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Applying Grey System Theory to Predict the Three Major Industries Structure Evolution in China

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ABSTRACT
GDP is one of the important indicators of the comprehensive performance of macroeconomic of a country in a given period, and also is the general term for the three major industries production value. The scientific and accurate analysis of the future industry structure evolution can contribute to the decision-making of the relevant departments, which is valuable in practice. This paper proposes an applying grey system theory to predict the three major industries structure evolution in China, which constructs a grey GM(1,1) model of the three major industries production value, verifies the model is usable for small sample size as a nonlinear model with high prediction accuracy, and uses the grey GM(1,1) model to predict the three major industries production value in the next five years. Results showed that the three major industries structure will be continuously optimized and adjusted, and the tertiary industry will play an increasingly important role in efficient and high-quality economic growth in China.
***Keywords**: Grey system, GM(1,1) model, three major industries, industry structure evolution, prediction accuracy*

1. INTRODUCTION

Gross domestic product (GDP) as one of the important indicators to measure the overall economic situation of a country, not only reflects the degree of a country's economic development, but also serves as a symbol of a country's comprehensive national strength and wealth[1-3]. In recent years, China's rapid economic development and significant improvement of comprehensive national strength are inseparable from the growth of GDP, and the three major industries production value plays an increasingly important role in GDP, is closely related to China's ongoing promotion of industrial structure adjustment strategies[4-6]. Therefore, it is important that analyzing the different contributions of the three major industries to GDP and the structure evolution of the three major industries in the future can promote the sustained and stable operation and high-quality development of the economy.

The data of GDP and the three major industries production value in China should be regarded as a dynamic, nonlinear, and uncertain time series. As far as I know, many methods are used to predict time series problems. These models can be generally divided into three main categories, including the statistical model, intelligent model, and grey system theory. Where the statistical models rely too much on collecting data and estimating parameters; the intelligent models, support vector machine and artificial neural network, require lots of data to train the model; The grey system theory is developed to solve uncertain and unknown system problems, and the grey prediction model is often named as GM based on grey system theory[7]. Over three decades of development, the grey model has been widely studied. Li et al.[8] proposed an applying grey system theory to predict the Chinese high-tech industries, the results show that grey system theory is suitable to investigate the relationship between industrial characteristics and innovation capabilities within Chinese high-tech industries. Tan et al.[9] integrated the method of BP artificial neural network with grey relational analysis method together as an Industrial economic forecasting. Wang et al.[10] presented an improved grey model prediction model to predict the Beijing's tertiary industry. Ma et al.[11, 12] used grey model to predict the natural gas consumption in China. Zheng et al.[13] proposed a new hybrid grey model, and obtained the predicted results that demonstrate that the structure of the industry in China will further transform and upgrade towards the capital deepening. In the above studies, scholars have applied the grey system and improved model to forecast the GDP or industry production value. According to the existing references, there is no research on the prediction of the three major industrial structures evolution in the future in China. It has been proved that the scientific and accurate analysis of the future industry structure evolution can contribute to the decision-making of the relevant departments

In this paper we will propose an applying grey system theory to predict the three major industries structure evolution in China. The remainder of this paper is organized as follows: Section 2 is dedicated to the previous developments of the GM(1,1) model, Section 3 describes the China's three major industrial structures prediction based on grey GM(1,1) model, including prediction model construction and validation, and three major industries production value prediction and analysis, and the conclusions are drawn in Section 4.

2. GREY GM(1,1) MODEL CONSTRUCTION

2.1. Model Basic Principles

In the research of the industry structure evolution in China, the adoption of the grey GM(1,1) model is mainly based on the following three points: (1) There are many influencing factors and uncertainties involved in the prediction of industry structure, which belong to the category of grey system research[14]. (2) The problem of industry structure prediction belongs to the category of nonlinear theory, traditional time series models such as regression prediction methods are difficult to obtain high prediction accuracy. (3) In the actual modeling process, the prediction of the future value by the nearest neighbor data tends to get better results, so the number of effective samples is limited, while the traditional prediction model can only achieve the ideal prediction accuracy based on the big data samples, otherwise it will cause the problem of underfitting and overfitting. The grey GM(1,1) model as a most typical model in grey prediction, comparing with other traditional models, this model is a non-linear model, which can be established with at least 4 sample data, and belongs to the "small sample" model with high prediction accuracy[7, 15, 16]. The grey GM(1,1) model is usually applied to five prediction methods: series, season, disaster, system and topology. In this paper, the series prediction is used, that is, a gray prediction model is constructed by using the known time series describing the characteristics of the prediction object, which is used to calculate the characteristics of the prediction object at a certain point in the future. Specific implementation steps are as follows:

First, let the known data variables form an initial time series $X^{(0)}$,

$$X^{(0)}=\left\{X^{(0)}(1), X^{(0)}(2), \cdots X^{(0)}(n)\right\}. \tag{1}$$

Second, accumulate the original data to avoid its random disturbance and form a new time series $X^{(1)}$.

$$X^{(1)}=\left\{X^{(1)}(1), X^{(1)}(2), \cdots X^{(1)}(n)\right\}. \tag{2}$$

Third, establish the corresponding differential equation of GM(1,1) model, assuming that $X^{(1)}$ satisfies the first-order differential equation. The differential equation defined as follows,

$$\frac{dX^{(1)}}{dt}+aX^{(1)}=b. \tag{3}$$

Where *a* represents the developing grey number, *b* represents the endogenous controlled grey number, and both of them can be obtained by the least square method.

Fourth, the parameters *a* and *b* are calculated by using the least square method, and set $\hat{a}=\begin{bmatrix} a \\ b \end{bmatrix}$ as the estimated matrix, then the differential equation can be expressed as $Y=B\hat{a}$, and can be obtained by using the least square method, as follows,

$$\hat{a}=\begin{bmatrix} a \\ b \end{bmatrix}=\left(B^T B\right)^{-1} B^T Y. \tag{4}$$

Among them

$$B=\begin{bmatrix} -\frac{1}{2}(X^{(1)}(2)+X^{(1)}(1)) & 1 \\ -\frac{1}{2}(X^{(1)}(3)+X^{(1)}(2)) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(X^{(1)}(n)+X^{(1)}(n-1)) & 1 \end{bmatrix} \tag{5}$$

$$Y=\left[X^{(0)}(2),\ X^{(0)}(3),\ \cdots\ X^{(0)}(n)\right]^T. \tag{6}$$

Fifth, substitute parameter estimators a and b into the equation (3), and solve the differential equation to obtain the prediction model, which is obtained as follows,

$$\hat{X}^{(1)}(k+1)=\left[X^{(0)}(1)-\frac{b}{a}\right]1^{-ak}+\frac{b}{a}. \tag{7}$$

Finally, the grey prediction model of the original data sequence obtained by subtraction, we can defined the equation is as follows,

$$\hat{X}^{(0)}(k+1)=\hat{X}^{(1)}(k+1)-\hat{X}^{(1)}(k). \tag{8}$$

2.2. Model Validation Indicators

Model validation is to measure the fitting accuracy between the original data sequence $X^{(0)}$ and the predicted data sequence $\hat{X}^{(0)}$. Usually, the relative error test method and the posterior difference test method are used to validate the accuracy of model prediction.

(1) Relative error test method. The accuracy level of the model can be judged by calculating the value of the average relative error. Using formula (9) and (10) as shown below, the residual e of the original data series and the predicted data series is first calculated, and then the average relative error V is obtained. The reliability and prediction effect of the model are judged through Table 1, where the smaller the average relative error is, the higher the prediction accuracy of the model is.

$$e=X^{(0)}(i)-\hat{X}^{(0)}(i) \tag{9}$$

$$V=\frac{|e|}{X^{(0)}(i)} \tag{10}$$

(2) Posterior difference test method. The accuracy level of the model by calculating the ratio of the posterior difference and the probability of small error. First, the mean value and variance of the original data sequence $X^{(0)}$ and the residual sequence e are calculated. Then the ratio of the posterior difference C and the probability of small error P are obtained.

Finally, the prediction accuracy of the model is judged by referring to the accuracy grade Table 2. The detailed formula is as follows,

$$C=\sqrt{S_2^2 / S_1^2} \tag{11}$$

Where, S_1^2 represents the variance of the original data sequence $X^{(0)}$, S_2^2 represents the variance of the residual sequence e, their detailed formula is as follows:

$$S_1^2=\frac{1}{n}\sum_{i=1}^{n}\left[X^{(0)}(i)-\bar{X}^{(0)}\right]^2 \tag{12}$$

$$S_2^2=\frac{1}{n}\sum_{i=1}^{n}\left[e(i)-\bar{e}\right]^2 \tag{13}$$

In equations (12) and (13), $\bar{X}^{(0)}$ represents the average value of the original data sequence $X^{(0)}$, $\bar{e}$ represents the average value of the residual sequence e, their detailed formula is as follows:

$$\bar{X}^{(0)}=\frac{1}{n}\sum_{i=1}^{n}X^{(0)}(i) \tag{14}$$

$$\bar{e}=\frac{1}{n}\sum_{i=1}^{n}e(i) \tag{15}$$

It is worth noting that, small error probability P represents the possibility of smaller error, whose equation is obtained as follows,

$$P=p\left\{\left|e(i)-\bar{e}\right|<0.6745S_1\right\} \tag{16}$$

Table 1 Reference table for relative error accuracy inspection level

Precision grade	Average relative error V
Level 1 (good)	0.01
Level 2 (Qualified)	0.05
Level 3 (barely)	0.10
Level 4 (Rejected)	0.20

Table 2 Reference table for the accuracy test level of the posterior difference

Precision grade	Posterior difference ratio	Small error probability
Level 1	<0.35	>0.95
Level 2	<0.5	>0.8
Level 3	<0.65	>0.7
Level 4	≥ 0.65	≤ 0.7

3. CHINA’S THREE MAJOR INDUSTRIAL STRUCTURES PREDICTION BASED ON GREY GM(1,1) MODEL

3.1. Experiment Preparation

In this paper, GDP and the three major industries production value in China from 2010 to 2019 are selected for modeling, which is from the website of the National Bureau of Statistics (http://data.stats.gov.cn/easyquery.htm?cn=C01). As shown in Table 3, GDP increased from 41211.9 billion yuan to 99086.5 billion yuan in the past decade, with an average annual growth rate of about 10.24%. The primary industry production value increased from 384.3 billion yuan in 2010 to 7046.6 billion yuan in 2019, with an average annual growth rate of about 6.97%, but its share of GDP dropped from 9.33% to 7.11%. The secondary industry production value increased from 191,626 billion yuan in 2010 to 386,165 billion yuan in 2019, with an average annual growth rate of about 8.1% and its share of GDP also dropping from 46.5% to 38.97%. The tertiary industry production value increased from 18206.1 billion yuan in 2010 to 53423.3 billion yuan in 2019, with an average annual growth rate of about 12.71%, and its share in GDP rising from 44.18% to 53.92%.

Although GDP and the three major industries production value in China have been developing steadily, there are some important signals with their proportions analysis. Such as, the primary industry accounts for the smallest proportion in the industrial structure and it shows a declining trend year after year. The secondary industry accounted for the largest proportion in the past, but it has shown a downward trend and has been surpassed by the tertiary industry in recent years. In addition, it can be seen from the average annual growth rate that the average annual growth rates of the primary and secondary industries are relatively low, and only the average growth rate of the tertiary industry exceeds the average annual growth rate of GDP.

3.2. Prediction Model Construction

According to definition of grey GM(1,1) model in Section 2.1, we need to predicate the three major industries production value in China. Next, we first predicate the primary industry production value from 2010 to 2019, the detail calculation process is as follows.

(1) Set initial time series $X^{(0)}$, and do an accumulation on it to get a new time series $X^{(1)}$,

$$X^{(0)} = \{38430.8,\ 44781.5,\ 49084.6,\ 53028.1,\ 55626.3,\ 57774.6,\ 60139.2,\ 62099.5,\ 64745.2,\ 70466.7\}$$

$$X^{(1)} = \{38430.8,\ 83212.3,\ 132296.9,\ 185325,\ 240951.3,\ 298725.9,\ 358865.1,\ 420964.6,\ 485709.8,\ 556176.5\}$$

(2) Construct the differential equation $\frac{dX^{(1)}}{dt} + aX^{(1)} = b$.

(3) Calculate $\left(B^T B\right)^{-1}$ and $B^T Y$, estimate parameters a and b by the least square method,

a=-0.0497067831467616，b=43701.3331381879.

(4) The prediction model of the primary industry production value is

$$\hat{X}^{(1)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right]1^{-ak} + \frac{b}{a}$$

$$=917613.2852l^{0.0497k}-879182.4852$$

Similarly, the secondary and tertiary industry production values can be predicted. Set initial time series and calculate the one-time accumulation series, construct the matrix B and Y, and obtain the corresponding parameters a and b after calculation $\left(B^T B\right)^{-1}$ and $B^T Y$, where a is -0.661488402526397 and -0.111821846636056, and b is 204187.608690272 and 189096.201698913, respectively.

By substituting the a and b parameters into the model respectively, the output value prediction models of the secondary industry and the tertiary industry production value can be obtained, respectively.

$$\hat{X}'^{(1)}(k+1) = 3278416.9548l^{0.0661k}-3086790.4548$$

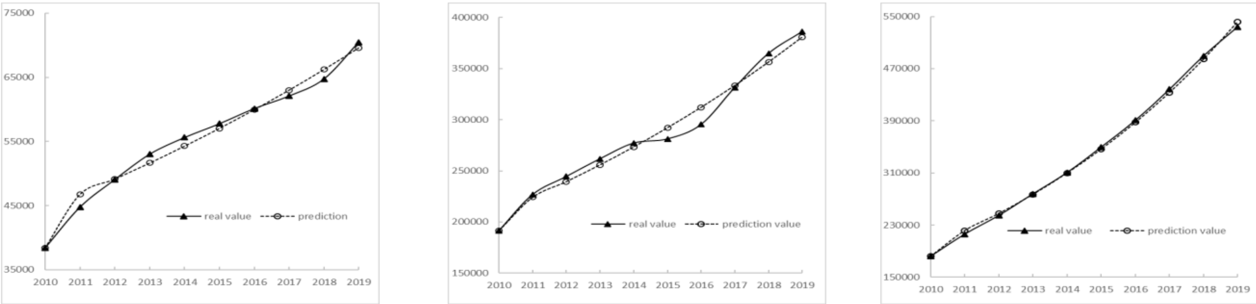
$$\hat{X}''^{(1)}(k+1)=1873110.7191l^{0.1118k}-1691048.8191$$

3.3. Prediction Model Validation

According to the grey GM(1,1) prediction model of the three major industries production value in Section 3.2, the three major industries production value from 2010 to 2019 can be calculated, and the error calculation is carried out with the actual data of the three major industries production value in the decade to test the prediction accuracy of the model obtained. Table 3 shown the comparison and error test between the real value and the predicted value of the three major industries production value in China, where “rel. err.” is the abbreviation of relative error, “avg. error” is the abbreviation of average relative error. According to the results in the Table 3, the average relative error of the three major industries structure evolution models is relatively small, which is 0.0161, 0.0209 and 0.0096 respectively.

Table 3 Comparison of the real and predicted production values of the three major industries and their error tests (unit: 100 million CNY)

Year	GDP	Primary industry			Secondary industry			Tertiary industry		
		real	predict	rel. err.	real	predict	rel. err.	real	predict	rel. err.
2010	412119.3	38430.8	38430.8	0	191626.5	191626.5	0	182061.9	182061.9	0.
2011	487940.2	44781.5	46764.2	0.0443	227035.1	224196.9	0.0125	216123.6	221614.4	0.0254
2012	538580	49084.6	49147.4	0.0013	244639.1	239528.7	0.0209	244856.2	247834.5	0.0122
2013	592963.2	53028.1	51652.1	0.0259	261951.6	255909.1	0.0231	277983.5	277156.7	0.0030
2014	643563.1	55626.3	54284.5	0.0241	277282.8	273409.6	0.0140	310654	309948.1	0.0023
2015	688858.2	57774.6	57051.0	0.0125	281338.9	292106.9	0.0383	349744.7	346619.1	0.0089
2016	746395.1	60139.2	59958.4	0.0030	295427.8	312082.9	0.0564	390828.1	387628.9	0.0082
2017	832035.9	62099.5	63014.1	0.0147	331580.5	333424.9	0.0056	438355.9	433490.7	0.0111
2018	919281.1	64745.2	66225.5	0.0229	364835.2	356226.4	0.0236	489700.8	484778.6	0.0101
2019	990865.1	70466.7	69600.5	0.0123	386165.3	380587.2	0.0144	534233.1	542134.5	0.0148
avg. err.		/	/	0.0161	/	/	0.0209	/	/	0.0096



(a) Primary industry (b) Secondary industry (c)Tertiary industry

Figure 1 Curve fitting between the real and predicted production value of the three major industries from 2010 to 2019

Refer to Table 1, the prediction accuracy of primary industry model and secondary industry model belong to the level 2, and the prediction accuracy of tertiary industry model reached the level 1, indicating that the grey GM(1,1) prediction model has a high level of credibility.According to the posterior difference test method in Section 2.2, the posterior difference ratio C of the three industries production value prediction models is 0.11983, 0.132987 and 0.036711 respectively, which are all less than 0.35, and the small error probability P is equal to 1. Refer to the Table 2, the above results shown that the prediction accuracy of the three models reached the reliability level 1.Figure 1 is drawn based on the real and predicted production value of the three major industries from 2010 to 2019, where subfigure 1 (a), (b) and (c) respectively represent the fitting curve of the real and predicted production value of the three major industries, the x-coordinate represents the year, the y-coordinate represents the industry production. In Figure 1, we all known that the curves of the real and predicted production value of the three major industries shown a good fitting.

In conclusion, the grey GM(1,1) prediction model applied in the three major industries production value prediction, the difference between the real and predicted value is very small. Therefore, the grey GM(1,1) model can be further used to predict the three major industries production value in China from 2020 to 2024, that is, research on the changing trend of the proportion of the three major industries production value in GDP.

3.4. Three Major Industries Production Value Prediction and Analysis

In the grey GM(1,1) model, the estimation of parameter a will affect the prediction accuracy, $-a < 0.3$ means that the model can be used for long-term prediction; $0.3 \le -a < 0.5$ means that the model can be used for short-term prediction; $0.5 \le -a < 0.8$ means that the model should be treated with caution when used for short-term prediction; $0.8 \le -a < 1$ means that the model with modified residual error should be adopted; $1 \le -a$ means that the model should not be used. In the above the three major industries production value prediction models, the development coefficient a is -0.0497067831467616, -0.0661488402526397 and -0.111821846636056, respectively, which means that these models can be used to predict the three major industries production value in the long-term.

In the process of the three major industries production value prediction from 2020 to 2024, the grey GM (1, 1) model first needs to complete the prediction of the three major industries production value in China, and then add up the predicted values to obtain the GDP value in the next five years. Finally, the proportions of the primary, secondary and tertiary industries in the industry structure of each year are calculated separately. The specific prediction results are shown in Table 4, where “Prod.” is the abbreviation of production value.

Table 4 China's three Major Industrial structures prediction from 2020 to 2024 (unit: 100 million CNY)

Year	Primary Prod.	Secondary prod.	Tertiary Prod.	GDP
2020	73147.62	406614.00	606276.39	1086038.01
2021	76875.43	434420.59	678007.14	1189303.17
2022	80793.23	464128.76	758224.62	1303146.60
2023	84910.68	495868.54	847932.91	1428712.13
2024	89237.98	529778.87	948254.92	1567271.76

In Table 4, we all known that China's economy will show a trend of sustained and rapid development in the next five years. Its specific performance is China’s GDP increase from 108603.8 billion yuan to 156727.1 billion yuan, in which the growth of the three major industries production value has a significant impact on GDP growth, where the primary, secondary and tertiary industries production value increased from 73147, 406614 and 606276 billion to 89238, 529779 and 948255 billion, respectively. Although the three major industries production value are increasing year by year, it can be seen that the proportion of the three major industries production value to GDP will continue to be optimized and adjusted in the next five years. As shown in Figure 2, the x-coordinate represents the year, the y-coordinate represents the proportion, and the dotted line represents the adjustment trend of the three major industries.

In Figure 2, the three major industries production value prediction in the next five years is as follows: the proportion of the primary industry production value in GDP will decrease year by year, from 6.7% to 5.7%, corresponding to the dotted line of linear prediction in the figure; the proportion of the secondary industry production value in GDP will also continue to decrease, from 37.4% to 33.8%, corresponding to the point line of linear prediction in the figure; and the proportion of tertiary industry production value in GDP is increasing year by year, which is expected to increase from 55.8% to 60.5%, corresponding to the horizontal line of linear prediction in the figure. Obviously, the tertiary industry develops more rapidly, and accounts for more than half of GDP and continues to increase, making the greatest contribution to GDP.

Further, through the analysis of the annual growth rate of the output value and GDP of the three major industries in the next five years, the annual growth rate of the three major industries production value is expected to reach 5.1%, 6.8% and 11.8%, respectively. While the annual average growth rate of China's GDP is expected to be 9.6%. Comprehensive consideration shows that the annual average growth rate of the primary and secondary industries production value is slow, and it is lower than the average annual growth rate of GDP. In contrast, the average annual growth rate of the output value of the tertiary industry is higher than that of GDP, which indicates that the tertiary industry will play an increasingly important role in China's economic growth in the next five years.

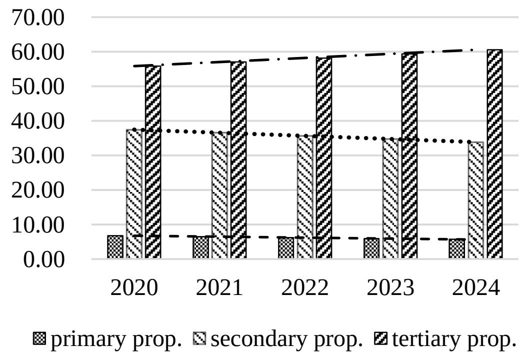


Figure 2 Three major industrial production value prediction from 2020 to 2024

4. CONCLUSION

This paper proposes a research on the three major industries production value prediction and structure evolution based on grey GM(1,1) model, and selects the data of the three major industries production value in China from 2010 to 2019 for modeling construction. The empirical analysis shows that the grey GM(1,1) model is a non-linear model with a small number of samples and high prediction accuracy, and it has a high degree of credibility for the prediction of the three major industries structure evolution. In the next five years, the prediction results of the proportion of the three major industries production value to GDP show that the three major industries structure will be continuously optimized and adjusted, and the tertiary industry will play an increasingly important role in efficient and high-quality economic growth in China. In summary, the GM(1,1) model is efficient to predict the three major industries production value in China and achieve the three major industries structure evolution results. However, it should be noticed that the GM(1,1) model is not applicable for all the series according to its mathematical formulation. There are some special factors, such as season and disaster factors, are not used in the analysis performed in this paper, and they are also what we need to study further.

In addition, the tertiary industry is dominated by the service industry, whose development not only better meet the diverse living needs of the people, but also provide more jobs to ensure full employment and maintain social stability. In the near future, even if the development speed of the tertiary industry surpasses the primary and secondary industries, it does not mean that the primary and secondary industries will decline in China. In the three major industries structure, the primary industry is the foundation of national life and is irreplaceable, the secondary industry is the foundation of national economic development, and the tertiary industry must depend on the primary and secondary industries in long-term development. Therefore, while vigorously pursuing the development of the tertiary industry, the state and enterprises should also maintain a strategy of active development for the primary and secondary industries to ensure the continued stable operation and high-quality development of China's economy.

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