Chinese residents’ cold chain logistics demand forecasting based on GM (1,1) model

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Cold chain logistics is a complex system, involving the whole process of temperature control of the entire chain from the packaging, transporting, storage and consumption of the products. The meeting of the market demand must be based on the forecasting. The main goal of this study is to forecast product demand values for cold chain logistics from 2010 to 2015 in China using GM (1,1). The residents’ consumption data of refrigerated and frozen food ranging from meat to milk were obtained from the China statistical yearbook of 2005 to 2009. A gray forecast equation of cold chain logistics demand is established and estimated by DPS 7.05 software so as to confirm its scientific and accurate forecasting system. The results show all the prediction accuracy of GM (1,1) model of the refrigerated and frozen food demand of historical data reached level 1 except average residual error, which reached level 2. So, we can see that the previous established GM (1,1) models have achieved good prediction effect. Meanwhile, by 2015, the amounts of products transported under refrigeration condition will be more than 55,649 tons, with a 4.3 proportion growth per year in the period of 2010 to 2015.

Key words: Cold chain logistics, demand forecasting, grey model, China.

INTRODUCTION

Food is the basis for human survival and development, so the security of food is of vital importance to human society. Driven by a strong growth in the sales of temperature sensitive healthcare products, the demand for cold chain logistic services is currently experiencing explosive growth. IMARC Group, one of the world’s leading research and advisory firms, finds that the total size of the healthcare cold chain logistic services market is expected to expand from its current figures of US$ 6.1 billion to nearly US$ 9.5 billion by 2016 (Xia, 2007).

Cold chain logistics is best defined as the maintenance of produce temperature throughout the demand-supply chain (from harvest to the consumer) (Beasley, 1998). Effective cold chain logistics is critical to enterprise success, as poor cold chain management will negatively impact product quality of perishable products: Softening, bruising, unwanted ripening, bacterial growth, texture degradation, etc. This may lead to the importer rejecting the consignment. With the new Food Safety Legislation now in force, cold chain management is also critical.

Infrastructure is a critical component in national and international trade in food and agricultural products, and it is in need of a development suited to the distribution and storage of chilled and frozen foods, as trade in food products has increasingly been including high value processed and prepared foods. However, at present, the domestic food and medicines perishable, easy metamorphic product are handled mostly in the open and not in the refrigerator, 80 to 90% of transportation tools available are ordinary truck, so the quality of perishable product has no guarantee. The loss of billions of dollars happened in transportation and circulation process in China every year. The direct cause of the dilemma is because of severity shortage of China's cold chain facilities and cold chain equipment to provide the low

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temperature protection. As is known to all, the cold chain facilities and equipment quantity must be in accordance with demand for products of cold chain logistics. So, in this paper, we predict demand for cold chain logistics products of the China objectively and accurately during 2011 to 2015, the results will provide basis for the government and practitioners to invest the cold chain logistics facilities and equipments.

LITERATURE REVIEW

Cold chain logistics originated in the 19th century, and with the invention of the refrigerator, all kinds of fresh and frozen food began to enter the market and consumers' family. After the 1930s, cold chain system is preliminarily established in Europe and the United States (Billiard, 2003). So far, Europe, the United States and other developed countries have shaped a complete cold chain system. In 1894, the American people Albert Barrier and the British people Ruddich first suggested the concept of cold chain. In the 1940s, the cold chain has attracted enough attention and rapid development.

From the views of research, the literature of cold chain has been in shortage in abroad. Bogata et al. (2005) think the cold chains management requires very careful temperature control and quick reactions when perturbations appear in temperature or time delays occur. They presented how sensitive such a chain can be and conclude that the analysis in the frequency space can be straight forward, more than the analysis in the time domain. Shabani et al. (2011) develop a linear pair model for selecting the best sales agents as a “Benchmark” in the presence of non-discretionary factors and imprecise data under free disposability assumption. Joshi et al. (2010) study the awareness, behavior and practices among Indian consumers, regarding maintenance of cold chain from retailer’s place to home and at homes within the framework of food safety. They reveal that the consumers do not have adequate awareness about refrigeration practices or consider themselves responsible for maintaining cold chain and food safety. Most food products are perishable and their shelf life can be greatly affected by temperature conditions in the supply chain: time/temperature control becomes a critical issue in fresh food logistics, and the efficient and effective tracking of cold chain conditions is one of the main points to be addressed.

Technical and managerial solutions are available in order to achieve this objective, but no methodologies exist to select the most suitable solution. By comparing two main approaches, Montanari et al. (2008) propose structured frameworks to identify the most appropriate managerial solution to be adopted in order to minimise the logistics cost. Joshi et al. (2011) develop a benchmarking framework that evaluates the cold chain performance of a company, reveals its strengths and weaknesses and finally identifies and prioritizes potential alternatives for continuous improvement.

In China, cold chain logistics originated in the 1950s’ meat product of foreign trade export. In 1982, China promulgated the food hygiene law which promoted the development of the cold chain. In recent years, beginning with the improved living standard of urban and rural residents and the change observed in their spending habits, the demand for aquatic products, fruits and flowers increased as the cold chain logistics increased, and then inevitably brought about the growth of cold-chain logistics.

The up-surge of focus on food quality in China and the increased focus on routine and systems strengthening for the delivery of high impact interventions has made a regional priority to strengthen cold chain logistics (CCL) system capacity to deliver quantity and quality health commodities at country level. China is seeking to build national capacities in CCL systems.

With the scientific research of the concept and development of cold chain, a variety of scholars emphasized the important significance of the cold chain logistics on China’s economic development and the existing problems in the process of development and countermeasures. On the contrary, only a small amount of scholars applied the statistic method to forecast the cold chain logistics demand. Lan and Ru (2008) classified the demand of Olympic food cold chain logistics, identified the subject of demand forecast and sort out thoughts to forecast the amount of persons taking part in the Olympic games. Li et al. (2011) with the cold chain logistics needs of aquatic products for example, established a demand forecast equation of cold chain logistics by multivariate linear regression analysis.

Although, multivariate linear regression (Li et al., 2011), neural network, support vector machine (Niu et al., 2007), grey forecasting methods (Lan et al., 2008) have been applied in the logistics demand forecasting, but it is rare for cold chain logistics prediction.

METHODOLOGY

Here, the algorithm of Grey forecasting model is introduced and discussed. In practice, owing to the variations of internal and external environment, the system development is usually irregular. Therefore, Deng (1982, 1989) proposed the Grey system theory to construct a Grey model for forecasting. Only four pieces of historical data are required in the Grey model. There is no strict hypothesis for the distribution of parent data. The main purpose of GM is to execute the short-term forecasting operation. The fundamental model of Grey prediction is the GM (1,1), a first-order differential model with only one input variable. The GM (1,1) model uses the most up-to-date data to predict future values. Chen et al. (2008) develop a GM (1,1) forecasting model to predict the future development for ChungHwa Telecom 3G market, associated with the solutions to market obstacles. They find that the Grey forecasting model is suitable for 3G market forecasting with only four-term historical data. Li et al. (2008) proposed a new prediction model which combines GM (1,1) model with time series ARIMA from statistics theory. A 3-points average model and Markov chain
model are also applied in the research. Wang and Hsu (2008) develop an improved method to forecast the output and trends of high technology industries in Taiwan. The Grey theory is combined with GA in the proposed model. The former is used to forecast the outputs of high technology industries and the latter is used to estimate the parameters of a forecasting model based on forecasting errors. They conclude that the proposed GA-based Grey model can be used to effectively reduce the errors in the forecasting process.

Wu et al. (2006) indicate that the types of historical data are smoothing and nonlinear. He suggests a 4-points rolling GM (1,1,a) in the Verhulst model with several values of the parameters to reduce absolute forecasting errors. Chang et al. (2005) construct a rolling Grey forecasting model (RGM) to forecast Taiwan’s annual semiconductor production. They find that the yearly survey of anticipated industrial production growth rates in Taiwan and the yearly percent changes in real GDP by US manufacturing industry are highly correlated. A Grey–Markov chain forecasting model DGDM (1,1,1) is combined with the Grey–Markov chain forecasting model to predict the time for which the deviation is over the limit of the tolerance. The result showed that high machining accuracy of forecasting can be achieved by the proposed DGDM (1,1,1). Hsu (2003) examines the precision of the Grey forecasting model and are highly correlated. A Grey–Markov chain forecasting model GM (1,1) is used to forecast Industrial Output Index (IC) industry. The results indicate that the Grey model is better suited to the short-term predictions than to mid- and long-term predictions.

In conclusion, these studies all show that the Grey forecasting model can improve the degree of accuracy based on merely four pieces of historical data. Their results demonstrated the ability of Grey system theory to effectively deal with incomplete and uncertain information. Therefore, there is a great opportunity for integrating the real-time data of cold chain with short-term forecasting merit of GM in the operation of supply chain.

GM (1,1) modeling [4] is a specific example of GM (n,h) modeling when n = 1 and h = 1. The order of the differential equation is one, and there is only one variable, namely series \(X^{(0)}\), in GM (1,1) modeling sequence. GM (1,1) modeling values are considered as the center of state in the Grey forecasting model. A group of original data with equal time interval is supposed

\[
X^{(0)} = \{X^{(0)}(1), X^{(0)}(2), \ldots, X^{(0)}(n)\}
\]

The first-order accumulated generating operation (1-AGO) of \(X^{(0)}\) is provided. The grey-generated model, based on the series

\[
\begin{align*}
X^{(1)} & = \{X^{(1)}(1), X^{(1)}(2), \ldots, X^{(1)}(n)\} = \left\{\sum_{r=1}^{r=n} X^{(0)}(t), \sum_{r=1}^{r=n} X^{(0)}(t), \ldots, \sum_{r=1}^{r=n} X^{(0)}(t)\right\} \\
\text{d}X^{(1)} & = aX^{(1)} = \mu \\
\end{align*}
\]

Where \(t\) denotes the independent variable in the system, \(a\) represents the developed coefficient, \(\mu\) is the controlled variable in the grey model. \(a\) and \(\mu\) are the parameters that required to be determined in the model.

Equation (3) is called the first-order grey differential equation and denoted by GM (1,1), where the first 1 stands for the first-order derivative of the 1-AGO series of \(X^{(0)}\), and the second 1 stands for only 1 series having to do with the grey system.

From Equations (2) and (3) and equation-least squares method, coefficient \(\hat{a}\) becomes

\[
\hat{a} = \left[ \begin{array}{c} a \\ \mu \end{array} \right] = (B^{T}B)^{-1}B^{T}Y_{n}\mu
\]

Furthermore, accumulated matrix B is

\[
B = \begin{bmatrix}
-\frac{1}{2} [x^{(0)}(2) + x^{(0)}(1)] & 1 \\
-\frac{1}{2} [x^{(0)}(3) + x^{(0)}(2)] & 1 \\
\vdots \\
-\frac{1}{2} [x^{(0)}(3) + x^{(0)}(2)] & 1
\end{bmatrix}
\]

The constant vector \(Y_{n}\) is

\[
Y_{n} = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}
\]

The approximate relationship given subsequently can be obtained by the substitution of \(\hat{a}\) in the differential equation and by solving Equation (3).

\[
\hat{X}_{1}(k+1) = \begin{bmatrix} \hat{X}^{(0)}(1) - \frac{\mu}{a} e^{-\frac{k}{a}} + \frac{\mu}{a} \\
\hat{X}^{(0)}(2) \\
\end{bmatrix}
\]

When \(\hat{X}^{(0)}(1) = \hat{X}^{(0)}(0)\), the sequence of one-order inverse-accumulated generating operation (IAGO) is acquired and the sequence must be reduced to obtain Equation (8).

\[
\hat{X}^{(0)}(k) = \hat{X}^{(1)}(k) - \hat{X}^{(1)}(k-1)
\]

Where \(\hat{X}^{(0)}(k)\) is the original series forecasts, \(\hat{X}^{(1)}(k)\) is the generated series for the forecasts. Suppose \(k=2,3, \ldots, N\), the sequence of reduction is obtained as follows
Table 1. The accuracy level of GM (1,1) modeling.

<table>
<thead>
<tr>
<th>Accuracy level</th>
<th>e(K)</th>
<th>Small probability error rate P</th>
<th>Posteriori poor value C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.01</td>
<td>&gt;0.95</td>
<td>&lt;0.35</td>
</tr>
<tr>
<td>2</td>
<td>0.05</td>
<td>&gt;0.8</td>
<td>&lt;0.5</td>
</tr>
<tr>
<td>3</td>
<td>0.10</td>
<td>&gt;0.7</td>
<td>&lt;0.65</td>
</tr>
<tr>
<td>4</td>
<td>0.20</td>
<td>≤0.7</td>
<td>≥0.65</td>
</tr>
</tbody>
</table>

\[
\hat{X}^{(0)} = (\hat{X}^{(0)} (2), \hat{X}^{(0)} (3), ..., \hat{X}^{(0)} (n))
\]  
(9)

After the previous model is generated and developed, further tests are necessary to understand the error of forecasted value and actual value. To demonstrate the efficiency of the proposed forecasting model, this article adopts the residual error test method to compare the actual value and forecasted value.

Suppose the original data as \( X^{(0)} (k) \) and the forecast value as \( \hat{X}^{(0)} (k) \), then their relative error is \( e(k) \)

\[
e(k) = \frac{X^{(0)} (k) - \hat{X}^{(0)} (k)}{X^{(0)} (k)}
\]  
(10)

The "Posterior variance examination" method is generally used to examine the precision of the grey model. The steps are as follows:

(a) Residual \( q^{(0)} (k) \)

\[
q^{(0)} (k) = x^{(0)} (k) - \hat{x}^{(0)} (k)
\]  
(11)

(b) Residual mean \( q \)

\[
q = \frac{1}{N} \sum_{k=1}^{N} q^{(0)} (k)
\]  
(12)

(c) Residual variance \( s^2_2 \)

\[
s^2_2 = \frac{1}{N} \sum_{k=1}^{N} (x^{(0)} (k) - \hat{x}^{(0)} (k))^2
\]  
(13)

(d) Mean of original data \( \bar{x} \)

\[
\bar{x} = \frac{1}{N} \sum_{k=1}^{N} x^{(0)} (k)
\]  
(14)

(e) Variance of original data \( s^2_1 \)

\[
s^2_1 = \frac{1}{N} \sum_{k=1}^{N} (x^{(0)} (k) - \bar{x})^2
\]  
(15)

(f) Posteriori poor value C and small probability error rate p

\[
C = \frac{S_2}{S_1}
\]  
(16)

\[
P = f\left(\left|q^{(0)} (k) - q\right| < 0.6745S_1\right)
\]  
(17)

The basic events number \( N \) contains with

\[
\left|q^{(0)} (k) - q\right| < 0.6745S_1
\]

The accuracy of GM (1,1) modeling is evaluated by C and p. Generally, the accuracy level of modeling is divided into four, which are shown in Table 1.

**Data**

The main goal of this study is to forecast product demand for cold chain logistics in China using GM (1,1). The residents' consumption data of refrigerated and frozen food range from meat to milk from 2005 to 2009 were obtained from the China statistical yearbook (Table 2) for building GM (1,1) model.

**THE GREY FORECASTING OF CHINESE RESIDENTS’ DEMAND FOR COLD CHAIN LOGISTICS**

This article applies a novel method, the Grey forecasting model, to accurately predict the value of Chinese residents’ demand for cold chain logistics. The known output values of each variety transported under refrigeration condition are shown in Table 1 in period of 2005 to 2009 which are used to accurately forecast the values of 2010, 2011,..., and 2015. By DPS7.05 software, the results are shown in Tables 3 and 4. The accuracy of the model was calculated as average residual error, small probability error rate P and posteriori poor value C when it reached level 1 and is shown in Table 3. This indicates that the forecasting accuracy of the GM (1,1) model is perfect.

Table 3, shows all the prediction accuracy of GM (1,1) model of the refrigerated and frozen food demand of
Table 2. Chinese residents’ consumption demand for Refrigerated and frozen food from 2005 to 2009 (in ten thousand tons).

<table>
<thead>
<tr>
<th>Year</th>
<th>Meat</th>
<th>Aquatic products</th>
<th>Fast-frozen Pasta</th>
<th>Fruit</th>
<th>Vegetables</th>
<th>Milk</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>6939</td>
<td>4420</td>
<td>136.0</td>
<td>16120.1</td>
<td>5650</td>
<td>2864.8</td>
<td>36187.6</td>
</tr>
<tr>
<td>2006</td>
<td>7089</td>
<td>4584</td>
<td>141.0</td>
<td>17102</td>
<td>5830</td>
<td>3302.5</td>
<td>38048.5</td>
</tr>
<tr>
<td>2007</td>
<td>6866</td>
<td>4748</td>
<td>170.7</td>
<td>18136.3</td>
<td>5650</td>
<td>3633.4</td>
<td>39204.4</td>
</tr>
<tr>
<td>2008</td>
<td>7279</td>
<td>4896</td>
<td>215.7</td>
<td>19220.2</td>
<td>5750</td>
<td>3781.5</td>
<td>41142.4</td>
</tr>
<tr>
<td>2009</td>
<td>7642</td>
<td>5120</td>
<td>247.7</td>
<td>20395.5</td>
<td>6020</td>
<td>3732.6</td>
<td>43157.8</td>
</tr>
</tbody>
</table>

Table 3. The forecasting accuracy of the GM (1,1) model.

<table>
<thead>
<tr>
<th></th>
<th>Average residual error</th>
<th>Small probability error rate P</th>
<th>Posteriori poor value C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meat</td>
<td>0.1245</td>
<td>0.2048</td>
<td>1.0000</td>
</tr>
<tr>
<td>Aquatic products</td>
<td>0.0116</td>
<td>0.0644</td>
<td>1.0000</td>
</tr>
<tr>
<td>Fast-frozen Pasta</td>
<td>0.1993</td>
<td>0.1011</td>
<td>1.0000</td>
</tr>
<tr>
<td>Fruit</td>
<td>0.0321</td>
<td>0.0036</td>
<td>1.0000</td>
</tr>
<tr>
<td>Vegetable</td>
<td>0.0827</td>
<td>0.3498</td>
<td>1.0000</td>
</tr>
<tr>
<td>Milk</td>
<td>-0.07</td>
<td>0.2854</td>
<td>1.0000</td>
</tr>
<tr>
<td>Sum</td>
<td>0.0163</td>
<td>0.0805</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

Table 4. The predictive value of Chinese residents’ demand for cold chain logistics (in ten thousand tons).

<table>
<thead>
<tr>
<th>Year</th>
<th>Meat</th>
<th>Aquatic products</th>
<th>Fast-frozen Pasta</th>
<th>Fruit</th>
<th>Vegetable</th>
<th>Milk</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010</td>
<td>7662.51</td>
<td>5292.59</td>
<td>301.88</td>
<td>21614.7</td>
<td>5896.03</td>
<td>3978.12</td>
<td>44902.9</td>
</tr>
<tr>
<td>2011</td>
<td>7889.33</td>
<td>5488.7</td>
<td>364.11</td>
<td>22920</td>
<td>5958.86</td>
<td>4136.24</td>
<td>46871.9</td>
</tr>
<tr>
<td>2012</td>
<td>8124.76</td>
<td>5692.08</td>
<td>439.17</td>
<td>24304.2</td>
<td>6026.11</td>
<td>4300.66</td>
<td>48927.2</td>
</tr>
<tr>
<td>2013</td>
<td>8367.85</td>
<td>5903</td>
<td>529.7</td>
<td>25772</td>
<td>6096.1</td>
<td>4571.61</td>
<td>51072.7</td>
</tr>
<tr>
<td>2014</td>
<td>8618.38</td>
<td>6121.73</td>
<td>638.89</td>
<td>27328.5</td>
<td>6167.94</td>
<td>4649.35</td>
<td>53312.2</td>
</tr>
<tr>
<td>2015</td>
<td>8876.42</td>
<td>6348.57</td>
<td>770.59</td>
<td>28978.9</td>
<td>6241.19</td>
<td>4834.16</td>
<td>55650</td>
</tr>
</tbody>
</table>

Average growth rate(%) | 2.6 | 3.7 | 2.06 | 6 | 0.8 | 4 | 4.3 |

historical data reached level 1. So, we can see that the previous established GM (1,1) models had achieved good prediction effect. Meanwhile, Table 4 shows that by 2015, the amounts of products transported under refrigeration condition will be more than 55,649 tons, with a 4.3 proportion growth per year in the period of 2010 to 2015.

Conclusions

This study has shed an interesting light on the demand forecasting of Chinese residents’ cold chain logistics. From the results in this study, the following conclusions can be drawn:

(1) The grey forecasting system GM (1,1) modeling using the data series and the time series were established, which can correctly describe the characteristics and development trend of the demand of cold chain logistics. It is suitable for the simulation control and the prediction analysis of original data series of cold chain logistics that have grey characteristics.

(2) The forecasting accuracy of the GM (1,1) model is high, here C and P belonging to 1 level. The model accuracy examination results show that GM (1,1) model is able to make accurate predictions for forecasting of the monotonous type of processes.

(3) Forecasting product demand is crucial to any supplier, manufacturer, or retailer. Forecasts of future demand will determine the quantities that should be purchased, produced, and shipped. In general practice, accurate demand forecasts lead to efficient operations and high levels of customer service, while inaccurate forecasts will inevitably lead to inefficient, high cost operations and/or poor levels of customer service. This study’s findings will be provided to help the functional departments and cold chain logistics enterprises and organizations to make decision about cold chain logistics facilities and equipment investment.
REFERENCES


