Demand Forecasting of Agricultural Cold Chain Logistics Based on Metabolic GM (1,1) Model

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Abstract. The cold chain logistics is an important part of the whole logistics industry, with the rapid development of China's economy, people's living standards rising, consumer demand transformation, people's demand for cold chain logistics is becoming more and more big, however, in the cold chain logistics industry, gradually increased demand for agricultural products in the public, this article selects 2014-2019 China's cold chain logistics of agricultural products Based on the metabolic GM(1.1) model, the demand of cold chain logistics of agricultural products in China in the next five years is predicted. The predicted experimental results can provide data reference for relevant departments, in order to provide theoretical support for promoting the balance between supply and demand of cold chain of agricultural products.

1. Introduction

At present, the speed of urbanization in China and the expansion and opening of major free trade zones have promoted the rapid development of China's cold chain industry. In the high-speed development of cold chain logistics industry, agricultural products cold chain logistics demand. With the increase of the demand of agricultural products, most scholars have also increased their research on the logistics of cold chain of agricultural products. Among them, Huang Qing xia [1] has made research on the enterprises of cold chain logistics of agricultural products in China. Bu Chen Yu et al. [2] predicted and analyzed the cold chain logistics of agricultural products in Jiangsu Province based on the grey Markov model. Based on GM (1.1) model, Wu Ying [3] et al. predicted and analyzed the cold chain logistics of agricultural products in Lu'an City. Zhang Xi cai [4] analyzed the economic characteristics and difficulties of China's cold chain logistics and put forward corresponding counter measures. Liang Yan [5] et al. predicted and analyzed the demand of agricultural products cold chain logistics in Tianjin based on multiple linear regression model. Fan Jian [6] planned and studied the development strategy of R Company's agricultural cold chain logistics. Li Zhan feng [7] made a prediction and analysis study on the cold chain logistics of agricultural products in Chongqing, and Zhang Qian [8] predicted the demand of cold chain logistics of agricultural products in Henan Province Large logarithmic literature is based on the grey system model of cold chain logistics of agricultural products demand is forecasted, but literature is a place of basic agricultural products cold chain logistics, this article is based on GM (1.1) model is forecasted demand for agricultural products cold chain logistics in our country, in order to provide the corresponding data analysis, to help the development of cold chain logistics of agricultural products in China.
2. Metabolism GM (1,1) Model

In actual modeling, some data are usually selected from the original data to establish the model. Metabolism GM (1,1) model improves the model accuracy by adding the latest data and removing the old data. Set $x^{(0)}(n+1)$ as the latest data, $x^{(0)}(1)$ is the oldest data, add the data of $x^{(0)}(n+1)$, remove the data of $x^{(0)}(1)$ to get a new data, the model established with this data is called metabolic model [10]; the modeling method and steps are similar to the conventional GM (1,1) model.

3. Empirical Analysis

According to the demand data of cold chain logistics of agricultural products in China published in Statistical Yearbook 2020, data of 2014 and 2019 are selected as modeling data, as shown in Table 1.

| Year | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|------|------|------|------|------|------|------|
| Quantity demanded | 9190 | 10530 | 12500 | 14750 | 18870 | 22563 |

3.1. Conventional GM (1,1) model

Select 2014 to 2018 data to construct the original sequence, $X^{(0)}= (9190,10530,12500,14750,18870)$ for magnitude ratio test sequence. It is calculated that $\lambda(k)$ is all in the interval $(e^{-\frac{2}{n+1}}, e^{\frac{2}{n+1}})$ and the original sequence has passed the test, so it can be used to build a model. The parameters $a=0.197$, $b=7440.132$ are obtained. The time response equation is obtained: 

$$\hat{x}^{(1)}(k) = \left( x^{(0)}(1) + \frac{7440.132}{0.197} \right) e^{0.197(k-1)} - \frac{7440.132}{0.197}, k=1, 2, 3, \ldots, n.$$ 

3.2. Metabolism GM (1,1) model

Remove $x^{(0)}(1)$ and add $x^{(0)}(k+1)$. The 5-dimensional data of 2015 and 2019 were selected to obtain the new original sequence, $X^{(0)}= (10530,12500,14750,18870,22563)$. The parameters $a=0.201$ and $b=8994.888$ are obtained, The time response equation is obtained: 

$$\hat{x}^{(1)}(k) = \left( x^{(0)}(1) + \frac{8994.888}{0.201} \right) e^{0.201(k-1)} - \frac{8994.888}{0.201}, k=1,2,3,\ldots,n.$$ 

3.3. Comparison of model accuracy

3.3.1. Precision comparison of conventional GM (1,1) models

Based on the conventional GM (1,1) model and the metabolic GM (1,1) model, the corresponding simulation data were calculated and the data of 2019 was predicted by the conventional GM (1,1) model. Then the residual values and relative simulation errors were calculated and the prediction accuracy of the two models was compared through the obtained data. See Table 2 for the specific data.

| Year | Real data | 5-dimensional GM (1,1) model | 5-dimensional metabolism GM (1,1) model |
|------|-----------|-------------------------------|----------------------------------------|
|      | Simulated data | Residual error | Relative error | Simulated data | Simulated data | Relative error |
| 2015 | 10530 | 10226.199 | 303.801 | 2.885% | 12315.158 | 184.842 | 2.86% |
| 2016 | 12500 | 12445.15 | 45.852 | 0.367% | 15063.759 | -313.759 | 1.31% |
| 2017 | 14750 | 15167.493 | -417.493 | 2.830% | 18425.815 | 444.185 | 1.34% |
| 2018 | 18870 | 18471.985 | 398.015 | 2.109% | 22538.243 | 24.757 | 0.110% |
| 2019 | 22563 | 22436.702 | 126.298 | 0.560% | 22538.243 | 24.757 | 0.110% |

Average relative error 0.0204 0.01517 0.110%
According to the analysis of comparative results, although the relative error of 5-dimensional conventional GM (1,1) model in 2016 is less than that of 5-dimensional GM (1,1) model, the 5-dimensional metabolic GM (1,1) model is better in terms of the average relative error and the relative error of other years. In addition, the 5-dimensional GM(1,1) model has a relative simulation error of 0.560% for the forecast data of 2019. Based on the above analysis, the 5-dimensional GM (1,1) model has a higher prediction accuracy.

3.3.2. Comparison of precision between 4-dimensional and 5-dimensional metabolism GM (1,1) models

Through the above analysis, the prediction accuracy of the 5-dimensional GM (1,1) model is better. In order to continue to improve the prediction accuracy of the model, the original sequence of the 5-dimensional GM (1,1) model is updated again in this paper. Will original sequence \( X^{(0)} = \{10530,12500,14750,18870,22563\} \) remove old data \( x^{(0)}(1) = 9190 \). select the 4-dimensional original sequence from 2016 to 2019: \( X^{(0)} = \{12500,14750,18870,22563\} \). The parameters \(-a = 0.207, b = 10862.167\) are obtained. The time response equation is obtained: \( \hat{x}^{(1)}(k) = \left( x^{(0)}(1) + \frac{10862.167}{0.207} \right) e^{0.185(k-1)} - \frac{10862.167}{0.207}, k=1, 2, 3,...,n \). Then, the accuracy of the corresponding data obtained is compared with the 5-dimensional GM(1,1) model. Finally, the number of applicants in 2020-2021 is predicted and analyzed. The specific data is shown in Table 3.

| Year | Real data | 5-dimensional GM (1,1) model | 4-dimensional GM (1,1) model |
|------|-----------|-------------------------------|-------------------------------|
|      |           | Simulated data | Residual | Relative error | Simulated data | Residual | Relative error |
| 2016 | 12500     | 12315.158 | 184.842 | 2.86%         | 14944.169 | -194.169 | 1.316%         |
| 2017 | 14750     | 15063.759 | -313.759 | 1.31%         | 18382.111 | 487.889  | 2.586%         |
| 2018 | 18870     | 18425.815 | 444.185 | 1.34%         | 22610.959 | -47.959  | 0.213%         |
| 2019 | 22563     | 22538.243 | 24.757  | 0.110%        | 22610.959 | -47.959  | 0.213%         |
| Average error | | 0.01517 | 0.01371 |

The results show that the 4-D GM (1,1) model is superior to the 5-D GM (1,1) model in terms of both annual relative errors and average relative errors, and compared to the original raw data \( \bar{\varepsilon} = 0.01371 < 0.02048 \). The prediction accuracy is high. Next, a 4-dimensional GM (1,1) model is selected to forecast the demand for agricultural products in the next five years.

3.4. Analysis and discussion

The 4-dimensional GM (1,1) model is used to forecast the number of postgraduate applicants from 2020 to 2025. The demand for five years is 278,126,650 tons 342,11,034 tons 420,813,365 tons 517,6283 tons 636,70320 tons. He demand for the cold chain of agricultural products in China from 2015 to 2019 and the finally predicted demand for 2020-2025 are both increasing year by year, because in recent years, with the improvement of the living quality of Chinese residents, the demand for agricultural products is also increasing year by year. In addition, due to the continuous improvement of the national economic level and urbanization rate, people's consumption intensity is gradually expanded. With the improvement of the domestic market, the demand will also increase year by year in the next few years, and it can be seen from the forecast data.

4. Conclusion

Compared with the conventional GM (1,1) model, the prediction accuracy of GM (1,1) model with the old data removed and the new data added is more accurate. Moreover, the data of GM(1,1) model are updated again (the old data are only removed in this paper), which can greatly improve the prediction accuracy of the model Article has carried on the forecast to the demand of agricultural products cold
chain logistics, and through the data update, improve the prediction accuracy, the final forecast in the next five years China's agricultural products cold chain logistics demand forecasting, through the data we can see the demand of agricultural products cold chain logistics in increase year by year, from the side also reflects the transformation of consumption and the increasing domestic demand, by predicting the agriculture. The demand for cold-chain logistics of products can provide help for related industries and promote the development of cold-chain logistics industry.

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