

Retraction

Retracted: Macroeconomic Short-Term High-Precision Combined Forecasting Algorithm Based on Grey Model

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] C. Li, "Macroeconomic Short-Term High-Precision Combined Forecasting Algorithm Based on Grey Model," *Security and Communication Networks*, vol. 2021, Article ID 7026064, 9 pages, 2021.

Research Article

Macroeconomic Short-Term High-Precision Combined Forecasting Algorithm Based on Grey Model

Cao Li 

Henan Finance University, Zhengzhou 451464, China

Correspondence should be addressed to Cao Li; caoli@hafu.edu.cn

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Using the characteristics of grey forecasting, which requires a small amount of sample data and a simple modeling process, to predict the main macroeconomic indicators in the early stage, combined with the filtering decomposition method and the production function method, establishes a short-term high-precision combination forecasting algorithm for macroeconomics based on the grey model. The algorithm uses the improved HP filter method in the HP filter method to study whether the potential economic growth rate can be more accurately measured, and the production function method is used to calculate the potential economic growth rate. First, the two methods are used to calculate the potential economic growth rate. The accuracy of this method finally established a combined model based on the two models for short-term forecasting. Under the premise of considering economic factors, the input data is preprocessed, and the high-precision combined forecast is used to finally obtain the macroeconomic forecast results. The calculation examples in the paper show that the method is feasible and effective.

1. Introduction

Accurate forecasting of the macroeconomy is a necessary prerequisite for the country's correct regulation and control of the macroeconomy. Macroeconomic indexes include gross domestic product (GDP), consumer price index (CPI), and retail price index (RPI). The gross domestic product (GDP) is the total value of the final products and services produced by a country or region in a certain period of time. The index can understand the economic situation of a country or region from a macro perspective. The consumer price index (CPI) reflects the price situation at the consumer level, and the index can reflect the degree of inflation or deflation to a certain extent. The retail price index of commodities (RPI) reflects the price changes of retail commodities, which can be used to understand the supply and demand of retail commodities in the market. In summary, the above-mentioned indicators are of great significance for understanding the macroeconomic situation. If the macroeconomic index can be predicted more accurately in advance, then the government and relevant macroeconomic control departments can propose forward-looking and

targeted macroeconomic control in advance. Policies are necessary to regulate and control the macroeconomy. For individuals, if they can understand the macroeconomy in advance, they can also make more reasonable personal investment and savings decisions [1]. Therefore, forecasting macroeconomic indexes have important research.

The economic system, especially the macroeconomic system, is a very complex system. In it, there are widespread nonlinear time-varying and uncertain interactions. Most of the various macroeconomic models established on the basis of econometrics are linear models. While linear models play a huge role, they also gradually expose their shortcomings. That is, it is difficult to grasp the nonlinear phenomena in the macroeconomic system, which will inevitably lead to increased errors in economic forecasts [2]. As a result, workers in the economics circle have done a lot of improvement work on various linear models, such as the establishment of piecewise linear models and parameter time-varying linear models, but the results are often not ideal, which forces people to seek some nonlinear tools for macroeconomics economic modeling [3].

Grey system theory is a theory that studies and solves grey system analysis, modeling, forecasting, decision-making, and control. Grey forecasting is the quantification carried out by the grey model $eM(1, 1)$ GM(1, M). It requires extremely modeling information. The less the convenient operation, the higher the modeling accuracy [4]. Grey system theory can still deal with many uncertain problems very well when the amount of information and data is relatively small. Therefore, its theory can expand the application range of uncertain systems [5, 6]. This theory usually fully extracts and mines the relevant laws existing in the system based on "partial" known information, finds information with actual value, and obtains "partial" unknown information by constructing a model [7, 8]. Since the grey system only needs a relatively small data sample size, it can get results with relatively high prediction accuracy [9]. Therefore, the grey system theory is usually considered as an advantageous theoretical method that can be used to solve some uncertain problems with characteristics such as a small amount of information and incomplete and discrete data.

Many scholars have made contributions to the problem of macroeconomic index forecasting. Among them, Xu et al. used the breakpoint vector autoregressive model to study the country's macroeconomic effects [10]. Zhang et al. used the mixed frequency Bayes vector autoregressive model (MF-BVAR) to predict China's macroeconomic indicators. Compared with the same frequency vector autoregressive model and the MIDAS model, MF-BVAR has better prediction accuracy [11]. Li et al. used Independent Recurrent Neural Network (Ind RNN) to predict China's GDP index, which solves the problem of gradient disappearance and gradient explosion of Recurrent Neural Network (RNN). Compared with RNN, Ind RNN is currently a more effective economic forecasting model [12]. At the same time, macroeconomic forecasting is a typical nonlinear problem. The reason is that the macroeconomic operation is affected by many factors, such as changes in policies and the level of economic development. Therefore, these factors must be considered in the process of forecasting. This paper combines the GM model with the combination algorithm and uses the GM(1, 1) model with different trade-offs on historical data to make preliminary predictions, and then these prediction results and the relevant economic factor parameters for each year are used as the high-precision combination prediction algorithm entering the final prediction result.

2. Grey Prediction Model

2.1. Grey Forecasting Principle. The grey system is a system that is between the white system and the black system and contains known and unknown information, and there is an uncertainty relationship between various elements in the system. The grey forecasting method is a time-related forecasting method applied to the grey system. Although the development trend that appears is random and disorderly, it is orderly and bounded. Therefore, by processing the original data of the system, looking for potential development laws from it, generating a regular sequence, and then establishing

it, the corresponding differential equation is used to predict the future trend of the system.

2.2. GM(1, 1) Model Steps. The most common grey forecasting model is the GM(1, 1) model. The modeling steps of the GM(1, 1) model are as follows.

2.2.1. Data Inspection and Processing. Suppose $x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\}$ is the original data of the index to be predicted. To ensure the feasibility of the GM(1, 1) model, it is necessary to calculate the sequence ratio $\sigma(t) = (x^{(0)}(t-1)/x^{(0)}(t))$, $t = 2, 3, \dots, n$. If all the calculated ratios satisfy $\sigma(k) \in (e^{-(2/n+1)}, e^{2/n+1})$, then the GM(1, 1) model can be established directly for prediction; otherwise, proper data processing is required.

This paper uses the translation processing method; after the original data Q^* is translated from the distance, a new sequence $x'^{(0)}(t)$ is obtained:

$$x'^{(0)}(t) = x^{(0)}(t) + Q^*. \quad (1)$$

Then, the level ratio deviation of the new sequence $\delta_{x'}(t)$ is

$$\delta_{x'}(t) = \frac{x'^{(0)}(t) - x'^{(0)}(t-1)}{x'^{(0)}(t)}. \quad (2)$$

The value of Q^* is derived by formula (1):

$$Q = \frac{|x^{(0)}(t) - x^{(0)}(t-1)|}{\delta_{x'}(t)} - x^{(0)}(t), \quad t = 2, 3, \dots, n, \quad (3)$$

$$Q^* = \max(Q). \quad (4)$$

Finally, after the model prediction calculation, the Q^* value is subtracted to restore.

2.2.2. Construction of GM(1, 1) Model. Suppose the original sequence is $x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\}$ and accumulate it once to generate 1-AGO [13]; then,

$$x^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)\}, \quad (5)$$

$$x^{(1)}(k) = \sum_{i=1}^k x^{(0)}(i), \quad k = 1, 2, \dots, n. \quad (6)$$

Then, the whitening differential equation is

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b. \quad (7)$$

Expressed in a discrete form, it can be written as

$$x^{(0)}(k+1) + az^{(1)}(k+1) = b. \quad (8)$$

In formula (8), $z^{(1)}(k+1) = (1/2)x^{(1)}(k) + (1/2)x^{(1)}(k+1)$ is the background value of $dx^{(1)}/dt$ at time $(k+1)$,

$-a$ is called the development coefficient, and b is called the grey effect.

Let $x^{(0)}$ be the initial sequence, $x^{(1)}$ the 1-AGO sequence of $x^{(0)}$, and $z^{(1)}$ the sequence of generating the mean value of $x^{(1)}$ nearest neighbors:

$$Y = \begin{pmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{pmatrix}, \quad (9)$$

$$B = \begin{pmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{pmatrix}.$$

Then, the parameter vector $u = [a, b]^T$ can be estimated according to the least square method:

$$\begin{aligned} \hat{u} &= [\hat{a}, \hat{b}]^T \\ &= (B^T B)^{-1} B^T Y. \end{aligned} \quad (10)$$

Use formula (8) to find the parameter value and substitute it into the solution obtained by the whitening differential equation, also known as the time response function:

$$x^{(1)}(t) = \left(x^{(1)}(0) - \frac{\hat{b}}{\hat{a}} \right) e^{-\hat{a}(t-1)} + \frac{\hat{b}}{\hat{a}}. \quad (11)$$

Then, the time response sequence in discrete form is

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{\hat{b}}{\hat{a}} \right) e^{-\hat{a}k} + \frac{\hat{b}}{\hat{a}}, \quad k = 1, 2, \dots, n. \quad (12)$$

Perform cumulative reduction to obtain the grey prediction sequence of $x^{(0)}$:

$$\hat{x}^{(0)}(k+1) = \left(1 - e^{-\hat{a}} \right) \left(x^{(0)}(1) - \frac{\hat{b}}{\hat{a}} \right) e^{-\hat{a}k}, \quad k = 1, 2, \dots, n. \quad (13)$$

2.3. Model Prediction Effect Test. The test of model prediction mainly adopts three methods: residual test, posterior error test, and correlation test [14].

2.3.1. Residual Error Test. Assuming that $\hat{x}^{(0)}(t)$ is the predicted value, $X^{(0)}(t)$ is the actual value, and then the absolute error value and the relative error value are, respectively, calculated:

$$\Delta^{(0)}(k) = \left| \hat{x}^{(0)}(k) - x^{(0)}(k) \right|, \quad (14)$$

$$\varepsilon(k) = \frac{\Delta^{(0)}(k)}{x^{(0)}(k)}, \quad t = 1, 2, \dots, n. \quad (15)$$

Then, the average relative error is $\bar{\varepsilon} = (1/n) \sum_{k=1}^n \varepsilon(k)$, and the relative prediction accuracy is $1 - \bar{\varepsilon}$. If the relative prediction accuracy is greater than 90%, it means that a better accuracy requirement has been met.

2.3.2. Postinspection Error Test. Calculate the standard deviation S_1 of the original series that is the actual value and the standard deviation S_2 of the absolute error series $\Delta^{(0)}$:

$$S_1 = \sqrt{\frac{\sum_{t=0}^n \left(X^{(0)}(t) - \bar{X}^{(0)} \right)^2}{n-1}}, \quad (16)$$

$$S_2 = \sqrt{\frac{\sum_{t=0}^n \left(\Delta^{(0)}(t) - \bar{\Delta}^{(0)} \right)^2}{n-1}}. \quad (17)$$

Then, the posterior difference is $C = S_2/S_1$, and the small error probability is $P = P(|\Delta^{(0)}(t) - \bar{\Delta}^{(0)}| < 0.6745S_1)$. Considering the two indicators of C and P comprehensively, the prediction effect of the model is divided into 4 levels, as shown in Table 1.

2.3.3. Relevance Test. Suppose $\hat{X}^{(0)}(t)$ is the predicted sequence and $X^{(0)}(t)$ is the actual sequence; then, the correlation coefficient and degree of correlation between the sequences $\hat{X}^{(0)}(t)$ and $X^{(0)}(t)$ are

$$\gamma_k = \frac{\min_{1 \leq k \leq n} |x^{(0)}(k) - \hat{x}^{(0)}(k)| + 0.5 \max_{1 \leq k \leq n} |x^{(0)}(k) - \hat{x}^{(0)}(k)|}{|x^{(0)}(k) - \hat{x}^{(0)}(k)| + 0.5 \max_{1 \leq k \leq n} |x^{(0)}(k) - \hat{x}^{(0)}(k)|}, \quad (18)$$

$$\gamma = \frac{1}{n} \sum_{k=1}^n \gamma_k. \quad (19)$$

$\gamma > 0.6$ is generally required, and the greater the correlation, the better the model prediction effect [15].

The input original sequence is the value of n years, and the actual predicted value can be obtained. The modeling data of the GM model allows different choices, but they must be equidistant and adjacent and must not have jumps. For example, in the prediction of the total industrial output value of the whole district, the value of the most recent years can be used to model, the sequence used for modeling can take different lengths, or the method of equal-dimensional information repetition can be used, that is, the GM (1, 1). The model predicts a value, and then the predicted value is added to the known number sequence. At the same time, in order not to increase the length of the sequence, remove the oldest data, keep the sequence of equal dimensions, and then build a GM (1, 1) model to predict. The next value is predicted one by one in this way, and it is made up one by one until the predicted goal is completed [16].

TABLE 1: Forecast effect grade table.

P	C	Prediction level
>0.95	<0.35	First level (good)
>0.80	<0.50	Level 2 (qualified)
>0.70	<0.65	Level 3 (barely qualified)
≤ 0.70	≥ 0.65	Level 4 (unqualified)

3. Macroeconomic Short-Term High-Precision Combination Forecasting Algorithm

3.1. Combination Prediction Algorithm. With the continuous development of information technology, forecasting technology is becoming more and more mature, and methods are emerging one after another. In practice, because the problems encountered and the known information are very different, the established models are different. Not all of these single models are suitable for the “optimal” model that requires comprehensive consideration, but this is often difficult to achieve. If these models can be integrated and the advantages of each model can be combined to obtain a model with higher accuracy, the combined forecasting model can be competent.

The combined model makes full use of the information of every single model, reduces the random influence of every single model, and improves the accuracy of the model. Therefore, the combined forecasting model considers a more comprehensive range than a single model.

The specific formula of the combination forecasting method:

$$\widehat{G} = \sum_{j=1}^m W_j \widehat{G}_j = W_1 \widehat{G}_1 + W_2 \widehat{G}_2 + \dots + W_m \widehat{G}_m, \quad (20)$$

where G_1, G_2, \dots, G_m represents the actual output; $\widehat{G}_1, \widehat{G}_2, \dots, \widehat{G}_m$ represents the potential output obtained by m methods; and W_1, W_2, \dots, W_m represents the weight of a single model. For the combination forecasting method, the choice of method and the choice of weight are the two most important factors that affect the combination forecasting method. We have selected the above two methods. There are many commonly used weights selection methods for weights, such as the Arithmetic average method, standard deviation method, and reciprocal variance method. This paper mainly chooses the reciprocal variance method. If the sum of squares of error D_j is small, the value of weight W is larger. If the sum of squares of error is larger, the value of weight W is smaller, so that the sum of squares of error of the combined forecasting method can be minimized. The specific formula is

$$W_j = \frac{D_j^{-1}}{\sum_{j=1}^n D_j^{-1}}, \quad (21)$$

$$\sum_{j=1}^n W_j = 1, \quad j = 1, 2, \dots, n,$$

$$D_j = \sum_{j=1}^n (G_t - \widehat{G}_{tj})^2. \quad (22)$$

3.2. Combination Algorithm Construction Based on Grey Model. This paper mainly uses the Cobb Douglas production function to estimate the potential growth rate of the country's economy [17].

The formula of Cobb Douglas production function is as follows:

$$Y_t = AK_t^\alpha L_t^\beta. \quad (23)$$

The formula of the Cobb Douglas production function is as follows: among them, the gross domestic product is Y_t , the capital stock is K_t , the labor input is L_t , and the technology level (total factor productivity) is A . The output elasticity of capital stock is α , and the output elasticity of labor is β . Take the logarithm of both sides of formula (23) to get

$$\ln Y_t = \ln(A) + \alpha \ln(K_t) + \beta \ln(L_t). \quad (24)$$

It is usually assumed that $\alpha + \beta = 1$; that is, the return to scale remains unchanged. Then,

$$\ln Y_t = \ln(A) + \alpha \ln(K_t) + (1 - \alpha) \ln(L_t). \quad (25)$$

The model estimation and prediction steps are as follows:

Firstly, the equation formed by the production function method is regressive to estimate the parameter values of α and β , namely, the output elasticity of capital and labor. Then, the total factor yields increase rate; namely, the residual value after deducting the contribution of factor input growth is calculated by using formula (23).

Secondly, the grey model is used to calculate the original time series of capital and labor variables and estimate the trend value of the TFP time series. According to the estimated production function α and β , the potential economic growth rate from 2001 to 2020 can be calculated by taking it into the production function.

4. China's Potential Economic Growth Rate Calculation

4.1. Data Source and Data Processing. This paper uses annual data from 2001 to 2020. The data mainly comes from the annual data column of the National Bureau of Statistics. The software used is EViews 8.0. First, obtain output, capital stock, and labor data, and then use the production function to calculate total factor productivity. In this way, the specific data of all economic indicators in the production function is prepared, and the next step of calculation can be carried out.

4.2. Potential Economic Growth Rate Calculation. To calculate the potential growth rate, it is necessary to estimate the three factors of potential total factor productivity, labor, and capital stock, and then use the existing growth accounting model to calculate the potential output. The first step is to use the trend elimination method to estimate the potential three factors, and the second step is to substitute each potential factor into the previous production function to get the potential economic growth rate.

Use the trend elimination method (HP filtering) to decompose and get the trend values of each element as shown in Table 2 (the data comes from economic statistics from 2001 to 2020 on the official website of the Chinese government).

It can be seen from Table 2 that both the potential labor force and potential capital stock are showing a trend of steady growth, and the growth rate is slowly slowing down. The potential total factor productivity has been fluctuating since 2001 and has been in a slow downward trend since 2008. Bring the results calculated above into the above production function. The results are shown in Table 3 (the data come from economic statistics from 2001 to 2020 on the official website of the Chinese government).

From the analysis of the actual growth rate and the potential growth rate given in Table 3, it can be compared in terms of the overall trend change and the actual and potential economic growth rates. From the perspective of overall trend changes, the actual growth rate is consistent with the potential growth rate. From 2000 to 2007, the economy began to recover and maintained rapid growth, with the actual growth rate reaching 14.18%, and the potential economic growth rate is correspondingly higher, reaching 14.43%; from 2008 to 2009, it was once again affected by the global economic credit crisis. The economy has dropped from 14.43% to 9.25%, and the economy has fallen sharply; from 2010 to 2020, the gap between the potential growth rate and the actual growth rate will gradually become smaller, and the output gap will become smaller, indicating that the market economy mechanism is more perfect and the government is working hard to transform the mode of economic development. It has achieved results, and the economy has been steadily declining in line with expectations, maintaining a reasonable, healthy, and green development, and the corresponding people's living standards have been significantly improved.

4.3. Potential Economic Growth Rate Comparison. The potential growth rate can be calculated from the above potential output and compared with the actual growth rate. The potential economic growth rate is shown in Figure 1.

It can be seen from Figure 1 that the change trend of the potential economic growth rate calculated by the above two methods has high consistency, and both show a trend of the first decline, slowly rise, and then slowly decline. At the same time, the other two methods have always calculated that the potential economic growth rate has always been greater than the actual growth rate. In particular, these two methods have low prediction accuracy in the early stage and may need to be further improved. In recent years, it can be seen that the two methods the models are good at calculating the potential economic growth rate, which has slowly approached the current potential growth rate, and the accuracy has been significantly improved. In recent years, the continuous economic decline is determined by the decline in the potential economic growth rate, which is objective and inevitable. The Wenchuan earthquake and the 2008 financial crisis used increased downward pressure on the economy, which was accidental. It can be seen from the above graph that, in the period of rapid economic growth, the potential economic growth rate of HP filtering has always been greater than the production function. Therefore, it is concluded that although the growth trend calculated by different methods is consistent, the production function is more effective in measuring the potential economic growth rate and accurate.

4.4. Different Model Analysis and Forecast. There are many methods for forecasting China's short-term potential growth rate. After the above calculation and comparative analysis, this paper intends to use the future trend of the factors in the production function method to predict the potential economic growth rate in the forecast. Methods for forecasting are the production function method, boosting HP filtering method (BIC), and combined forecasting method.

The following three methods are used for forecasting. The forecasting idea of the production function is specifically expressed as decomposing the economic growth momentum into three parts, TFP, labor, and capital, and predicting the future growth trend of the three elements using the autoregressive average model (ARIMA), then bringing it into the framework of the production function method, and finally calculating the predicted potential economic growth rate. The prediction idea of HP filtering is to obtain the actual value from the ARIMA model to predict the actual GDP, then the potential output is decomposed by HP filtering, and finally the potential economic growth rate is calculated. The combined forecasting method is based on the combination of the production function and the boosting HP filtering method. Because a single model has certain limitations in measurement and forecasting, multiple models are given different weights and combined into a new forecasting model.

The first is to use R to build a predictive model, including corresponding p and q values, stationarity test, and specific

TABLE 2: Potential elements after eliminating the trend method.

Year	Potential labor	Potential capital stock	Potential total factor productivity
2001	74001.95	233734.8	0.5037
2002	74545.97	265247.9	0.5004
2003	75032.14	303732.4	0.4881
2004	75481.5	351245.2	0.4815
2005	75912.04	410030.1	0.5024
2006	76331.5	482499.2	0.5126
2007	76750.29	571063.4	0.5423
2008	77186.54	677826.1	0.5235
2009	77637.28	804239.4	0.5451
2010	78089.85	950832.5	0.5189
2011	78528.23	1117028.1	0.5173
2012	78946.31	1301269.3	0.5125
2013	79342.64	1501172	0.5036
2014	79762.38	1713983	0.4889
2015	80052.36	1936453	0.4731
2016	80157.75	2165904	0.4669
2017	81253.56	2296829	0.4628
2018	81986.26	2326953	0.4596
2019	82569.99	2401965	0.4559
2020	80269.95	2301263	0.4469

TABLE 3: Potential output and its potential growth rate.

Year	Potential output	Real GDP	Actual growth rate (%)	Potential economic growth rate (%)
2001	106148.5	108602.8	8.31	10.53
2002	118409.2	120951.7	9.15	10.63
2003	130706.5	133879.5	10.02	11.35
2004	147242.3	151305.2	10.12	11.43
2005	176461.5	180291.5	11.41	12.41
2006	209748.3	211107.9	12.68	13.78
2007	2524418.5	250597.8	14.18	14.43
2008	300972.1	296292.3	9.68	9.25
2009	355116.2	349256.5	9.39	8.71
2010	390826.9	389683.5	10.58	10.23
2011	454635.1	451268.9	9.61	9.47
2012	527673.1	526256.8	7.81	8.26
2013	579568.9	580369.1	7.76	9.57
2014	634593.4	636693.4	7.45	8.25
2015	686103.8	685539.1	7.09	7.81
2016	734759.6	731296.2	6.81	7.37
2017	790963.5	790384.5	6.91	7.15
2018	868289.3	874569.2	6.74	6.68
2019	923693.2	943695.4	6.65	6.58
2020	723953.5	752636.4	5.98	6.35

ARMA model format. Factors potentially worth the ARIMA model are shown in Table 4.

According to the estimation results in Table 4, it can be seen from the Q statistic and the p value that the original hypothesis is that the residual autocorrelation coefficient is 0, and the original hypothesis is accepted, which is a pure random sequence. Secondly, the specific combination forecasting formula calculated is as follows:

$$\hat{y}_t = 0.47\hat{y}_{ta} + 0.53\hat{y}_{tb}. \quad (26)$$

In the formula, a represents the lifting filter method and b represents the production function method. The weight value is obtained by calculating the sum of squared errors of

the actual output and the potential output. First, the sum of squared errors of the lifting filter method is calculated as 3668617919157.32. The sum of the squared error of the generating function is 3662495598382.68. Then the weights are 0.47 and 0.53 according to the reciprocal variance method.

Generally speaking, the potential output of the three methods has been calculated, so the predictive ability has become a concern for everyone. Regarding the accuracy of the model, most of the indicators are based on the error between the actual value and the predicted value, such as the average absolute percentage. The specific formulas for error, root mean square error, and Hill inequality coefficients are as follows:

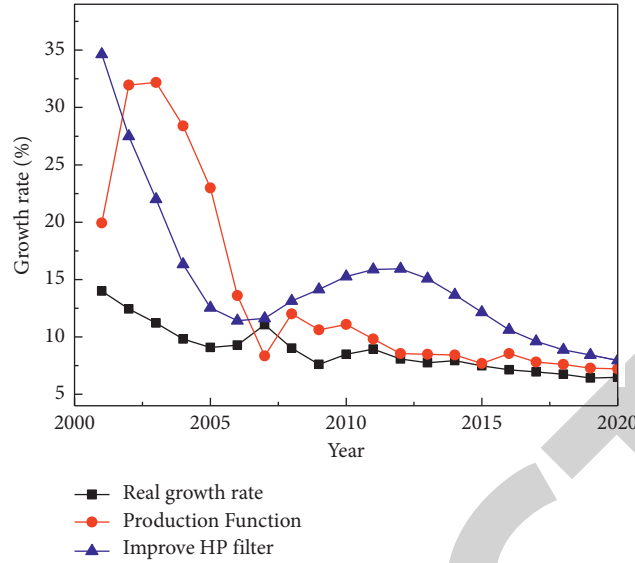


FIGURE 1: Potential economic growth rate.

TABLE 4: Factors potentially worth the ARIMA model.

	Labor force	Capital stock	TFP	Real LnGDP
Stationarity test	Nonstationary	Nonstationary	Nonstationary	Nonstationary
Original sequence	Nonstationary	Nonstationary	Nonstationary	Nonstationary
First difference	Nonstationary	Nonstationary	Smooth	Smooth
Second-order difference	Smooth	Smooth	***	***
ARIMA model	ARIMA (0, 2, 1)	ARIMA (1, 2, 0)	ARIMA (0, 1, 1)	ARIMA (1, 1, 1)
Ljung-Box Q statistics	5.4228	4.1934	4.5982	5.6121
p values	0.3664	0.5219	0.4668	0.2512

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{\hat{y}_i}{y_i} \right| \times 100, \quad (27)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2}, \quad (28)$$

$$\text{Theil IC} = \frac{\sqrt{(1/n) \sum_{i=1}^n (\hat{y}_i - y_i)^2}}{\sqrt{(1/n) \sum_{i=1}^n \hat{y}_i^2} + \sqrt{(1/n) \sum_{i=1}^n y_i^2}}, \quad (29)$$

Compare the accuracy of these three indicators according to the above three formulas: see Table 5.

It can be seen from Table 5 that the prediction accuracy of the combination forecasting method is significantly better than that of the other two functions. Under the condition of clear indicators, the combination forecasting method has the advantages of high prediction accuracy and high error tolerance. It is generally believed that the above three indicators are as small as possible. From the perspective of a single model, the production function is more accurate than improving the HP filtering measurement accuracy, and the combined model is better than all the single models in the article, indicating that the combined model can combine with a single model for more accurate calculations and predictions.

The following uses the ARMA model to predict the potential growth rate of China’s economy in the next five years (2021–2025) using data from 2001–2020 without considering external factors and policy changes that affect future economic fluctuations. The specific values of the forecast are shown in Table 6.

According to the data in Table 6, this paper uses the lifting filter method and the production function method for forecast analysis, combines the advantages of the two single forecasting models to establish a combined forecasting model, and uses the three methods to analyze China’s 2021–2025. The GDP is forecasted. From the growth trend, the potential growth rate of China’s economy in three ways will continue to decline in the next few years, and the growth rate will slow. This shows that, with the disappearance of demographic dividend, industrialization dividend, and globalization dividend, China has entered the range of continuous decline in growth rate, and the downward trend is obvious. The prediction result of HP filtering is greater than that of the production function method, which is consistent with the optimistic expectations of the previous filtering decomposition calculation. Because the combined forecasting model considers more factors comprehensively, the predicted value is more reliable. According to the forecast method of growth rate and the discovery of potential growth rate, the national economic growth rate in the next five years will be 6.72%, 6.51%, 6.23%, 6.12%, and 5.90%, the

TABLE 5: Comparison of model accuracy.

Model	RMSE	MAPE	Theil IC
Combination forecasting	2935.3	1.6264	0.0038
HP filter	7269.3	3.2578	0.0093
Production function method	4493.0	2.0038	0.0058

TABLE 6: Forecast of economic growth rates from 2021 to 2025.

Year	Improve HP filter	Production function method	Combination forecasting
2021	6.88	6.53	6.72
2022	6.68	6.32	6.51
2023	6.42	6.01	6.23
2024	6.38	5.95	6.12
2025	6.21	5.63	5.90

average is 6.28%, and the forecast range fluctuates between 5.90% and 6.7%. The fluctuation range is not large, which is in line with the policy guidelines for achieving rapid and stable economic development.

After the previous analysis, we know that the weight of the production function method is relatively large, and the specific growth value is more closely related to several variables in the production function model. The potential capital stock and potential employment growth rate are declining, and the economic growth rate will naturally be affected by it. However, the growth rate of total factor productivity (TEP) has not exceeded the impact of the decline in capital and employment growth, so the potential growth rate decline is an inevitable trend. However, the economic growth rate is a dynamic concept. When it is subject to occasional shocks or policy influences, the path of economic growth will change, and the estimation of potential growth rates cannot capture the impact of these shocks in advance. For example, from the end of 2019 to the current public health emergency (coronavirus disease 2019, COVID-19), China's economy fell sharply in the first quarter. The actual economic growth rate currently known is -6.8%, and the economy has regressed. Therefore, for 2020 the actual economic growth rate for the whole year will definitely be significantly lower than the estimated potential economic growth rate.

5. Conclusion

According to the production function, the calculation of the HP filter, and the prediction results of the three methods, in recent years, the gap between the potential growth rate of China's economy and the current development situation has been narrowing, indicating that China's economy potential is being used, but it has been low. The actual growth rate indicates that the economic potential needs to be fully utilized. Based on the combined forecast results, the potential economic growth rate in the next five years will show a fluctuating downward trend between [5.89%, 6.7%], indicating a downward trend in the future economy. It is inevitable. First, technological progress has not outperformed the diminishing marginal rate of investment. The second is affected by the deterioration of the external

economic environment and the epidemic, such as the global spread of new coronavirus pneumonia, which has led to the suspension of domestic and foreign economies, and the number of US stocks. The second circuit breaker will inevitably have an impact on China's economy. China's economy will definitely be stable and change, so the long-term economic growth rate will be slightly lower than expected. This year's economic growth rate is likely to drop below 5%, so it can only be used for the future. A reference basis for economic expectations and decision-making. In the future work, we need to use the neural network to modify the residual of grey prediction results, so as to solve the complex uncertainty problem in the development trend of data. In addition, the prediction methods that can be applied to nonisochronous sampling data and isochronous sampling data may be further studied.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no known conflicts of interests or personal relationships that could have appeared to influence the work reported in this paper.

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