ISSN: 1813-4890

# Analysis of Influencing Factors and Scale Forecast of My Country's Cross-border E-commerce B2C based on Grey Theory System

Jia Luo, Jiefang Liu

School of Economics and Management, Tianjin University of Technology and Education, Tianjin 300222, China

## Abstract

**With the rapid development of the Internet, the rapid rise of E-commerce, and the rapid development of Cross-border E-commerce, this paper analyzes the influencing factors and scales of Cross-border E-commerce B2C on the basis of Cross-border E-commerce. This paper uses grey correlation to analyze the influencing factors of my country's Cross-border E-commerce B2C, and uses the gray Markov model to model and analyze the growth scale of my country's Cross-border E-commerce B2C. The results show that the two factors of total postal business and per capita GDP have a strong correlation with Cross-border E-commerce B2C, and the four factors of online users' shopping scale, online payment users, residents' per capita disposable income and express delivery It shows a strong correlation to Cross-border E-commerce B2C, and the four factors of mobile Internet users, per capita consumption expenditure of residents, gross domestic product, and gross national income show a strong correlation to Cross-border E-commerce B2C; using gray Marko The scale value of Cross-border E-commerce predicted by the husband is closer to the real value, and the simulation error is also reduced.**

## Keywords

**Cross-border E-commerce B2C; Gray Correlation; Gray Markov Model.**

## 1. Introduction

The rapid development of the Internet has enabled the sharing of information resources around the world. The rapid rise of E-commerce has made people not limited to offline trading activities, but also online trading activities for daily learning. The development of Cross-border E-commerce has made E-commerce is not only limited to domestic products; foreign products can also be purchased on E-commerce platforms. In order to meet the shopping needs of consumers, major E-commerce platforms have also launched international product sections, such as: Tmall Global, JD Worldwide, etc. The development of Cross-border E-commerce can reflect that people's living standards and quality of life have generally improved, and people have begun to pay attention to excellent products from all over the world. In recent years, with the development of novel coronavirus pneumonia, my country has also issued a series of relevant policies and laws and regulations for the development of Cross-border E-commerce. The scale prediction provides a certain reference for the research and development of Cross-border E-commerce B2C.

## 2. An Overview of the Relevant Theories

### 2.1. Cross-border Electronic Commerce

Cross-border Electronic Commerce is an online transaction model that connects domestic and foreign countries through four streams of logistics, business flow, information flow and capital flow based on Internet information technology. Resource elements replace entity resource elements. The rapid development of the Internet has enabled the sharing of information resources around the world. The rapid rise of E-commerce has also led to the rapid development of Cross-border E-commerce. Online shopping has become a part of people's lives, ranging from a pen to a large home appliance [1,2].

Cross-border Electronic Commerce B2C is a transaction mode in Cross-border E-commerce. B2C (Business to Consumer) refers to a business-to-consumer E-commerce transaction activity. A series of online trading activities.

### 2.2. Grey System Theory

Grey system theory is a research method that can effectively solve uncertainty problems such as small data, few samples, and poor information. Information, this method studies the system from the internal structure and parameters of the system, in order to emphasize the cognition of the laws of reality. Through the analysis of this series of uncertain, small sample and poor information data, useful value is extracted.

Grey system theory was first proposed by Professor Julong Deng, a famous scholar in my country in 1982. After the grey system theory was first proposed, it has attracted many scholars to continue to study and explore in the field of grey system theory, and has been received by scholars and scholars from all over the world. Close attention and strong support from academia; in the discussion of many disciplines and research fields, grey system theory has been repeatedly used and studied, so many excellent results have been achieved in this field[4] .

### 2.3. Markov

Markov is a discrete stochastic process that describes a sequence of states whose value depends on a finite number of preceding states [15]. A Markov chain is a random, memoryless discrete process, and a Markov process whose time and state are both discrete is a Markov chain. A Markov chain is a sequence of random variables with Markov properties. Markov chains are widely used in mathematical modeling of chemical reactions, queuing theory, market behavior and grey system forecasting [5,6].

The extensive application of Markov provides scholars with new research directions and methods, as well as new research ideas for other disciplines and research fields [7,8].

## 3. Literature References

### 3.1. Grey Relational Analysis Model

Quantify the amount of feature mapping required by the system and various related factors, and convert them into dimensionless data with roughly similar orders of magnitude through the action of operators.

Be $X_0=(x_0(1),x_0(2),\cdots,x_0(n))$ the system characteristic behavior sequence, and

$$X_1=(x_1(1),x_1(2),\cdots,x_1(n))$$
$$\cdots\cdots$$
$$X_i=(x_i(1),x_i(2),\cdots,x_i(n))$$
$$\cdots\cdots$$
$$X_m=(x_m(1),x_m(2),\cdots,x_m(n))$$

is a sequence of related factors, Given a real number $\gamma(x_0(k),x_i(k))$, if the real number

$$\gamma(X_0,X_i)=\frac{1}{n}\sum_{k=1}^{n}\gamma(x_0(k),x_i(k))$$

Satisfy:

Normative

$$0<\gamma(X_0,X_i)\le 1,\gamma(X_0,X_i)=1\Leftarrow X_0=X_i$$

Proximity

$\gamma(X_0,X_i)=1\Leftarrow X_0=X_i$ smaller, $\gamma(x_0(k),x_i(k))$ bigger

Then $\gamma(X_0,X_i)$ is called the gray correlation degree of $X_i$ and $X_0$, and $\gamma(X_0,X_i)$ is the correlation coefficient between $X_i$ and $X_0$ at the point, also called conditions Normative, Proximity are the gray correlation axioms[3].

#### 3.1.1. Grey Absolute Correlation

Let the system behavior sequence $X_i=(x_i(1),x_i(2),\cdots,x_i(n))$, record

$$(x_i(1)-x_i(1),x_i(2)-x_i(1),\cdots,x_i(n)-x_i(1))$$

For

$$X_i-x_i(1),\text{ let } s_i=\int_1^n (X_i-x_i(1))dt \tag{1}$$

Then

$$\varepsilon_{0i}=\frac{1+|s_0|+|s_i|}{1+|s_0|+|s_i|+|s_i-s_0|} \tag{2}$$

is the grey absolute correlation between $X_0$ and $X_i$.

#### 3.1.2. Grey Relative Correlation

Let the system behavior sequence $X_i=(x_i(1),x_i(2),\cdots,x_i(n))$, record $(\frac{x_i(1)}{x_i(1)},\frac{x_i(2)}{x_i(1)},\cdots,\frac{x_i(n)}{x_i(1)})$

For

$$X_i'=\frac{X_i}{x_i(1)},\text{ let}|s_i'|=\left|\sum_{k=2}^{n-1}x_i'^0(k)+\frac{1}{2}x_i'^0(n)\right| \tag{3}$$

Then

$$r_{0i}=\frac{1+|s_0'|+|s_i'|}{1+|s_0'|+|s_i'|+|s_i'-s_0'|} \tag{4}$$

is the grey relative correlation between $X_0$ and $X_i$.

#### 3.1.3. Grey Comprehensive Correlation

$\varepsilon_{0i}$ and $r_{0i}$ are the gray absolute correlation degree and gray relative correlation degree of $X_0$ and $X_i$, respectively, $\theta\in[0,1]$, then it is called

$$\rho_{0i}=\theta\varepsilon_{0i}+(1-\theta)r_{0i} \tag{5}$$

is the grey comprehensive correlation degree of $X_0$ and $X_i$.

#### 3.1.4. The Application of Grey Relational Degree

On the basis of previous research by scholars, the influencing factors of Cross-border E-commerce B2C selected in this paper are: gross national income, gross domestic product, per capita GDP, per capita disposable income of residents, per capita consumption expenditure of residents, online payment The ten influencing factors of users, online shopping user scale, mobile Internet users, total postal business, and express delivery are recorded as: $X_1$, $X_2$, $X_3$, $X_4$, $X_5$, $X_6$, $X_7$, $X_8$, $X_9$, $X_{10}$, also remember that the scale of Cross-border E-commerce B2C transactions is $X_0$.The data of each influencing factor are shown in Table 1 below (Data sources: National Bureau of Statistics, China Internet Network Information Center, WJS)

**Table 1.** Data on relevant factors affecting the scale of Cross-border E-commerce B2C transactions from 2017 to 2020

| Influencing factors | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|
| gross national income (100 million yuan) | 830945.7 | 915243.5 | 983751.2 | 1006363.3 |
| gross domestic product (100 million yuan) | 832035.9 | 919281.1 | 986515.2 | 1013567 |
| per capita GDP (yuan) | 59592 | 65534 | 70078 | 71828 |
| per capita disposable income of residents(yuan) | 25974 | 28228 | 30733 | 32189 |
| per capita consumption expenditure of residents(yuan) | 18322 | 19853 | 21559 | 21210 |
| online payment the ten influencing factors of users (ten thousand person) | 51104 | 56893 | 63305 | 80500 |
| online shopping user scale (ten thousand person) | 51443 | 56892 | 63882 | 74939 |
| mobile Internet users (100 million yuan) | 127153.7 | 127481.5 | 131852.6 | 134851.9 |
| total postal business (ten million pieces) | 9763.7 | 12345.2 | 16229.6 | 21053.2 |
| express delivery (ten million pieces) | 4005591.9 | 5071042.8 | 6352291 | 8335789.4 |
| Cross-border E-commerce B2C transactions (100 million yuan) | 11928.8 | 15120 | 20475 | 28375 |

Substitute the above data into the above formulas (1, 2, 3, 4, 5) through calculation, and obtain the correlation degree values of each influencing factor as shown in Table 2 below.

**Table 2.** Correlation of related factors

| Correlation factor | grey absolute correlation | grey relative correlation | grey comprehensive correlation |
|---|---|---|---|
| gross national income | 0.5307 | 0.705 | 0.6178 |
| gross domestic product | 0.53 | 0.707 | 0.6185 |
| per capita GDP | 0.9427 | 0.7021 | 0.8224 |
| per capita disposable income of residents | 0.7535 | 0.7047 | 0.7291 |
| per capita consumption expenditure of residents | 0.6556 | 0.6931 | 0.6743 |
| online payment the ten influencing factors of users | 0.8053 | 0.7622 | 0.7838 |
| online shopping user scale | 0.8368 | 0.7476 | 0.7922 |
| mobile Internet users | 0.7223 | 0.6311 | 0.6767 |
| total postal business | 0.868 | 0.9612 | 0.9146 |
| express delivery | 0.5018 | 0.9354 | 0.7186 |

By sorting the values of the correlation indicators in the above table, we can obtain the total postal business $X_9$> per capita GDP $X_3$> online users' shopping scale $X_7$> online payment users $X_6$> per capita disposable income of residents $X_4$> express delivery $X_{10}$>mobile Internet users $X_8$>residential per capita consumption expenditure $X_5$>gross domestic product $X_2$>gross national income $X_1$.

## 3.2. Grey Markov Prediction Principle and Method

### 3.2.1. Principles of Grey Predictive Modeling

Let the original data be $x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n)$, the non-negative sequence $x(0) = (x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n))$, and accumulate it once to get $x(1) = (x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(n))$, where the $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1, 2, ..., n$ accumulation sequence overcomes the volatility and randomness of the original sequence, and converts it into an increasing sequence with strong regularity. Prepare the predictive model.

Differential equation

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{6}$$

Grey prediction model $GM(1,1)$, where a, b are constants,

$$B = \begin{bmatrix} -0.5(x^{(1)}(2)) + (x^{(1)}(1)) & 1 \\ -0.5(x^{(1)}(3)) + (x^{(1)}(2)) & 1 \\ \vdots & \vdots \\ -0.5(x^{(1)}(n)) + (x^{(1)}(n-1)) & 1 \end{bmatrix} \tag{7}$$

It can be obtained by least squares fitting: $\hat{a} = [a, b]^T = (B^T B)^{-1} B^T Y$, where $Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ 7x^{(0)}(n) \end{bmatrix}$, The solution of differential equation (6) is

$$\hat{x}^{(1)}(k+1) = (x^{(0)}(1) - \frac{b}{a})e^{-ak} + \frac{b}{a}, k = 1, 2, ..., n \tag{8}$$

Equation (8) is the prediction formula of the sequence. Since Equation (8) is the predicted value of the sequence generated by one accumulation, the restored predicted value of the original sequence can be obtained by Equation (8)[4].

$$\hat{x}^{(1)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k), k = 1, 2, ..., n \tag{9}$$

### 3.2.2. Grey Markov Prediction Model

Let the original data $x^{(0)}(k)(k=1,2,\cdots,n)$ be a non-stationary random sequence that conforms to the characteristics of Markov chain, and divide the value of $x^{(0)}(k)(k=1,2,\cdots,n)$ into s different states, and any state $\otimes_i$ is expressed as

$$\otimes_i = [b_{1i}, b_{2i}], i = 1,2,\cdots,s$$

where $b_{1i}, b_{2i}$, is a constant that needs to be set according to the state division [9,10]. here are $s$ states $\otimes_1, \otimes_2, \cdots, \otimes_s$, in the $M$ period of the observation record, and the state $\otimes_i\ (i = 1,2,\cdots,s)$ appears $M_i$ times, so

$$p_i = \frac{M_i}{M} \tag{10}$$

The probability is approximated in terms of frequency, then

$$p_{ij} = \frac{M_{ij}}{M_i}$$

Similarly, an approximation of the $m$ -step state transition probability can be obtained

$$a_{ij}(m) = \frac{M_{ij}(m)}{M_i}, i = 1,2,\cdots,s \tag{11}$$

Select the state corresponding to the largest one in $(a_{i1}, a_{i2}, \cdots, a_{is})$ as the prediction result, that is,

$$\max\{a_{i1}, a_{i2}, \cdots, a_{is}\} = a_{ik} \tag{12}$$

it can be predicted that the next step the system will turn to state $\otimes_k$ [11,12]. Markov correction to the predicted value of GM (1,1).

Denote the relative error percentage between the predicted value and the actual value of GM(1,1) as $F$ , and divide it into i states according to the positive and negative and the magnitude of the relative error percentage value in the GM(1,1) model, corresponding to state $F_1, F_2, \cdots, F_S$, respectively The value of each state interval is denoted as $[F_{s-}, F_{s+}]$[13,14].

In summary, the stateful transition matrix is:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1s} \\ a_{21} & a_{22} & \cdots & a_{2s} \\ \vdots & \vdots & \vdots & \vdots \\ a_{s1} & a_{s2} & \cdots & a_{ss} \end{bmatrix}$$

Then the correction formula is:

$$\hat{X}_{(k)}^{(0)} = x_{(k)}^{(0)} \times [1 - (F_{i-} + F_{i+})/2] \tag{13}$$

## 3.3. Application of the Model

### 3.3.1. Application of GM (1,1) Model

Select the Fig.1（2015-2021）Cross-border E-commerce B2C transaction scale data in the following figure to carry out GM (1,1) forecast and grey Markov forecast respectively (Data sources: WJS).

According to the (2015-2021) Cross-border E-commerce B2C transaction scale data in Fig.1 and the principle of the grey prediction model, using the MATLAB program to calculate, the calculation can be obtained:

$$a = -0.27, b = 6639.81$$

$$\hat{a} = [a,b]^T = (B^T B)^{-1} B^T Y = \begin{bmatrix} -0.27 \\ 6639.81 \end{bmatrix}$$

$$\hat{x}^{(1)}(k+1) = \left(4374 - \frac{6639.81}{-0.27}\right) e^{0.27k} + \frac{6639.81}{-0.27}, k = 1,2,\cdots,n$$

ISSN: 1813-4890

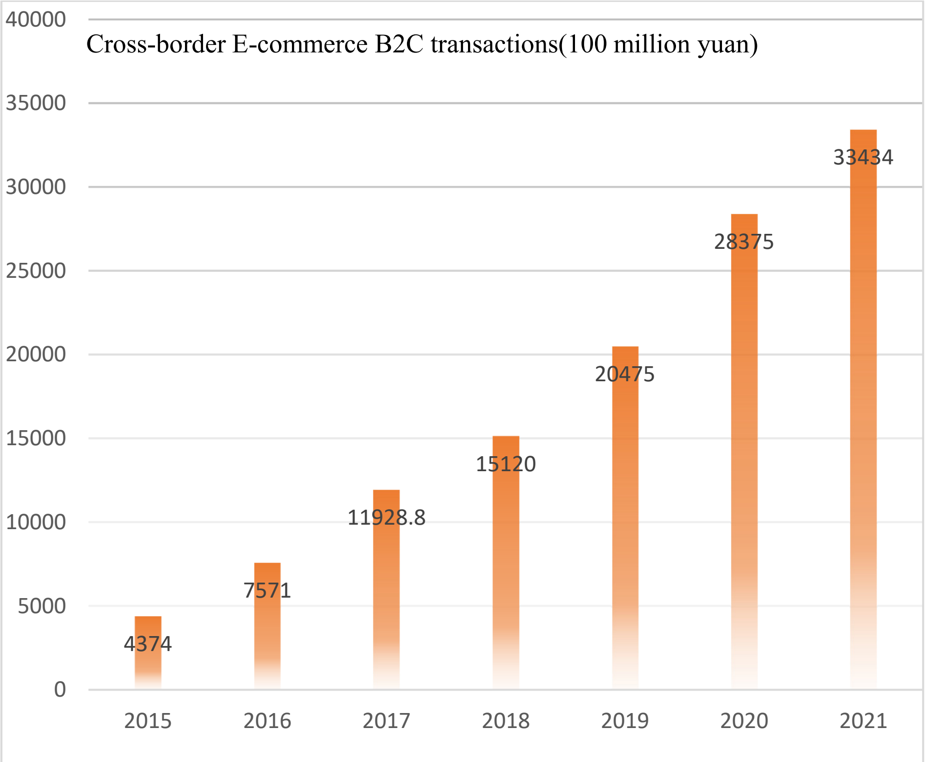


**Fig 1.** Scale of Cross-border E-commerce B2C transactions

By substituting the data in Figure 1 into the above formula, the following table 3 GM (1,1) predicted value of rural E-commerce transactions can be obtained.

**Table 3.** GM (1,1) predicted value

| Years | Actual value (100 million yuan) | GM (1,1) Predictive value (100 million yuan) | Relative simulation error |
|---|---|---|---|
| 2015 | 4374 | 0 | 0 |
| 2016 | 7571 | 8975.87 | 18.56% |
| 2017 | 11928.8 | 11765.17 | 1.37% |
| 2018 | 15120 | 15421.26 | 1.99% |
| 2019 | 20475 | 20213.5 | 1.28% |
| 2020 | 28375 | 26494.95 | 6.63% |
| 2021 | 33434 | 34728.39 | 3.87% |

### 3.3.2. Application of GM (1,1) Model

**Table 4.** Interval division table

| Status | Interval | Year | Quantity |
|---|---|---|---|
| M1 | [1%,2%] | 2017,2018, 2019 | 3 |
| M2 | [2.1%,8%] | 2020, 2021 | 2 |
| M3 | [8.1%,19%] | 2016 | 1 |

The predicted value of the gray system is revised by using Markov chain, in order to make the predicted value of the transaction scale data of Cross-border E-commerce B2C closer to the real value. According to the relative simulation error results calculated in Table 3 above, the relative simulation error can be divided into 3 intervals, and the minimum interval is 1.28%, the maximum interval is 18.56%, and the upper and lower limits of the interval are closed intervals.

Then the divided three intervals are: $[1\%,2\%]$, $[2.1\%,8\%]$, $[8.1\%,19\%]$, respectively denoted as: $M_1, M_2, M_3$.

The state interval is divided by the relative simulation error of the above predicted values, as shown in Table 4.

From the state interval of the rural E-commerce transaction scale in Table 4 above, the Markov state transition matrix can be obtained as:

$$A=\begin{bmatrix} 2/3 & 1/3 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix}$$

The predicted value of gray rural E-commerce transaction scale data after using Markov chain correction is shown in Table 5 below.

**Table 5.** Grey Markov predictions

| Years | Actual value (100 million yuan) | GM (1,1) Predictive value (100 million yuan) | Relative simulation error | Markov predictions Value (100 million yuan) | Markov Prediction Relative Simulation Error |
|---|---|---|---|---|---|
| 2015 | 4374 | 0 | 0 | 0 | 0 |
| 2016 | 7571 | 8975.87 | 18.56% | 7904.77 | 4.41% |
| 2017 | 11928.8 | 11765.17 | 1.37% | 11944.34 | 0.13% |
| 2018 | 15120 | 15421.26 | 1.99% | 15193.36 | 0.49% |
| 2019 | 20475 | 20213.5 | 1.28% | 20521.32 | 0.23% |
| 2020 | 28375 | 26494.95 | 6.63% | 27904.11 | 1.66% |
| 2021 | 33434 | 34728.39 | 3.87% | 33058.91 | 1.12% |

# 4. Conclusion

## 4.1. Grey Relation

Generally speaking, if the correlation degree < 0.5, the two factors are considered to have a low degree of correlation; 0.5 ≤ correlation degree < 0.6, the two factors are considered moderately correlated; 0.6 ≤ correlation degree < 0.7, the two factors are considered to be strongly correlated; 0.7 ≤ correlation degree < 0.8, there is a strong correlation between the two factors; 0.8 ≤ correlation < 1.0, indicating that there is a strong correlation between the two factors.

According to the degree of correlation of the above influencing factors, the degree of influence factors of Cross-border E-commerce B2C can be ranked as follows: the total postal business and per capita GDP show a strong correlation to Cross-border E-commerce B2C. The four factors of user shopping scale, online payment users, residents' per capita disposable income, and express delivery show strong correlation with Cross-border E-commerce B2C. Mobile Internet users, residents' per capita consumption expenditure, GDP, and gross national income These factors show a strong correlation to Cross-border E-commerce B2C.

## 4.2. Grey Markov Prediction

In order to compare and analyze the prediction accuracy of the grey Markov model and the traditional GM (1,1) model, the actual transaction scale value and the predicted value using the above two models are shown in the Cross-border E-commerce B2C transaction scale data from

2015 to 2021. Pictured above. From the comparison of the prediction results of GM (1,1) and Markov correction in Table 5, it can be clearly seen that the relative error of the prediction value of the traditional GM (1,1) model is between 1.37% and 18.56%, and the absolute relative error is between 1.37% and 18.56%. The average value is 5.62%; the relative error of the predicted value by the grey Markov model is between 0.13% and 4.41%, and the absolute value of the relative error is 1.34% on average, which is much better than the traditional GM (1,1) model. Therefore, the gray Markov model is more accurate in predicting data with volatility and is closer to the true value.

## Acknowledgments

Natural Science Foundation (71871084).
Ministry of Education, Humanities and social science projects(20YJC630083).

## References

[1] Y.Y. Shi, E.X. Wang and J.J. Li:Prediction of cross border E-commerce logistics market in China, Journal of Science & Technology Review,Vol. 38 (2020) No.5, p.105-112.

[2] Y.S. Liu, D.B. Chen: The Synergetic Measurement of Cross-border E-commerce and Model Logistics based on the Synergetic Degree Model of the Compound System,Journal of China Business and Market,Vol. 30 (2016) No.5, p.106-114.

[3] X. D. Zhang:Correlation analysis of influencing factors of Cross-border E-commerce development based on grey theory,Journal of Finance and Accounting for International Commerce, (2020) No.1, p.89-92+96.

[4] G. H. Yang,Y. Yan and H.Z.Yang:Application of improved GM(1,1) grey prediction model,Journal of Nanjing University of Science and Technology,Vol. 44 (2020) No.5, p.575-582.

[5] Y. Feng, M.D. Ye: Research on a Grey-Markov China Prediction Model Based on the Range Correction of State Intervals, Journal of Geomatics,Vol. 46 (2021) No.4, p.65-68.

[6] P.Y.Li, A.C.Cao and Y. H. Zhang: Free Cash Flow Forecast Based on Improved Grey Markov Model, Journal of Friends of Accounting, (2020) No.23, p.144-150.

[7] J. J. Li, W. M. Liu and H. M. Fei: Prediction of Farmers' Income in Jilin Province Based on Gray Markov Model, Journal of Northeast Agricultural Sciences,Vol. 45 (2020) No.6, p.106-109+139.

[8] Y. Li, X. Bai: Forecast of wheat yield based on new dimensional unbiased grey Markov model ,Journal of Jiangsu Agricultural Sciences,Vol. 49 (2021) No.15, p.181-186.

[9] X. Y. Wang,C. Q. Yang: Prediction of Dangerous Weather Influence Range Based on Residual Grey Markov Model, Journal of Computer and Information Technology,Vol. 30 (2022) No.2, p.38-41.

[10] Q. You：The application of grey Markov prediction model in the trend of college students changing majors, Journal of Computer & Digital Engineering,Vol. 49 (2021) No.9, p.1878-1883.

[11] L. Zhang: Prediction of Coal Spontaneous Combustion Based on Improved Grey Markov Chain Model, Journal of Inner Mongolia Coal Economy, (2020) No.16, p.142-143.

[12] W. T. Mo: Application of grey-markov model for high slope deformation prediction ,Journal of Shanxi Architecture,Vol. 46 (2020) No.6, p.73-74.

[13] Q. Z. Wei, Y. Yang, L. Y. Li and H.Z. Wei:Predict Model for Foreign Exchange Based on Grey-Markov, Journal of Computer and Modernization, (2020) No.2, p.12-15.

[14] F. H. Shu: Prediction of Flour Consuption and Thoughts on Grain Safety in China Based on the Grey-Markov Model, Journal of Modern Flour Milling Industry,Vol. 33 (2019) No.4, p.48-54.

[15] X. F. Yang: The Application of Grey Markov Model in Forecasting the Number of Tourists, Journal of Yibin University,Vol. 19 (2019) No.12, p.110-116.