical factor weighted moving average forecast results | Forecast error | Forecast error rate |
|---------|-----------------|--------------------------------------------------------|----------------|--------------------|
| 2011.1  | 13612           |                                                        |                |                    |
| 2011.2  | 12665           |                                                        |                |                    |
| 2011.3  | 14515           |                                                        |                |                    |
| 2011.4  | 10539           | 13779                                                  | 3240           | 30.7%              |
| 2011.5  | 11730           | 12157                                                  | 427            | 3.6%               |
| ...     | ...             | ...                                                    | ...            | ...                |
| 2013.9  | 15793           | 9149                                                   | 6644           | 42.1%              |
| 2013.10 | 15600           | 12290                                                  | 3310           | 21.2%              |
| 2013.11 | 23179           | 14345                                                  | 8834           | 38.1%              |
| 2013.12 | 24936           | 30133                                                  | 5197           | 20.8%              |
| Average | 12816           | 12276                                                  | 2571           | 19.2%              |

3.3 Results and analysis

After considering the weight of seasonal factors, the predicted value is closer to the actual value, and the volatility is stronger than the traditional weighted moving average method. The monthly average error rate is 19.2%, which is better than the previous model. The model eliminates the influence of lag to some extent. But the variance is large and the uncertainty is high. Because the model uses point-to-point value, the accuracy is very high in a certain range, but the error value is large in the range of gentle demand.

4. Conclusions

The forecast of the inventory demand of automobile after-sales parts is related to the inventory optimization and decision-making, the sales of parts, and more importantly, the satisfaction of consumers \(^4\). In view of the limitation of the traditional moving average method, the improved method is used to predict the sales volume of automobile aftermarket parts, so as to control the inventory reasonably. The results show that the improved method has a certain improvement in the prediction accuracy. However, this model is not universal, but only considers the cyclical impact of warehousing demand for auto parts, and the specific assignment needs to be determined by the inherent law of specific data.

Acknowledgments

This paper is funded by the university's high-level talent research project, the project number is 100606650001, and the name is “auto parts supply chain resource optimization research”.

References

[1] YANG Jing ya, SUN Lin fu. Demand prediction of parts inventory for customer service based on QPSO SVR[J]. Computer engineering and design, 2015, 036(009):2539-2543,2571.
[2] JIN Chun, CAO Di, WANG Cong. etc. A Synthetic Integrated Model to Forecast the Demand for Automobile Parts in 3PL Warehouse[J]. Journal of Systems and Management, 2018, 027(006):1157-1165.

[3] SHI Wei hai. Research on Application of demand forecasting model for auto parts enterprises [D]. Shanghai Jiao tong University, 2014.

[4] LIAO Wei zhi, SUN Lin fu, DU Ping an. Service oriented auto parts demand forecasting model [J]. Computer integrated manufacturing system, 2010(08):212-216.