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Demand Forecasting Optimization in Supply Chain

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Abstract. To deal with the low accuracy of demand forecasting in supply chain, this paper uses the genetic algorithm to estimate the developing coefficient and the control variable of the GM(1,1) model and predicts the demand of every level in supply chain with this forecasting model, then uses a negotiation algorithm based on game theory to optimize the demand forecast when demand forecast disruption occurs among every level of supply chain. Results are very encouraging as this optimization clearly improves the accuracy of demand forecasting in supply chain.

Keywords: Demand forecasting; Supply chain; Game theory; Genetic algorithms; Grey model

1. Introduction

Demand forecasting, as the content in supply chain management, is the source of operation and the start of optimization in supply chain. Consequently, how to choose the appropriate method to improve the accuracy of demand forecasting in supply chain has been the focus of attention for decision-makers. During the past studies about demand forecasting in supply chain, Mccarthy and Golicicp [1] considered that it will result in high inventory costs if the enterprises can’t make an accurate market prediction, which is called "bullwhip effect"; Chang and Fyffe studied the forecast sales of seasonal goods disruption problem; Xiaowo Tang provided a combination forecast model of demand; Institute of Industrial Control Technology of Zhejiang University, who introduced MAS(Multi-Agent System) technology, focuses on the structure of prediction system in supply chain; Qi Wu [2] has combined the wavelet kernel support vector machine and particle swarm optimization method in the demand forecast of manufacturing system. Upon analysis, the enterprises generally forecast layer by layer, focusing on studying the forecasting method, and failed to give an ideal solution when demand forecast disruptions occur among every level of traditional supply chain.

With the development of economy, the competition among traditional independent enterprises has transformed into that among supply chains, and the member companies of the chain can only achieve the max benefits from the competitive advantage of the supply chain. However, there are lots of new problems when the supply chain comes to meet the need of customers, and the most serious is that the concerns of the supply chain members are different. Then, the demand predictions of every level may vary. Thus, we need to optimize the forecasting results of all enterprises in supply chain to make the benefits of supply chain maximized and improve the overall competitiveness of the supply chain.

This paper uses genetic algorithm instead of the least squares to estimate the developing coefficient and the grey input of the GM (1,1) model. For the theoretical shortcoming of the paper[3], we use new methods to determine the scope of the parameters and predict the needs of the production and the sales in one two-level supply chain with this forecasting model. Then, we develop a negotiation strategy based on game theory to deal with the conflicts between production forecasting and sales forecasting and make the final demand forecast of the supply chain optimized.

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2. Description of the Model

Manufacturers and distributors who are risk-neutral intend to make the benefits of supply chain maximize. For the historical data of productions and sales are private, manufacturers and distributors can only predict their needs based on their private information, and then consider the mutual benefits and costs of supply chain based on their own predictions, and ultimately obtained the demand forecasting which is beneficial to both.

Now, we consider one supply chain of second floor composed of one manufacturer (M) and one distributor (D). Manufacturer's unit cost is Cm, and manufacturer's demand of prediction for the next stage is Qs based on historical data of productions. The distributor (D) purchases goods from the manufacturer (M) at the price of W, and sell them at the price P to the end customers, the unit cost of inventory is Cd for the distributor (D). The distributor's demand of prediction for the next stage is Qd based on historical data of sales.

3. Methods of Demand Forecasting

3.1 Original grey forecasting model(GM)

Grey forecasting model is a gray process which treats one variable data series changed over time and establish of a dynamic model of a differential equation to make predictions. The grey differential equation is formed by an original time series $x^{(0)}(k)$ using accumulated generating operation (AGO) technique. It denoted as follows:

$$x^{(0)}(k)+az^{(1)}(k)=b,\ k\geq 2 \tag{1}$$

where z is background value, $z^{(1)}(k)=[x^{(1)}(k)+x^{(1)}(k-1)]/2$, $x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i)$, a is a developing coefficient, and b is a control variable.

Eq. (1) can be denoted through white process as follows:

$$\frac{dx^{(1)}(k)}{dk}+ax^{(1)}(k)=b\ . \tag{2}$$

To solve Eq. (2), we use the discrete sequence whitening equations and the inverse accumulated generating operation (IAGO) to get the forecasting value:

$$\hat{x}^{(0)}(k)=\left[x^{(0)}-\frac{b}{a}\right]e^{-a(k-1)}\left(1-e^{a}\right), \tag{3}$$

where $k=2,3,\ldots,n,\hat{x}^{(0)}(k)=x^{(0)}(1)$.

3.2 Ga-based grey forecasting model

1) Genetic algorithm (GA)

Genetic algorithm (GA) is a powerful stochastic search and optimization method based on the mechanics of natural selection and natural genetics. Some problems solved effectively by conventional algorithms of optimization can often get good results with genetic algorithms optimization technologies, so genetic algorithm is often used in many practical problems, such as function optimization, automatic control, image recognition, machine learning and so on. Generally genetic algorithm includes three basic operations: reproduction, crossover and mutation [7].

2) GA based grey forecasting model

In the traditional GM (1,1) model, we use the least squares method to solve the developing coefficient: a and the control variable: b. But studies show that when the matrix is close to degenerate, the performance of the least square method is not good enough [4]. In addition, the background values generated by the adjacent of cumulative numbers can’t be representative of the all values effective, so greater average error may occur when we use gray differential equations to get the response time. As defects exist if background values are selected with the least square method, the traditional GM (1,1) model is not always ideal. To solve this problem, we use genetic algorithms instead of the traditional method to obtain the optimized values of a and b in GM (1,1), and make the grey forecasting model more accurate.

Many studies have pointed out that the GM (1,1) is not suitable for the rapid developing data series, Deng [5] proved that, the traditional GM (1,1) makes sense only if |a| <2. Liu Si-feng [5] pointed that GM (1,1) is not suitable as a predict model when | a |> 0.5. Because the developing coefficient reflects the growth of the raw data which can be seen from the following formula:

$$\begin{aligned} 1-\frac{\hat{x}^{(0)})(k+1)}{\hat{x}^{(0)})(k)} &= 1-\frac{\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k)}{\hat{x}^{(1)}(k)-\hat{x}^{(1)})(k-1)} \\ &= 1-\frac{e^{-ak}-e^{-a(k-1)}}{e^{-a(k-1)}-e^{-a(k-2)}} \\ &= 1-e^{-a} = const \end{aligned} \tag{4}$$

when |a| <0.5, the growth rate varies from -64.87% to 39.35%, and most of the data series do not change exceed this range. So we can get $0<b<0.5x^{(1)}(k)+0.75x^{(0)}(k)$ from Eq. (1) and |a| <0.5, where k ≥ 2. Because, the genetic algorithm gets better when the range is smaller [7], so we take k = 2.

So, this paper gets |a| <0.5, $0<b<0.5x^{(1)}(1)+1.25x^{(0)}(2)$.

We take the values of a and b into the Eq. (1) for forecasting in the iterative process of genetic algorithm, and take the average absolute error rate between the predicted sequence and the original sequence as the objective function:

$$MAPE = \left[\sum_{t=1}^{n} \left| \frac{A_t - \hat{A}}{A_t} \right| \Big/ n \right] \times 100\%$$

where $\hat{A}$ is the predicted value, A_t is the actual value. Then we find out the optimal parameters what evolved by many generations, and take the values of a and b into the Eq. (3) to predict.

3) *The process of GA based grey forecasting model*

The process of GA based grey forecasting model is briefly highlighted below:

Step 1: Encoding.

The string lengths of a and b depend on the accuracy of results. If the string length of binary code is 20-bit, it can produce 220 different codes.

Step 2: Assessment of individual fitness detection.

We calculate the value of the fitness and select of the larger individual fitness as the parent. Then, we set the rule of transition between the value of the objective function and the individual fitness. The fitness function of the improved GM (1,1) is set as the following form:

$$f_i = \left(\frac{1}{MAPE} \right), i = 1,2,\ldots, pop\_size \quad , \tag{6}$$

where, pop_size is the number of chromosomes.

Step 3: Selection, crossover and mutation.

The individuals with low fitness are replaced by new individuals generated by the crossover and mutation, and individuals with high fitness are retained after many generations of evolution in the process of initial population.

Step 4: Set the stop conditions.

When the loops of genetic algorithm get to the specified number, or the objective function MAPE gets to minimum, we stop the genetic manipulation and output the optimum values a and b, otherwise we go to step 2.

Step 5: Grey forecasting.

We take the values of a, b into Eq. (3) and get the sequence of predictive value.

4. Negotiation Strategy of Supply Chain

For the historical data of production and sales is private information, the enterprises in supply chain can only do their own business forecasts in the process of demand forecasting in supply chain. At the same time, the actual data of production and sales makes different, so forecasting for production and sales is different. Although there may be more needs, the actual manufacturer can only produce goods based on the prediction, so do the distributors. Then, there will be a conflict between the production forecast demand of manufacturers and the marketing forecast demand of distributors in the supply chain. So we need to negotiate the predicted results to obtain a predictive value which benefits everyone in the supply chain.

The deviation between the forecasts of the manufacturer and distributor in the supply chain can be coordinated with the game theory [8]. Manufacturers and distributors can reach a contract or cooperation to take the same strategy, so the game between them is cooperative in order to achieve the overall optimization for the supply chain. Meanwhile the conflicts between them can perform as their balance between the benefits and costs which include production costs and shortage costs [9].

The condition which needs to negotiate the conflicts of demand forecasting of the supply chain can be set as follows: (Qm - Qd) / Qm> 10% [10], Where it is assumed that Qm is less than t Qd.

Now we assume that Qm is less than Qd. Qm is the end forecast of the manufacturer for the market demand, then the manufacturer has two strategies for productions: Qm and Qd. When the manufacturer takes his own amount of Qm, the productions may be insufficient, and this can lead to shortage loss; When the manufacturer takes the amount of Qd, there will be overproductions, and this can lead to loss of surplus products;

Qd is the end forecast of the distributor for the market demand, then distributor has two strategies: Qd and Qm. When the distributor takes his own amount of Qd, there may be excess for the inventory, and this can lead to loss of surplus products; When the distributor takes his own amount of Qm, there may be shortage for inventory, and this can lead to shortage loss.

When Qd is greater than Qm, the situation is similar. As a result, we can draw the profits (payoff function) of the manufacturer (M) and the distributor (D) as follows:

$$\prod_m = (W - Cm)\overline{Q} - \alpha_1\left(Qm - \overline{Q}\right)^+ - \alpha_2\left(\overline{Q} - Qm\right)^+$$

$$\prod_d = (P - Cd - W)\overline{Q} - \beta_1\left(Qd - \overline{Q}\right)^+ - \beta_2\left(\overline{Q} - Qd\right)^+$$

where, $(Z)^+ = \max(0, Z)$; $\overline{Q}$ is the final result of demand, and its value is the Qm and Qd; α_1 and α_2 are the manufacturer's unit loss of shortage and unit loss of surplus productions; β_1 and β_2 are the distributor's unit loss of shortage and unit loss of the surplus productions.

We can calculate the matrix of benefits between M and D, and search maximal profits of the total supply chain: $\prod_{m+d} = \prod_m + \prod_d$. Then e can obtain the optimal demand of the supply chain: $\overline{Q}$.

5. Empirical Examples

The in-sample data used in this example was from China FAW Group Corporation's data of automobile production and sales from 1998 to 2006. These sample data were obtained from the China Automotive Industry Yearbook. We find that the set of data can be used with grey model by the analysis on the sequence of the data. For the actual sales data is closer to the market demand, we use sales data from 1998 to 2006 to construct grey model, and use the traditional GM (1,1) and GM(1,1) improved by the method in this paper to predict the sales demand for 2007 and 2008. Also we forecast the company's demand of the car production based on the data of the historical production, and optimize the final results of sales forecast of the supply chain with proposed negotiation strategy based on game theory with the help of forecasting of the productions.

5.1 Formulating the three compared models

1) Original GM(1,1)

The original time series $x^{(0)}$ is obtained as $x^{(0)}$ = 17.173, 18.842, $\cdots$, 116.570] based on China FAW Group Corporation's data of automobile sales from 1998 to 2006. The parameters of a and b of original GM (1,1) are estimated by the least square method through Eq. (2) and Eq. (3), and we get a=-0.2078，b=24.3601. The original GM (1,1) model is listed as follows:

$\hat{x}^{(0)}(k) = [x^{(0)}(1) + \frac{24.3601}{0.2078}]e^{0.2078(k-1)}(1 - e^{-0.2078})$, where, $k = 2,3,\ldots,n$.

2) Genetic algorithms-based GM(1, 1)

According to the operations steps, This paper uses genetic algorithms to estimate a and b of GM(1,1). The parameters include crossover rate: 0.6, mutation rate: 0.05, population size: 80, and the style of encoding is binary. The improved GM(1,1) model is listed as follows:

$$\hat{x}^{(0)}(k) = [x^{(0)}(1) + \frac{13.12131}{0.2388}]e^{0.2388(k-1)}(1 - e^{-0.2388})$$

where, $k = 2,3,\ldots,n$.

3) Optimized forecasting results

If there is a conflict between the production forecast demand of manufacturers and the marketing forecast demand of distributors in the supply chain, we need to negotiate the final predicted results of sales. We also need to predict the demand of productions of the China FAW Group Corporation which is shown in Table Ⅰ, and we get the strategy based on the forecast of productions and sales. The optimized result is shown in Table Ⅱ.

TABLE I. FORECASTED VALUES OF PRODUCTIONS OF THE CHINA FAW GROUP CORPORATION

Year	Actual value (thousand)	Predicted value (thousand)
1998	168.35	168.35
1999	191.62	236.45
2000	210.18	296.63
2001	419.79	372.11
2002	561.79	466.81
2003	858.74	585.61
2004	993.55	734.63
2005	983.66	921.59
2006	1176.81	1156.12
2007	1464.90	1450.33
2008	1503.99	1819.41

TABLE II. FORECASTED VALUES OF PRODUCTIONS OF THE CHINA FAW GROUP CORPORATION

Year	Actual value (thousand)	GM(1,1)		GA-based GM(1,1)		Optimized forecastedresults	
		Model Value	Error(%)[a]	Model Value	Error(%)[a]	Model Value	Error(%)[a]
1998	171.73	171.73	0.000	171.73	0.000	171.73	0.000
1999	188.42	310.42	-64.750	194.53	-3.240	236.45	-25.491
2000	219.91	382.12	-73.761	246.99	-12.316	296.63	-34.887
2001	407.50	470.37	-15.429	313.61	23.040	372.11	8.685
2002	565.49	579.01	-2.391	398.20	29.583	466.81	17.450
2003	854.36	712.74	16.576	505.61	40.820	585.61	31.456
2004	1007.50	877.36	12.917	641.98	36.280	734.63	27.084
2005	982.78	1079.99	-9.892	815.14	17.058	921.59	6.226
2006	1165.70	1329.43	-14.046	1035.00	11.212	1035.00	11.212
MAPE(%)[a]		23.307		19.283		18.055	
2007	1435.98	1636.48	-13.963	1314.17	8.483	1450.33	-0.999
2008	1532.92	2066.55	-34.811	1668.63	-8.853	1668.63	-8.853
MAPE(%)		24.387		8.624		4.926	

[a] MAPE(%)=Error(%)= $\left[\sum_{t=1}^{n}\left|\frac{A_t - \hat{A}}{A_t}\right| \Big/ n\right] \times 100\%$,where $\hat{A}$ is the predicted value, A_t is the actual value.

5.2 Empirical results

Comparing the results of the above, we can draw the conclusions easily as follows: The GM(1,1) improved based on genetic algorithm is higher than the traditional GM(1,1) on the degree of the historical data fitting from 1998 to 2006. More important, the accuracy of the demand prediction on 2007 and 2008 optimized by the negotiation strategy has been improved significantly. In GM(1,1), The identifications of the developing coefficient and the control variable play a key role ,and it has great impact on the prediction accuracy. We use the least square method to work out the parameters in the traditional GM(1,1), while it is not always the most appropriate way in some basic assumptions ,and this limits the accuracy of the traditional GM(1,1). In this paper, the prediction model uses genetic algorithm to optimize the parameters instead of the least square method, and makes the degree of the data fitting improve significantly, and the degree of the forecast accuracy is superior to the traditional GM (1,1). Finally, we negotiate the conflict between the predictions of the productions and sales and make the final demand forecast of the supply chain optimized.

6. Conclusions

Demand forecasting, as the content in supply chain management, is the source of operation and the start of optimization in supply chain, so it is the focus for decision-makers to choose the right method to improve the accuracy of demand forecasting in supply chain. This paper improves the process of solving the parameters of GM (1,1) with genetic algorithm based on the initial solution, and overcomes the weaknesses of using the least square method. At the same time, we use game theory-based negotiation strategy to optimize the conflict between the predicted results of production and sales in supply chain. The test shows that the improved GM(1,1) is superior to the traditional GM(1,1) on the data fitting and the accuracy of prediction. At last, the accuracy of the final prediction is greatly improved when it's optimized with the negotiation strategy.

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