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Forecasting Methods to Reduce Inventory Level in Supply Chain

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Abstract

Based on the two-level supply chain composed of suppliers and retailers, we assume that market demand is subject to an ARIMA(1, 1, 1). The supplier uses the minimum mean square error method (MMSE), the simple moving average method (SMA) and the weighted moving average method (WMA) respectively to forecast the market demand. According to the statistical properties of stationary time series, we calculate the mean square error between supplier forecast demand and market demand. Through the simulation, we compare the forecasting effects of the three methods and analyse the influence of the lead-time L and the moving average parameter N on prediction. The results show that the forecasting effect of the MMSE method is the best, of the WMA method is the second, and of the SMA method is the last. The results also show that reducing the lead-time and increasing the moving average parameter improve the prediction accuracy and reduce the supplier inventory level.

Keywords

Supply Chain, Forecasting Method, ARIMA(1, 1, 1) Model, Mean Square Error

1. Introduction

Inventory problem has been an important problem in supply chain. Enterprise in the supply chain has been looking for ways to reduce their inventory levels because savings in inventory levels will eventually translate into cost savings over time. In order to control inventory, we must improve the forecasting accuracy. Many pieces of literature have proved that information sharing is an effective method to improve forecasting accuracy and reduce average inventory level. Suppliers hope to have stable quantity, stable variety demand, abundant and flexible delivery time, while retailers hope suppliers can deliver goods efficiently. Information sharing promotes the coordinated operation of supply chain. When sharing sales forecasting and inventory information, suppliers can know the demand and inventory of retailers in advance. Thus, we can shorten the delivery time, reduce the demand difference, and reduce the inventory cost and shortage cost [1] [2]. However, because of the importance of information, enterprises are reluctant to share information about themselves. Supply chain enterprises can only rely on improving forecasting accuracy to reduce their inventory level. Scholars at home and abroad put forward many methods to improve the accuracy of prediction. These methods analyze supply chain demand forecasting and inventory control from different aspects. The literature [3] [4] [5] has studied two-level supply chain under ARMA(1, 1), AR(1) and MA(1) demand processes. It studied effects of single exponential smoothing method and simple moving average method on mean square error and inventory level, which show that the saving of inventory cost depends on the improvement of forecasting accuracy. The literature [6] [7] use simple moving average method and weighted moving average method to forecast demand based on ARMA(p, q) demand process. The research shows that forecasting can save the inventory cost. The literature [8] [9] introduced exponential smoothing method and simple moving average method to infer downstream demand, and studied how manufacturers prepare inventory. Feng [10] shows that as for ARIMA(1, 1, 1) demand process, using moving average method to forecast the demand on lead-time can reduce the phenomenon of demand amplification. There are also many scholars optimizing some forecasting methods to improve the forecasting accuracy. Rhee improved forecast accuracy by controlling scheduled orders [11]. Huang [12] improved the forecasting accuracy of order demand by optimizing genetic algorithm. In some ways, the above strategies reduce the bullwhip effect and improve the forecasting accuracy. However, some errors will inevitably occur when using these strategies to forecast, and these errors will be amplified by suppliers step by step in the supply chain, which will lead to large fluctuations in the inventory system [13]. Therefore, this study starts from forecasting methods and forecasting errors to study the influence of three different forecasting strategies on supplier.

We base our modeling framework on the works of Tliche *et al.*, considering the two-level supply chain composed of a supplier and a retailer. Different from the previous time series demand model, we assume that the market demand obeys an autoregressive integrated moving average model ARIMA(1, 1, 1). We adopt the minimum mean square error method, the simple moving average method and the weighted moving average method to forecast the retailer's demand, and take the mean square error as an indicator to measure the forecasting effect.

2. Framework Model Assumptions

We consider a simple two-level supply chain composed of a supplier and a retailer. We keep the same assumptions as in Tliche *et al.*'s model, excepting the

ARIMA(1, 1) demand process. The parameters of the demand process are known. Both the supplier and the retailer use periodic review system. At time period *t*, the retailer first receives an order x_t from the market, and then checks its inventory, and before the period t ends, send out the order to the supplier. We assume that the order information transfer time is zero.

The supplier starts to forecast the retailer's orders at the end of the period $t-L-1$, then prepare the goods and send them to the retailer. Although the supplier does not receive the order from the retailer until the end of the period *t*, the supplier has already sent the goods to the retailer at the end of the period *t*. Due to the difference between the supplier's forecasting and the retailer's actual order, the retailer may receive more or less goods. The retailer can store the surplus goods for next period using. As for the insufficient part, the supplier will reissue the insufficient goods to the retailer. L represents the retailer's order lead-time (the time from production to delivery). The retailer's order lead-time is non-zero and deterministic.

Time-series process is widely used to simulate the demands of products in different fields. At time period t ($t=1,2,\cdots$), We assume that arriving demand is an invertible causal process ARIMA(1, 1, 1) at the retailer. Let x_t be the ARIMA(1, 1, 1) demand process at the retailer, such as

$$\phi(B)(1-B)x_t=\theta(B)\varepsilon_t \tag{1}$$

where $\phi(B)=1-\phi_1 B$, $\theta(B)=1-\theta_1 B$, B is the lag operator, ϕ_1 is autoregressive coefficient, θ_1 is moving average coefficient. $\{\varepsilon_t\}$ represents the fluctuation error of demand, independent and identically distributed at each period, $E(\varepsilon_t)=0$, $Var(\varepsilon_t)=\sigma^2$. The equivalent form is

$$x_t=(1+\phi_1)x_{t-1}-\phi_1 x_{t-2}+\varepsilon_t-\theta_1\varepsilon_{t-1} \tag{2}$$

According to the sufficient and necessary conditions that ARIMA is causal and invertible, we can get the condition of model ARIMA(1, 1, 1) stability is $\{\phi_1 \| \phi_1|<1\}$, and the condition of model ARIMA(1, 1, 1) invertibility is $\{\theta_1 \| \theta_1|<1\}$.

Use the linear equation of the fluctuation error term ε_t to represent the demand function x_t, then

$$x_t=\varepsilon_t+\psi_1\varepsilon_{t-1}+\psi_2\varepsilon_{t-2}+\psi_3\varepsilon_{t-3}\cdots=\sum_{j=0}^{\infty}\psi_j\varepsilon_{t-j} \tag{3}$$

where $\psi_0=1$, $\psi_1=1+\phi_1-\theta_1$, $\psi_j=(1+\phi_1)\psi_{j-1}-\phi_1\psi_{j-2}$, $j=2,3,\cdots$.

According to the characteristics of the demand equation, it can be concluded that the total demand of retailers over the $L+1$ review periods is

$$\sum_{i=1}^{L+1}x_{t+i}=\sum_{i=1}^{L+1}\sum_{j=0}^{\infty}\psi_j\varepsilon_{t+i-j} \tag{4}$$

3. Suppliers Production Strategy

The supplier's production strategy is based on the forecasting demand or the retailer's order. Since the supplier makes production plans in advance, the strategy is based on the supplier's own forecast rather than the retailer's order. We consider the three forecasting methods: Minimum Mean Square Error method (MMSE), Simple Moving Average method (SMA) and Weighted Moving Average method (WMA). Our objective is to find the most accurate forecasting method. The mean square error (MSE) is a good matric to measure the difference between the forecast and the true demand, and easy to compute. So we use it to compare the three prediction methods. The less the mean square error is, the more effective the forecasting method is.

3.1. Principle of Minimum Mean Square Error Prediction

The supplier adopts the MMSE method. According to the characteristics of demand process, at the time period $t+L$, the true value of market demand is

$$x_{t+L} = \left(\varepsilon_{t+L} + \psi_1\varepsilon_{t+L-1} + \psi_2\varepsilon_{t+L-2} + \cdots + \psi_{L-1}\varepsilon_{t+1}\right) + \left(\psi_L\varepsilon_t + \psi_{L+1}\varepsilon_{t-1} + \cdots\right) \quad (5)$$

where $\varepsilon_t, \varepsilon_{t-1}, \cdots$ are known and $\varepsilon_{t+L}, \varepsilon_{t+L-1}, \cdots, \varepsilon_{t+1}$ are unmeasured. Suppose the retailer's forecasting demand at the period $i+L$ is

$$f_{t+L}^{MMSE} = \psi_0^*\varepsilon_t + \psi_1^*\varepsilon_{t-1} + \psi_2^*\varepsilon_{t-2} + \cdots \quad (6)$$

The mean square error between the forecast and the demand is

$$E\left(x_{t+L} - f_{t+L}^{MMSE}\right)^2 = \left(1 + \psi_1^2 + \cdots + \psi_{L-1}^2\right)\sigma^2 + \sum_{j=0}^{\infty}\left(\psi_{L+j} - \psi_j^*\right)^2\sigma^2 \quad (7)$$

To minimize the mean square error, if and only if

$$\psi_j^* = \psi_{L+j} \quad (8)$$

Therefore, at time period $t+i$, under the principle of minimizing the mean square error, the forecast is

$$f_{t+i}^{MMSE} = \psi_i\varepsilon_t + \psi_{i+1}\varepsilon_{t-1} + \psi_{i+2}\varepsilon_{t-2} + \cdots \quad (9)$$

The mean square error of the supplier's forecasts over the $L+1$ review periods is

$$\begin{aligned} MSE^{MMSE} &= E\left(\sum_{i=1}^{L+1} x_{t+i} - \sum_{i=1}^{L+1} f_{t+i}^{MMSE}\right)^2 = Var\left(\sum_{i=1}^{L+1}\left(x_{t+i} - f_{t+i}^{MMSE}\right)\right) \\ &= Var\left(\sum_{i=1}^{L+1}\left(\varepsilon_{t+i} + \psi_1\varepsilon_{t+i-1} + \psi_2\varepsilon_{t+i-2} + \cdots + \psi_{i-1}\varepsilon_{t+1}\right)\right) \\ &= Var\left(\sum_{i=0}^{L}\psi_i\varepsilon_{t+1} + \sum_{i=0}^{L-1}\psi_i\varepsilon_{t+2} + \cdots + \sum_{i=0}^{1}\psi_i\varepsilon_{t+1} + \sum_{i=0}^{0}\psi_i\varepsilon_{t+1}\right) \\ &= \left(\sum_{i=0}^{L}\psi_i\right)^2\sigma^2 + \left(\sum_{i=0}^{L-1}\psi_i\right)^2\sigma^2 + \cdots + \left(\sum_{i=0}^{0}\psi_i\right)^2\sigma^2 \\ &= \sigma^2\left[\sum_{i=0}^{L}\left(\sum_{j=0}^{i}\psi_j\right)^2\right] \end{aligned} \quad (10)$$

3.2. Principle of Simple Moving Average Prediction

The supplier adopts the SMA method. The predicting values of the market demand at period $t+i$ is

$$f_{t+i}^{SMA} = \frac{x_t + x_{t-1} + x_{t-2} + \cdots + x_{t-N+2} + x_{t-N+1}}{N} \tag{11}$$

where $x_t, x_{t-1}, \cdots, x_{t-N+1}$ are the true demand at period $t, t-1, \cdots, t-N+1$, and N is the order of the simple moving average. Then, the sum of the foercasts over the $L+1$ review periods is

$$\sum_{i=1}^{L+1} f_{t+i}^{SMA} = (L+1)\left(\frac{x_t + x_{t-1} + x_{t-2} + \cdots + x_{t-N+2} + x_{t-N+1}}{N}\right) = (L+1) f_{t+1} \tag{12}$$

The mean square error of the supplier's forecasts over the $L+1$ review periods is

$$\begin{aligned} MSE^{SMA} &= E\left(\sum_{i=1}^{L+1} x_{t+i} - \sum_{i=1}^{L+1} f_{t+i}^{SMA}\right)^2 \\ &= Var\left(\sum_{i=1}^{L+1} x_{t+i} - (L+1)\left(\frac{x_t + x_{t-1} + x_{t-2} + \cdots + x_{t-N+2} + x_{t-N+1}}{N}\right)\right) \\ &= Var\left(\sum_{i=1}^{L+1} x_{t+i}\right) + (L+1)^2 Var(f_{t+1}) - 2(L+1)\text{cov}\left(\sum_{i=1}^{L+1} x_{t+i}, f_{t+1}\right) \\ &= (L+1)\gamma_0 + 2\sum_{i=1}^{L} i\gamma_{L+1-i} + (L+1)^2\left[\frac{\gamma_0}{N} + \frac{2}{N^2}\sum_{i=1}^{N-1} i\gamma_{N-i}\right] \\ &\quad - \frac{2(L+1)}{N}\sum_{i=1}^{L+1}\sum_{k=0}^{N-1}\gamma_{i+k} \end{aligned} \tag{13}$$

where $\gamma_k = \text{cov}(x_{t+k}, x_t)$ is the covariance of x_{t+k} and x_t in the demand process ARIMA(1, 1, 1) that only depends on the length of period translation and has nothing to do with the start period and the end period. They are determined by

$$\begin{aligned} \gamma_0 &= \gamma(x_t, x_t) = (1+\phi_1)\gamma_1 - \phi_1\gamma_2 + \sigma^2(1-\theta_1\psi_1) \\ \gamma_1 &= \gamma(x_t, x_{t+1}) = (1+\phi_1)\gamma_0 - \phi_1\gamma_1 - \sigma^2\theta_1 \\ &\vdots \\ \gamma_k &= \gamma(x_{t+k}, x_t) = (1+\phi_1)\gamma_{k-1} - \phi_1\gamma_{k-2} \quad (k \geq 2) \end{aligned} \tag{14}$$

3.3. Principle of Weighted Moving Average Prediction

The supplier adopts the WMA method to forecast next period demand, and the forecasting value at period $t+i$ is

$$f_{t+i}^{WMA} = \sum_{i=1}^{N} y_i x_{t+1-i} \tag{15}$$

where y_i is the weight vector, and $\sum_{i=1}^{N} y_i = 1$, $y_i \geq 0$, $\forall i \in \{1 \cdots N\}$. The total forecasting demand over the $L+1$ review periods is

$$\sum_{i=1}^{L+1} f_{t+i}^{WMA} = (L+1)\left(\sum_{i=1}^{N} y_i x_{t+1-i}\right) \tag{16}$$

The mean square error of the supplier's forecasts over the $L+1$ review periods is

$$\begin{aligned} MSE^{WMA} &= E\left(\sum_{i=1}^{L+1} x_{t+i} - \sum_{i=1}^{L+1} f_{t+i}^{WMA}\right)^2 = Var\left(\sum_{i=1}^{L+1} x_{t+i} - (L+1) f_{t+i}^{WMA}\right) \\ &= Var\left(\sum_{i=1}^{L+1} x_{t+i}\right) + (L+1)^2 Var\left(f_{t+i}^{WMA}\right) - 2(L+1)\operatorname{cov}\left(\sum_{i=1}^{L+1} x_{t+i}, f_{t+i}^{WMA}\right) \\ &= (L+1)\gamma_0 + 2\sum_{i=1}^{L} i\gamma_{L+1-i} + (L+1)^2\left[\gamma_0 \sum_{i=1}^{N} y_i^2 + 2\sum_{j=1}^{N-1}\left(y_j \sum_{i=j+1}^{N} y_i \gamma_{i-j}\right)\right] \\ &\quad - 2(L+1)\sum_{i=1}^{L+1}\sum_{j=1}^{N} y_i \gamma_{i+j-1} \end{aligned} \tag{17}$$

To determine the weights of the WMA method, we solve the optimization problem

$$\begin{cases} \min MSE^{WMA} \\ \sum_{i=1}^{N} y_i = 1 \\ y_i \geq 0, \forall i \in \{1 \cdots N\} \end{cases} \tag{18}$$

The objective function is convex and the constraint conditions are linear equality constraint and linear inequality constraint. In each iteration, the initial feasible point is selected and the feasible point is taken as the starting point. The constraint acting at this point is taken as the equality constraint, and the objective function is minimized under this constraint, while the other constraints are left alone. After finding a new and better feasible point, repeat the above process until the best point is found. In this paper, according to the effective set method, we use MATLAB program iteration, and then the optimal weights for different objective functions and constraint functions are obtained.

From the three subsections we conclude that the SMA method is easy to compute and therefore is easy to use in practice, but it relies on the observations of the most recent N periods, does not apply to the processes with curvilinear trends and seasonal trends, and therefore can be used only for short-term prediction. The MMSE method is applicable to a wide range, but difficult to compute. With repect to the WMA method, it is easier to compute than the MMSE method, more difficult than the SMA method, and not applicable for long-term prediction as the SMA method.

4. Simulation Calculation

In this section, we through numerical simulation to analyze the influence of parameters on the mean square error, and how these parameters affect the mean square error. According to the equation mode of parameters, we summarize some measures that can help managers control inventory. We use the effective set method to calculate the optimal weight, and apply the optimal weight to our simulation experiment. All the values selected in this paper have been used in the previous literature. The selected data simulation results are the most clear, so it is shown as an example. Through a large number of simulations, we find that the simulation results obtained by selecting other data are the same. In the simulation part, we use MATLAB programming software design the algorithms.

It can be seen from the expression of mean square error that the size of mean square error is related to parameters L, N, ϕ_1, θ_1. Since parameters ϕ_1, θ_1 do not determine changes in inventory strategy and order form, and it has no effect on demand forecasting in lead-time, so we are not going to talk too much about their values. We only consider the influence of lead-time L and sampling period N on the mean square error.

4.1. Comparison of the Three Prediction Methods

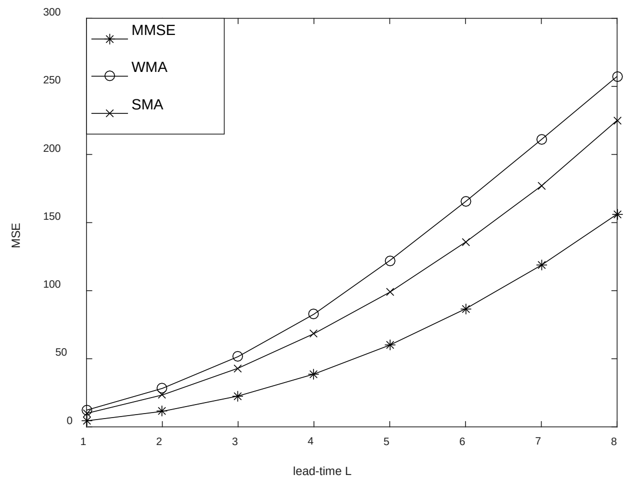
In the first part of the simulation, we take the regression coefficient, the moving average term and the moving average parameter as follows: $\phi_1 = -0.25$; $\theta_1 = -0.1$; $N = 12$. The mean square errors of the three forecasting methods varying with the lead-time L are shown in **Figure 1(a)**. The mean square errors percentage reductions of the MMSE method relative to the other forecasting methods are shown in **Figure 1(b)**.

It can be seen from **Figure 1(a)** that no matter which forecasting method is adopted, the error of the demand forecast will increase as the lead-time increases. This is consistent with the facts. As the lead-time increases, the forecast period becomes longer, which leads to a larger forecasting error. When the lead-time L is given, it can be seen from **Figure 1(a)** that the mean square error of the MMSE method is significantly smaller than that of the SMA method or the WMA method, and the forecasting effect is the best. The mean square error of the SMA method is the most, and the forecasting effect is the worst. The mean square error of the WMA method is between the MMSE method and the SMA method, and its forecasting effect is also between them. It is suggested that managers can shorten the forecast lead-time as much as possible in order to improve the forecasting accuracy and reduce inventory holding.

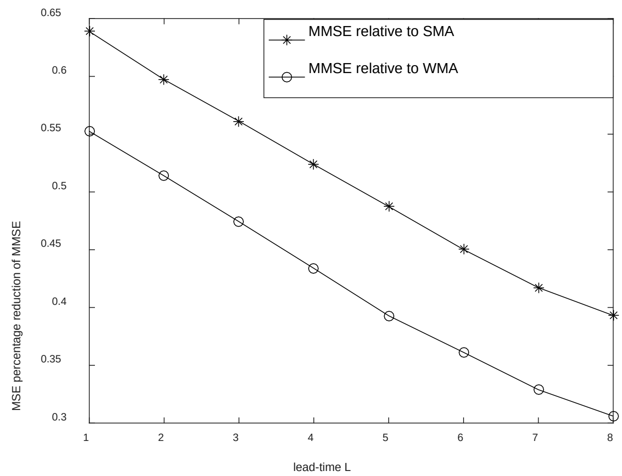
From **Figure 1(b)**, when the lead-time L is smaller, the mean square errors percentage reductions of the MMSE method relative to the others are more. With the lead-time L increases, the mean square errors percentage reductions decrease. It implies that the prediction gaps between the MMSE method and the other methods narrow as the lead-time L increases.

4.2. Comparison between Simple Moving Average Method and Weighted Moving Average Method

In the second part of the simulation, we take the regression coefficient and moving average term, lead-time as follows. $\phi_1 = -0.8$; $\theta_1 = -0.1$; $L = 5$. Since the MMSE method does not rely on the moving average parameter N, we mainly compare the SMA with the WMA method in this part. The mean square errors of the two forecasting methods varying with the moving average parameter N are shown in **Figure 2(a)**. The mean square errors percentage reduction of the WMA method relative to the SMA method is shown in **Figure 2(b)**.

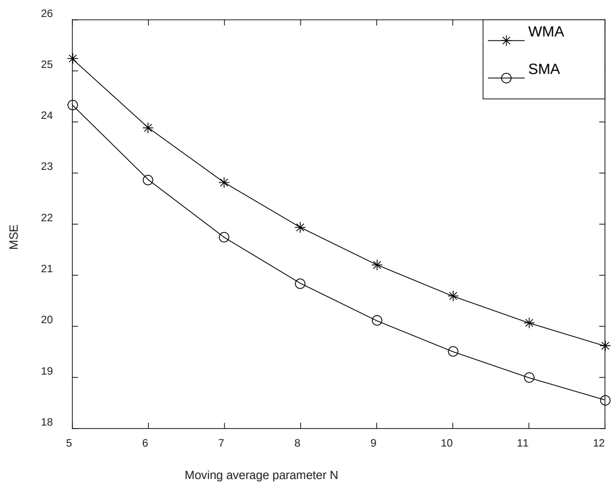


(a)

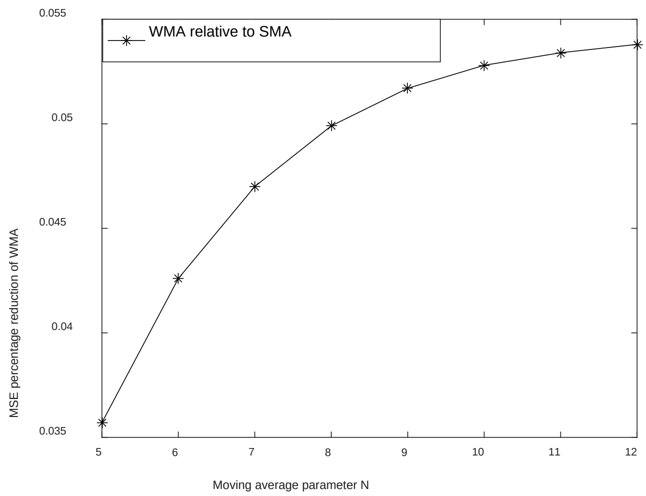


(b)

Figure 1. (a) MSE varies with the lead-time L; (b) The MSE percentage reduction of the MMSE method.



(a)



(b)

Figure 2. (a) MSE varies with the moving average parameter N; (b) The MSE percentage reduction of the WMA method.

As can be seen from **Figure 2(a)**, when changing N among $[5,12]$, the mean square error of the SMA method or the WMA method decreases with the increase of N. When the moving average parameter N is given, the mean square error of the SMA method is greater than that of the WMA method. The forecasting effect of the WMA method is better than that of the SMA method. It is consistent with the fact, the more the moving average parameter N is, the better the forecasting effect is. We suggest that managers increase the moving average parameter N as much as possible in order to improve the forecasting accuracy.

Figure 2(b) shows that when the moving average parameter N is more, the mean square errors percentage reduction of the WMA method relative to the SMA method is more. As the moving average parameter N increases, the mean square errors percentage reduction increases. It implies that the prediction gap between the two moving average methods increases as the moving average parameter N increases.

5. Results and Discussion

This paper mainly studies three forecasting methods in the two-level supply chain. We calculate the mean square error of the three forecasting methods and analyze the influence of the lead-time L and the moving average parameter N on mean square error. The results show that reducing the lead time and increasing the moving average parameter can improve the forecasting accuracy. Different forecasting methods have different forecasting effects. With the mean square error as the evaluation indicator, we conclude that the forecasting effect of the MMSE method is the best, of the WMA method is the second, and of the SMA method is the last. Not every forecasting method can be applied to all situations, so supplier should choose the forecasting method scientifically and practically.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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