http://ansinet.com/itj

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 13 (13): 2204-2210, 2014
ISSN 1812-5638 / DOI: 10.3923/itj.2014.2204.2210

An Improved GM(1, 1)-Markov Model in Supply Chain Disruption and its Application in Demand Prediction

[1,2]Youyu Chen and [1,2]Chunxia Liu
[1]College of Business Administration, Hunan University,
[2]Department of Business Administration, Hunan University of Finance and Economics,
Changsha, Hunan, China

Abstract: To better the prediction accuracy of the conventional Grey Model GM(1, 1) under the condition of supply chain disruption, the residuals are improved, the original data are classified into normal and abnormal values and the appropriate upper and lower disruption values are identified; normal situations and disruption are predicted, respectively by the application of the improved GM(1,1), the improved GM(1,1) is far from perfect yet, for the predicted results gotten from the model is unable to tell whether it was normal or abnormal. Markov chain method gets this problem resolved, as it can estimate the probabilities of each situation (normal or abnormal) that may happen accurately so that it can reach the forecast expectations for the next time. Finally, 48 week sales volume of an electronic product was applied in this text to test this model. The result indicates that the model not only have the ability to improve prediction accuracy but also enhance the operability of prediction to a certain degree. This improved GM(1,1)-Markov model has made a significant broken through in the requirements of the conventional GM(1,1) for original data. Therefore it can be applied to sequential data prediction in supply chain disruption or mutation and provide demand prediction for enterprises with scientific basis and effective real-time guidance.

Key words: GM(1,1), supply chain disruption, improved GM(1,1)-Markov model, prediction accuracy

INTRODUCTION

Today, supply chain disruption management has been developed as a focus of academic studies and enterprises attach great importance to it. In a supply chain, spatial-temporal changes increase the probability of disruption and the dynamic effects of economic fluctuations, what's worse, natural disasters, terrorism, computer viruses and other external environmental factors make supply chains more vulnerable, adding to the probability of supply chain disruption, furthermore, increasing the difficulty of supply chain disruption management. In this backdrop, many scholars carried out qualitative studies on daily operating at the risk of supply chain and quantitative research based on supply chain design and supply chain emergency coordination. At the present moment, there are quite a few researches on demand prediction of supply chain disruption, which is hard to motivate the present study.

Grey system theory (Deng, 1985) was put forward by Professor Julong Deng. Its research object is an uncertain system with samples and deficient information. With the advantages of simple modeling process and concise modeling expression, grey system theory is widely used in various fields such as economy, tourism, medicine, water conservation, anime and real estate (Sun *et al*., 2013). However it is only applied in stable speed changes sequence. Particularly, when data sequences vary to a large extent, there is a major error in the forecasting results. Therefore, many scholars have made some improvements on this (Zhou and He, 2013; Golmohammadi and Mellat-Parast, 2012; Zhao *et al*., 2012; Wang *et al*., 2013; Su *et al*., 2014).

MATERIALS AND METHODS

Grey prediction model: In the Grey prediction model GM(1,1), the original sequence is produced cumulatively as the time sequence increase progressively. The corresponding approximate differential equations are constructed to display the development of data sequence. What follows are the processes of model construction and solutions.

Step 1: If the original time sequence is given as $x^{(0)} = (x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n)$, in which n is the figure for the original data and $x^{(1)}$ is cumulatively generated in relation to $x^{(0)}$, i.e., I-AGO, then $x^{(1)} = (x^{(1)}(1), x^{(1)}(2),...,x^{(1)}(n)$ is achieved, in which:

Corresponding Author: Youyu Chen, College of Business Administration, Hunan University, Changsha, Hunan, China

$$x^{(1)}(i)=\sum_{i=1}^{n}x^{(0)}(i)$$

i = 1, 2,...n. If there is not any special notification, the value i will remain the same in the following.

Step 2: Test the quasi-smoothness of $x^{(0)}$ and the quasi-index pattern of $x^{(1)}$. The quasi-smooth coefficient is:

$$p(i+1)=\frac{x^{(0)}(i+1)}{x^{(1)}(i)}$$

If p(i)<0.5, then the quasi-smooth conditions are generally satisfied. The quasi-index pattern target is:

$$\sigma^{(1)}(i+1)=\frac{x^{(1)}(i+1)}{x^{(1)}(i)}$$

If $\sigma^{(1)}(i)\epsilon[1, 1.5]$, then the quasi-index pattern is generally satisfied (Wa, 2010).

Step 3: If p(i+1) <0.5, $\sigma^{(1)}(I+l)\epsilon[1, 1.5]$ then the albefaction differential equation of GM(1,1) is (Eq. 1):

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=b \qquad (1)$$

In which, a is the development grayscale, b is the grey action quantity, a and b are uncertainty coefficients, t indicates time. The traditional method is that the sequence $x^{(1)}$ uses the adjacent mean value to generate the sequence $w^{(1)}$, that is, $w^{(1)}=(w^{(1)}(1), w^{(1)}(2), ...,w^{(1)}(n))$, in which $w^{(1)}(i+1) = 0.5\, x^{(1)}(i) +0.5x^{(1)}(i+1)$. Therefore, the corresponding differential equation to the albefaction differential Eq. 2 is:

$$x^{(0)}(i)+a\, w^{(1)}(i) = b \qquad (2)$$

Step 4: Construct matrix B, matrix Y and matrix A, in which:

$$B=\begin{bmatrix}-w^{(1)}(2) & 1\\ \vdots & \vdots\\ -w^{(1)}(n) & 1\end{bmatrix}, Y=\begin{bmatrix}x^{(0)}(2)\\ \dots\\ x^{(0)}(n)\end{bmatrix}, A=\begin{bmatrix}a\\ b\end{bmatrix}$$

and therefore Eq. 2 can be equally changed into Eq. 3:

$$Y = BA \qquad (3)$$

Then the method of minimal squares is used to achieve $\hat{A} = (B^T B)^{-1} B^T Y$ and the approximate solutions $\hat{a}$ and $\hat{b}$ can be obtained.

Step 5: Put $\hat{a}$ and $\hat{b}$ into the grey differential equation and the discrete corresponding functions are achieved (Eq. 4):

$$\begin{cases}\hat{x}^{(1)}(1)=x^{(0)}(0)\\ \hat{x}^{(1)}(i+1)=\frac{\hat{b}}{\hat{a}}+e^{-\hat{a}i}(x^{(1)}(0)-\frac{\hat{b}}{\hat{a}})\end{cases} i\geq 1 \qquad (4)$$

Step 6: $\hat{x}^{(1)}(i+1)$ is recovered by cumulative reduction and the prediction value of the original data is achieved (Eq. 5):

$$\begin{cases}\hat{x}^{(0)}(1)=x^{(0)}(1)\\ \hat{x}^{(0)}(i+1)=\hat{x}^{(1)}(i+1)-\hat{x}^{(1)}(i)\end{cases} i\geq 1 \qquad (5)$$

Step 7: Precision test

- Point wise test

Absolute error:

$$\varepsilon^{(0)}(i) = x^{(0)}(i)- \hat{x}^{(0)}(i)$$

Relative error:

$$e(i)=\frac{|\varepsilon(t)|}{x^{(0)}(i)}\times 100\%$$

- Posterior difference ratio

$$s_1=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[x^{(0)}(i)-\bar{x}^{(0)}\right]^2}$$

in which:

$$\bar{x}^{(0)}=\frac{1}{n}\sum_{i=1}^{n}x^{(0)}(i),\ s_2=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[\varepsilon(i)-\bar{\varepsilon}^{(0)}\right]^2}$$

in which:

$$\bar{\varepsilon}^{(0)}=\sum_{i=1}^{n}\varepsilon^{(0)}(i),\ c=\frac{s_2}{s_1}$$

accuracy range is acceptable if c [0.35, 0.65]. When c becomes smaller, the range of prediction errors decreases and therefore the accuracy increases.

- Frequency of minor errors

$$P=p\{|\varepsilon(i)-\bar{\varepsilon}|<0.6745s_1\}$$

Accuracy range is acceptable if P∈[0.7, 0.95]. When P becomes larger, the probability of minor errors increases, therefore, the accuracy increases. The accuracy test is shown in Table 1.

Table 1: Accuracy test

Levels	Results	Average relative error (ARE)	Posterior difference ratio C	Frequency of minor errors P
1	Very good	≤0.01	<0.35	>0.95
2	Good	≤0.05	<0.50	>0.80
3	Ordinary	≤0.1	<0.65	>0.70
4	Disqualified	≤0.20	≥0.65	≤0.70

Improved GM(1,1) model in the disruption case: When original data sequence shows or basically shows a trend of index growth and data changes with a moderate speed, a good prediction accuracy can be reached with GM(1,1) model; but there may be abnormal points on the original data sequences of each node enterprise of supply chain due to supply chain disruption, making the trend of index growth pause or vibrate and the speed of data change unsmooth, which will show a poor growth trend or fail in rendering a growth trend ultimately, as a result, the GM(1,1) model become invalid. This study tries to solve the problem.

Original data are divided into two categories by application of the residual data of conventional GM(1,1): one is normal values, that is, the predicted values deviate little from the actual value and the other is abnormal values, that is, predicted values deviate much from the actual values. Abnormal value is also called as disruption value. Owing to positive and negative residuals, the disruption values are also positive and negative; when the positive residuals are bigger than the disruption values, they are called upper disruption values; when the negative residuals are less than disruption values, they are called lower disruption values. The time points at the upper and lower disruption values are called upper disruption points and lower disruption points separately.

Under normal conditions, the normal values corresponding to normal points are singled out to form a normal value sequence $x_0^{(0)}$; in the lower disruption case, the lower disruption values corresponding to the lower disruption points are singled out to form a lower disruption value sequence $x\_^{(0)}$; in the upper disruption case, the upper disruption values corresponding to the upper disruption points are singled out to form an upper disruption value sequence $x_+^{(0)}$. All three of these situations, the calculation method of prediction functions is identical to the calculation method for the conventional GM(1,1).

Improved GM(1,1)-Markov model in the disruption case: The prediction results of the improved GM(1,1) model are not perfect, because the prediction results have no corresponding time, namely it is not known whether it is normal or abnormal at the next time. However, the time can be determined by Markov chain method.

Step 1: Markov chain and k-step transition probability matrix.

Assuming the state space S of the random process $\{x(i),\ i\in I\}$ is a denumerable set of R, any parameter $i_1<i_2<\ldots<i_n$ in the corresponding I and any state in S that makes $\{x(i_1) = m_1, x(i_2) = m_2,\ldots, x(i_{n-1}) = m_{n-1}\}>0$ established have $p\{x(i_n) = m_n\}$, then $\{x(i),\ i\in I\}$ is called Markov chain and recorded as $P_{ij}(k) = P\ \{x_{m+k} = j|\ x_m = i\}\ i, j\in S$, which indicating the probability of the system in the state j at the time m+k under the condition of the system is in state I at the time m. Sort $p_{ij}^{(k)}$ in order to get a m×n transition probability matrix that is called k-step transition probability matrix of Markov chain, of which:

$$p_{ij}^{(k)} \geq 0 \text{ and } \sum_{i=1}^{n} p_{ij}^{(k)} = 1$$

Step 2: State division and transition probabilities calculation.

State division is to divide data series into a number of more or less equal interval ranges, of any state interval $Ei = [E_{1i}, E_{2i}]$, i = 1,2,...,n. If the total number of data sequence transferred from the state E_i to the state E_j is m_{ij} times and the number of occurrences of the state E_i is m_1, then:

$$P_{ij}^{(k)} = \frac{m_{ij}}{m_i}$$

For a non-stationary random sequence, provided that it meets the characteristics of Markov chain and sounds reasonable its state division is to divide the data unequally according to the actual situations.

Step 3: Prediction based on the transition probability matrix.

$p_{ij}^{(k)}$ describes the possibility of the current state E_i turning to state E_j in the future. According to the principle of maximum probability, the state corresponding to the maximum of p_{ij} is selected as the predicted result, that is, when $\text{Max}\{p_{i1}, p_{i2},\ldots,p_{in}\} = p_{ij}$ (i = 1,2,…,n) it can be predicted that the system in the next step will change to the state E_j ; if it is known that the state vector at the time is $A(t)= (a_1(t), a_2(t),\ldots,a_i(t))$ then $A(t+m)= A(t+m-1)\times p^{(k)}$, so a prediction basis can be provided to the predictors according to A(t+m).

RESULTS AND DISCUSSION

Background and sources of data: In early 2008, Hunan Province suffered a rare cold disaster and the ice disaster led to a large area of transport paralysis and widespread power outages, resulting in direct economic losses of RMB 151.65 billion. In September 2008, the global financial crisis burst so that the global economic activities were in trouble. During the ice disaster, a Hunan electronic manufacturing enterprises generated power with their own generators and continued production to cope with power outages, however, due to the problem of road icing its sales figure (100 boxes) still was affected. After the outbreak of the global financial crisis, together with the rising costs and increasing export pressure, the enterprise encountered bottlenecks in development, so the sales was also affected accordingly. Table 2 shows the weekly sales of certain categories of electronic products from November 1, 2007 to October 1, 2008.

Conventional GM(1,1) model in the supply chain disruptive case

Step 1: The sales sequence value is established as $x^{(0)}$; the cumulative sequence I-AGO is established as $x^{(1)}$.

Step 2: Then test the quasi-smoothness of $x^{(0)}$ and the quasi-index pattern of $x^{(1)}$. If $i>3$, then $p(i)<0.5$, $\sigma^{(1)}(i) \in [1, 1.5]$ and the requirements of the quasi-smoothness and the quasi-index pattern are met.

Step 3: Construct the matrix B and the constant matrix Y and achieve $\hat{\alpha} = -0.004557$, $\hat{b} = 651.0963$, Put $\hat{\alpha}$ and $\hat{b}$ into the grey differential equation and achieve the discrete corresponding function:

$$\begin{cases} \hat{x}^{(1)}(1) = 616 \\ \hat{x}^{(1)}(i+1) = 143494.2752e^{0.004557i} - 142878.2752 \end{cases} i \geq 1$$

Step 4: Achieve the prediction value of the original data:

$$\begin{cases} \hat{x}^{(0)}(1) = 616 \\ \hat{x}^{(0)}(i+1) = 143494.28e^{0.0046(i-1)}(e^{0.0046} - 1) \end{cases} i \geq 1$$

Step 5: Accuracy test.

By calculation, the average relative error ARE = 0.013248, which indicates that ARE≤ 0.05.

- Posterior difference value C

By calculation, the results are c = 0.8407, which shows c≥0.65.

- Frequency of minor errors P

By calculation, the results are p = 0.6875, indicating that frequency of minor errors p≥0.70.

In conclusion, the calculation process and results show that the required accuracy cannot be met due to the influence and interference of long-term data mutation and disruption.

The calculation results of predictive value ($\hat{x}^{(0)}$), the relative error e(i) and the absolute error e(i) are shown in Table 3.

Improved GM(1,1) model in the supply chain disruptive case: In order to ensure the smooth supply of goods, the enterprise would hold not more than 10% of the normal demand stability; when the absolute value of the sales exceeds 10%, the enterprise should establish a corresponding early-warning mechanism; especially, when the sales is lower than -10%, the enterprise should establish a corresponding early-warning mechanism and take appropriate measures to ensure the recovery in supply.

The node enterprise applied the residual data of conventional model GM(1,1) and the original data were classified into two categories: One is normal values, that is, the predicted values deviate from the actual values by less than 10%; the other is abnormal values, that is, the predicted values deviate from the actual values by more than 10%. There are a total of 37 normal values of the node enterprise with the predicted values deviating from the actual values by less than 10% and 11 abnormal values of it with the predicted values that deviate from the actual values by more than 10%. The calculation process is omitted here and here the relevant results are given

Table 2: Weekly sales (hundred boxes) of some electronic product between 1st November 2007 and 1st October 2008

Time	Sales	Time	Sales	Time	Sales	Time	Sales	Time	Sales
1	616.00	11	570.00	21	760.16	31	791.50	41	829.32
2	623.80	12	575.12	22	758.33	32	793.10	42	835.36
3	640.66	13	580.61	23	760.65	33	800.75	43	840.59
4	655.75	14	570.62	24	766.70	34	806.40	44	670.63
5	670.31	15	560.42	25	763.57	35	801.50	45	660.81
6	685.52	16	563.55	26	773.20	36	807.10	46	665.52
7	694.32	17	730.32	27	778.66	37	814.75	47	670.11
8	710.51	18	738.31	28	780.80	38	824.21	48	672.66
9	722.58	19	745.55	29	783.50	39	821.26		
10	732.32	20	750.63	30	786.40	40	827.57		

Table 3: Calculation results of conventional model GM(1,1)

Time	1	2	3	4	5	6	7	8	9	10	11	12
$\hat{x}^{(0)}$	616	655.40	658.39	661.40	664.42	667.45	670.50	673.56	676.64	679.73	682.83	685.95
$\varepsilon^{(0)}(i)$	0	-31.60	-17.73	-5.65	5.89	18.07	23.82	36.95	45.94	52.59	-112.83	-110.83
e(i)	0	-5.07	-2.77	-0.86	0.88	2.64	3.43	5.20	6.36	7.18	-19.80	-19.27
Time	13	14	15	16	17	18	19	20	21	22	23	24
$\hat{x}^{(0)}$	689.09	692.23	695.39	698.57	701.76	704.97	708.19	711.42	714.67	717.93	721.21	724.51
$\varepsilon^{(0)}(i)$	-108.48	-121.60	-134.97	-135.02	28.56	33.34	37.36	39.21	45.49	40.40	39.44	42.19
e(i)	-18.68	-21.31	-24.08	-23.96	3.91	4.52	5.01	5.22	5.98	5.33	5.18	5.50
Time	25	26	27	28	29	30	31	32	33	34	35	36
$\hat{x}^{(0)}$	727.82	731.14	734.48	737.84	741.21	744.59	747.99	751.41	754.84	758.29	761.75	765.23
$\varepsilon^{(0)}(i)$	35.75	42.06	44.18	42.96	42.29	41.81	43.51	41.69	45.91	48.11	39.75	41.87
e(i)	4.68	5.44	5.67	5.50	5.40	5.32	5.50	5.26	5.73	5.97	4.96	5.19
Time	37	38	39	40	41	42	43	44	45	46	47	48
$\hat{x}^{(0)}$	768.73	772.24	775.76	779.31	782.87	786.44	790.03	793.64	797.27	800.91	804.57	808.24
$\varepsilon^{(0)}(i)$	46.02	51.97	45.50	48.26	46.45	48.92	50.56	-123.01	-136.46	-135.39	-134.46	-135.58
e(i)	5.65	6.31	5.54	5.83	5.60	5.86	6.01	-18.34	-20.65	-20.34	-20.06	-20.16

Table 4: Calculation results of normal values based on conventional model GM(1,1)

Time	1	2	3	4	5	6	7	8	9	10
$\hat{x}^{(0)}$	616	675.51	680.05	684.62	689.22	693.85	698.51	703.20	707.93	712.69
$\varepsilon^{(0)}(i)$	0	-51.71	-39.39	-28.87	-18.91	-8.33	-4.19	7.31	14.65	19.63
e(i)	0	-8.29	-6.15	-4.40	-2.82	-1.21	-0.60	1.03	2.03	2.68
Time	11	12	13	14	15	16	17	18	19	20
$\hat{x}^{(0)}$	717.47	722.30	727.15	732.03	736.95	741.91	746.89	751.91	756.96	762.05
$\varepsilon^{(0)}(i)$	12.85	16.01	18.40	18.60	23.21	16.42	13.76	14.79	6.61	11.15
e(i)	1.76	2.17	2.47	2.48	3.05	2.17	1.81	1.93	0.87	1.44
Time	21	22	23	24	25	26	27	28	29	30
$\hat{x}^{(0)}$	767.17	772.32	777.51	782.74	788.00	793.29	798.62	803.99	809.39	814.83
$\varepsilon^{(0)}(i)$	11.49	8.48	5.99	3.66	3.50	-0.19	2.13	2.41	-7.89	-7.73
e(i)	1.48	1.09	0.76	0.47	0.44	-0.02	0.27	0.30	-0.98	-0.96
Time	31	32	33	34	35	36	37			
$\hat{x}^{(0)}$	820.31	825.82	831.37	836.95	842.50	848.24	853.94			
$\varepsilon^{(0)}(i)$	-5.56	-1.61	-10.11	-9.38	-13.26	-12.88	-13.35			
e(i)	-0.68	-0.20	-1.23	-1.13	-1.60	-1.54	-1.59			

Table 5: Calculation results of lower disruption values based on conventional model GM(1,1)

Time	1	2	3	4	5	6	7	8	9	10	11
$\hat{x}^{(0)}$	570	550.58	563.66	577.05	590.76	604.79	619.16	633.86	648.92	664.34	680.12
$\varepsilon^{(0)}(i)$	0	24.54	16.95	-6.43	-30.34	-41.24	51.47	26.95	16.60	5.77	-7.46
e(i)	0	4.27	2.92	-1.13	-5.41	-7.32	7.68	4.08	2.49	0.86	-1.11

merely. The calculation results of normal values are shown in Table 4. The calculation results of lower disruption values are shown in Table 5.

The predicted values of original data corresponding to the normal data:

$$\begin{cases}\hat{x}^{(0)}(1)=616\\ \hat{x}^{(0)}(i+1)=100530.10e^{0.0067(i-1)}(e^{0.0067}-1)\end{cases} i\ge 1$$

by calculation, ARE = -0.0007 $\le$0.01, p = 0.9730>0.95 and c = 0.2714<0.35 and its accuracy is very high. The predicted values of lower disruption data:

$$\begin{cases}\hat{x}^{(0)}(1)=570\\ \hat{x}^{(0)}(i+1)=23178.85e^{0.0235(i-1)}(e^{0.0235}-1)\end{cases} i\ge 1$$

ARE = -0.0067 $\le$0.01, p = 0.7273>0.70 and c = 0.5139<0.65 and the accuracy is qualified.

Improved GM(1,1)-Markov model in the supply chain disruptive case: The prediction time for node enterprises in the supply chain can be determined by Markov chain method. As residuals, they can be classified into 5 states according to enterprises own needs.

State 1: Accurately, that is, the absolute value of the relative errors is within 5%.

State 2: In the underestimated state, that is, the absolute value of the relative errors is 5-10%.

State 3: In the overestimated state, that is, the absolute value of the relative errors is −10- −5%.

State 4: In the obvious overestimate state, that is, the absolute value of the relative errors below −10%.

State 5: In the obvious underestimate state, that is, the absolute value of the relative errors is over 10%. As State 5 does not appear, 5×5-order transition probability matrices can be simplified into 4×4-order transition probability matrix and:

$$p^{(1)} = \begin{bmatrix} 0.5 & 0.4 & 0.1 & 0 \\ 0.0769 & 0.8462 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0.1 & 0 & 0 & 0.9 \end{bmatrix}$$

is available; because when there is no two or more elements of a row with the same or similar probability, the future turning of the state could be determined immediately, thus there is no need to consider the second step and multiple steps.

Sales prediction based on the transition probability matrix: As the 48th week is in state 4, thus $A(48) = (0, 0, 0, 1)$ and $A(49) = A(48)\ p^{(1)} (0.1, 0, 0, 0.9)$, the absolute predicted value of the 49th week is 713.44 and that of conventional GM(1,1) model is 821.3423 at this time, the subsequent predicted values can be achieved likewise.

CONCLUSION

As the business environment is a complex and volatile gray system, for the time series with disruption or mutation, original data are divided into normal value and abnormal value based on the conventional GM(1, 1) to find the corresponding upper and lower disruption values. Under normal conditions, a normal sequence consists of the normal values and an upper and lower disruption sequence consists of the upper and lower disruption values, respectively and then the corresponding prediction functions are calculated by the application of GM(1,1). Finally, Markov chain method is used to judge whether it is normal or abnormal at the next time and estimate the probabilities of each situation that may happen accurately in order to reach the forecast expectations for the next time.

The empirical study of an electronic enterprise in Hunan in 2008 suffering from the influence of ice damage shows that the improved GM (1,1)-Markov model can improve the prediction accuracy and enhance the operability of prediction. The 48 weeks of sales volume of the enterprise's electronic products during the demonstration was used as historical data to build a conventional GM(1,1), the results show that the conventional GM(1,1) of sales sequence does not pass the accuracy inspection due to the effect and interference of long-term data mutations and disruptions. Based on conventional GM (1,1), the enterprise's original data are classified into two categories: One is normal values, that is its predicted values deviate from the actual values by less than 10% with a total of 37 belong to this kind and the other is abnormal values, that is its predicted values deviate from the actual value by over 10% with a total of 11. On this basis, a prediction function of normal value sequence and lower disruption value sequence was calculated by using the GM(1, 1), respectively and the results show that the accuracy of such normal value sequence is good and the accuracy of the lower disruption value sequence is qualified. The predicted values for the next time can be determined based on Markov chain method and the residuals are divided into 5 states according to the enterprise's own needs and are predicted based on a transition probability matrix.

This combined method of the improved grey prediction model and Markov-chain method not only solves the critical issue on whether it is normal or abnormal at the next time but also predicts the predicted values for the next time accurately. For one thing, this method improves the fitting degree and prediction accuracy and enhances the stability and reliability of prediction. For another thing it can be applied to supply chain disruptions or salutatory time series. Besides it can also provide scientific theoretical basis and effective real-time guidance for the enterprise's need prediction.

ACKNOWLEDGMENTS

This study is supported by Natural Science Foundation of China under Grant No. 71172194 and supported by the Science and Technology Department of Hunan Province under Grant No. 2013FJ3080. Science and Technology Programs of Hunan Province, 2012GK3064, 2012GK4006.

REFERENCES

Deng, J.L., 1985. GM model of grey system theory. J. Fuzzy Math., 2: 23-32.

Golmohammadi, D. and M. Mellat-Parast, 2012. Developing a grey-based decision-making model for supplier selection. Int. J. Prod. Econ., 137: 191-200.

Su, L., X. Wang, B. Guo and X. Li, 2014. Gray correlation analysis of shanghai input-output of science and technology based on grounded theory. Inform. Technol. J., 13: 966-971.

Sun, W., J. Wang and H. Chang, 2013. Forecasting carbon dioxide emissions in china using optimization grey model. J. Comput., 8: 97-101.

Wa, D., 2010. The GM (1,1) forecast model of the Tibet rural consumption expenditure trends and effect factors analysis. Stat. Res., 4: 79-82.

Wang, B., J.L. Tao, D.F. Liu and X.B. Chen, 2013. Dynamic evaluation model of networked manufacturing resources based on grey target decision. Inform. Technol. J., 3: 534-537.

Zhao, Z., J. Wang, J. Zhao and Z. Su, 2012. Using a grey model optimized by differential evolution algorithm to forecast the per capita annual net income of rural households in China. Omega, 40: 525-532.

Zhou, W. and J.M. He, 2013. Generalized GM (1,1) model and its application in forecasting of fuel production. Applied Math. Modell., 37: 6234-6243.