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Research Article

Back-Propagation Neural Network and ARIMA Algorithm for GDP Trend Analysis

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GDP (gross domestic product) is a key indicator for assessing a country's or region's macroeconomic situation, as well as a foundation for the government to develop economic development strategies and macroeconomic policies. Currently, the majority of methods for forecasting GDP are linear methods, which only take into account the linear factors that affect GDP. GDP (gross domestic product) is widely regarded as the most accurate indicator of a country's economic health. GDP not only reflects a country's economic development over time but can also reflect its national strength and wealth. As a result, the GDP trend forecast partially reflects China's transformation and future development. The time series ARIMA (Autoregressive Integrated Moving Average) model and the BPNN (BP neural network) model are combined in this article to create the ARIMA-BPNN fusion prediction model. The predicted values of the two models were then weighted averaged to obtain the predicted values of the linear part of the improved fusion model. To get the predicted values of the improved fusion model, we weighted average the residual parts of the two models, predict the nonlinear residual with BPNN, and add the predicted values of the two parts. It is applied to the actual GDP forecast in H province from 2019 to 2022, and the actual forecast verifies the effectiveness of the fusion forecast model in the actual forecast.

1. Introduction

GDP (gross domestic product) is a representative index that reflects the final results of production activities in a given region during a given accounting period and measures the scale, speed, structure, and benefits of national economic development. It is also the primary index for determining economic development strategic objectives [1]. The purpose of GDP forecasting is to analyze and deal with previous year's GDP data, as well as to use certain tools and methods to predict future GDP trends, which will allow us to see clearly the economic growth trend in the process of national economic reform and development mode transformation and to make a more accurate choice for current work. More and more people are paying attention to the changing state of national GDP [2, 3]. Economic globalisation, of course, brings with it more challenges and difficulties. People are paying more attention to the economy, and the gross domestic product, which represents the national economic situation, is receiving more attention from the country and the people [4].

It is beneficial for social workers to understand the national economy by scientifically analyzing the past GDP data and mastering its development trends and changes. For local and national departments, we can formulate relevant policies according to the analysis results and provide a reference. At present, there are many methods to forecast GDP, most of which use linear methods, such as introducing various influencing factors into the model for linear simulation. This method only considers the linear factors affecting GDP [5]. The GDP of a country or a province is often affected not only by these linear factors but also by various nonlinear factors. At present, domestic scholars mainly use traditional single models such as the ARIMA (Autoregressive Integrated Moving Average) model, BPNN (BP neural network), and gray system to predict GDP [6–8]. Generally, time series prediction is not carried out from a single linear ARIMA or from a single nonlinear neural network or other nonlinear prediction methods, and these methods only consider one of the relationships of time series prediction, which will definitely make the prediction result not very accurate.

To better understand the evolution and changes in GDP, we must use scientific methods and historical GDP data to forecast values in the coming years, which will provide more scholars with useful information about the national economy [9]. Furthermore, the state and government can use the findings of our data analysis to develop appropriate strategies. As a result, this paper chooses the fusion model of BPNN and ARIMA to forecast the GDP of H province and compares the model results to find the best model to forecast the GDP. The findings of our study can be applied to H province's future economic development. This will be of great assistance to the relevant government departments in developing policies and standards.

This paper develops a fusion model by combining the advantages and disadvantages of the ARIMA and BPNN models. This paper develops a new and improved fusion model. The BPNN model is used to predict weighted nonlinear residuals. The improved fusion model's predicted value is finally obtained by adding the predicted values of the two parts. BPNN and fusion model prediction accuracy is greatly improved by the improved fusion model. This fusion model can also predict similar data, which has practical implications.

2. Related Work

Prediction is defined as speculating or measuring something ahead of time. More specifically, prediction means that we use the information we already have in our hands to calculate things that will happen in the future or whose occurrence trend is unknown, using certain methods and laws that we have mastered in advance, so that we can know the process, trend, and even results of the possible development of things ahead of time. And, since ancient times, prediction technology has been evolving at a rapid pace.

At present, a single model is used for forecasting in many fields in China, including ARIMA and BPNN. Literature [10] focuses on analyzing the application of ARIMA in time series analysis with examples, while literature [11] further empirically tests the effectiveness of ARIMA in time series prediction and studies fusion prediction with grey correlation. In reference [12], BPNN was used to forecast the stock index in China, and in reference [13], the BPNN algorithm was improved and used to forecast the market sales. Literature [14] established a fusion model combining the ARIMA model and the multiple regression model to predict the total industrial output value of a province. Literature [15] predicts China's GDP with time series analysis method, and the prediction accuracy is quite high. Literature [16] uses the ARIMA model to forecast the GDP of a city, the relative error of the model results is small, and the model fits well. Literature [17] models the incidence of AIDS in a city and establishes a time series analysis model. This empirical analysis process has certain guiding significance for epidemic control.

In recent years, with the continuous development of the Internet, the neural network algorithm, one of the machine learning algorithms, has also made progress. Many scholars have applied artificial neural networks in practice, mainly in the fields of environment, engineering, and information. Literature [18, 19] combined the BP neural network to predict water resources in a certain province, and the results show that this model is suitable for predicting water resources. The BP neural network established in reference [20] has relatively low prediction error for the power plant, and the model is considerable. Literature [21] established the BP neural network fusion prediction model, and literature [22] predicted the demand of the built-up area in a province, and the prediction result was ideal. The ARIMA model and exponential smoothing method are weighted in literature [23] to predict China's per capita GDP, and the results are better than the single model. Literature [24] uses the ARIMA model and the genetic algorithm to improve the neural network model, which has been well used in a province's GDP forecast. Literature [25] uses China's CPI data to forecast by using a fusion model. Literature [26] uses ARIMA-BPNN to forecast based on CPFR demand.

Through the analysis of existing research at home and abroad, it can be known that the time series model, regression analysis, neural network, and integrated network of several models are mainly used for GDP, but the fusion forecasting model is relatively less used for GDP research in H province. Therefore, this paper establishes the traditional ARIMA model and modified BP neural network and combines them into a new fusion model to analyze the GDP of H province more accurately.

3. Research Method

GDP is not only a representative index reflecting the final results of production activities in a certain area in the accounting period and measuring the scale, speed, structure, and benefits of national economic development but also a main index for formulating strategic objectives of economic development. In this paper, the combination of BPNN and ARIMA models is used to forecast and analyze the per capita GDP of H province, which is of great significance for the relevant departments to correctly understand the current situation of economic development and accurately formulate economic development strategies.

3.1. Overview of Basic Model

3.1.1. Back Propagation. One of the characteristics of ANN (artificial neural network) is that it imitates the behavior of the animal neural network, and it is an information system. The idea of the artificial neural network mainly comes from the nervous system of our brain and imitates us to do some complicated work.

The reason why ANN is so popular is that it can deal with nonlinear problems. At present, as far as we know, there are dozens of representative models produced by ANN, among which BPNN and its extended forms are the most widely used.

(1) Working Principle of BPNN. The forward propagation stage of the signal is a stage included in the working process of BPNN, and the other stage included in it is the backward propagation stage of error.

The whole process is so cyclical that when the experimental error is less than the given error, the learning process is terminated. Its structure is shown in Figure 1.

The artificial neuron, as a simple processor, can weight and sum incoming signals:

$$y = \sum^{n} x_i w_i + b, \quad (1)$$

in which, $x_1, x_2, \cdots, x_n$ represent the input value, $w_1, w_2, \cdots, w_n$ represent the weight, b represents the threshold, and y represents the output of neurons.

Assuming that the neural network has n input neurons, m output neurons, and p hidden layer neurons, the output of neurons is

$$x_i^1 = \sigma\left(\sum_{j=1}^{n} w_{ij}^0 x_j + b_i\right), \quad i = 1, 2, \cdots, p. \quad (2)$$

The output of neurons in the output layer is

$$y_i = \sum_{j=1}^{p} w_{ij}^0 x_j^1 + b_i, \quad i = 1, 2, \cdots, m. \quad (3)$$

The excitation function adopts the logarithmic sigmoid function, then

$$\sigma(x) = \frac{1}{1 + e^{-x}}. \quad (4)$$

3.1.2. ARIMA Model. The so-called ARIMA model refers to a model established by transforming a nonstationary time series into a stationary time series and then regressing only its lag value as well as the present value and lag value of the random error term.

Parameter identification of the ARIMA model mainly depends on two factors: autocorrelation function and partial autocorrelation function and their correlation function diagram.

For a sequence $\{Y_t\}$, its jth autocorrelation coefficient is defined as its jth autocorrelation divided by its variance, i.e.,

$$\rho_j = \frac{\rho_j}{\rho_0}. \quad (5)$$

It is a function about j, so we will also call it autocorrelation function, and we generally write it as $ACF(j)$. The partial autocorrelation function $PACF(j)$ is the correlation between two lag variables after removing the influence of the lag term.

The ARIMA model of time series has the following structure:

$$\begin{cases} \Phi(B)\nabla^d x_t = \Theta(B)\varepsilon_t, \\ E(\varepsilon_t) = 0, \operatorname{Var}(\varepsilon_t) = \sigma_\varepsilon^2, E(\varepsilon_s \varepsilon_t) = 0, s \neq t. \end{cases} \quad (6)$$

$E(\varepsilon_s \varepsilon_t) = 0$, arbitrary $s < t$.

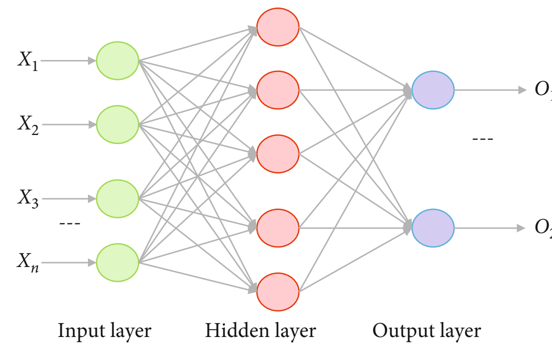

Figure 1: BPNN structure.

$x_t$represents the time series data, andx_t and its correlation are $x_{t-i}(i = 1, 2, \cdots, p)$; ε_t represents the residual term, and ε_t is related to $\varepsilon_{t-j}(i = 1, 2, \cdots, q)$; B represents the delay operator, which satisfies $B^n x_t = x_{t-n}$; p represents autoregressive order; q represents the moving average order; d represents the difference order; ∇ represents the difference operator; and $\nabla^d = (1 - B)^d$.

$\Phi(B)$ represents the polynomial of the autoregressive coefficient, and the specific expression is as follows:

$$\Phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p. \quad (7)$$

$\Theta(B)$ represents the moving average coefficient polynomial, and the specific expression is as follows:

$$\Theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q. \quad (8)$$

ε_t is a white noise sequence independent of x_{t-i} and ε_{t-j}, satisfying

$$\varepsilon_t = \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} - \varphi_0 - \varphi_1 x_{t-1} - \varphi_2 x_{t-2} - \cdots - \varphi_p x_{t-p} - x_t. \quad (9)$$

3.2. Sample Selection and Pretreatment. The GDP of H province from 2010 to 2020 is selected as the research sample, the GDP data from 2010 to 2014 as the training sample, and the GDP data from 2011 to 2020 as the test sample, and different evaluation criteria are used to evaluate the model test results.

The best ARIMA model is first determined. Second, the momentum factor is used to optimize the BP neural network when it is being built. The error of neural network fitting is used again to construct a neural network to further correct the error and fully extract the sequence information, based on the test results.

We normalise the data to speed up network training convergence because the data is large, and its specific function is to transform the data into samples in a unified unit, whether for calculation or modelling. We must first unify our measurement units, because if data normalisation processing is all positive, it will quickly lead to low learning efficiency. As a result, we normalise the data and treat it as a range of numbers. The following is the normalisation formula:

$$\bar{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}. \quad (10)$$

3.3. Fusion of BPNN and ARIMA Model

3.3.1. Overview of Fusion Model. Judging from the prediction results of the ARIMA model and single BPNN, the model is effective for short-term prediction of GDP data, which has certain reference value, but it also has some shortcomings. The prediction of the BPNN model is not very good, and the prediction is not very stable.

The relative error of the ARIMA model is less than 1%. Compared with general models, the ARIMA model has a good prediction effect. Of course, we can analyze the model from a deeper perspective. From the extraction of data information by the two models, we can get that the ARIMA model extracts the linear features of data, while the BPNN model extracts the nonlinear features of data.

In this chapter, we will combine the two models into a new fusion model. The GDP data of H province has linear and nonlinear characteristics. We use residual series to express the nonlinear part. We use the BPNN model to predict it and add the predicted values of the two parts to form a new fusion model. This model is used to forecast the GDP of H province. Therefore, in this paper, the traditional time series model and neural network model are combined into a new model to forecast GDP more effectively.

3.3.2. Fusion Model Classification. According to the mapping relationship between the fusion model and the single model, it can be divided into linear and nonlinear modes. According to the different ways of weighting each individual prediction model, it can be divided into optimal and nonoptimal fusion models. Among them, the optimal fusion model is that the objective function gets the maximum value when the constraint condition is small and finally calculates the weight of the fusion model. And the determination of the nonoptimal fusion model is to obtain the fusion prediction weight according to the principle that the variance is inversely proportional to the weight.

In this paper, the parallel fusion model is used, and its basic idea is to give different weights to each model according to the prediction results of each single model, so as to improve the prediction accuracy by fusion. The flow chart is shown in Figure 2.

Let the predicted object f have n prediction methods, in which the predicted value f_i of the ith method, where $i = 1, 2, \cdots, n$, is used, and the fused predicted value obtained by weighting these n predicted values constitutes the final predicted result of f. Its basic form is

$$f = w_1 f_1 + w_2 f_2 + \cdots + w_i f_i, \quad i = 1, 2, \cdots, n, \quad (11)$$

in which $w_1, w_2, \cdots, w_i$ are the coefficient of the weight of each prediction method and $\sum_{i=1}^{n} w_i = 1, i = 1, 2, \cdots, n$.

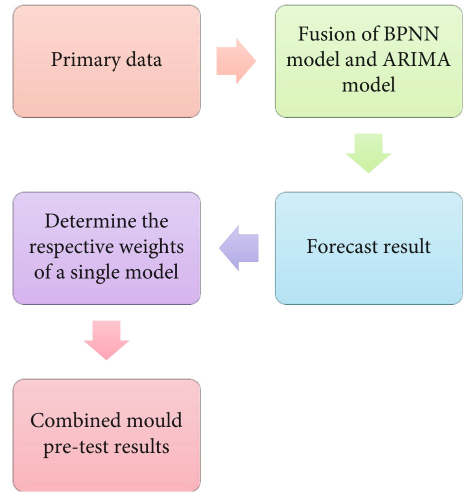

Figure 2: Fusion model flow chart.

3.3.3. Establish an Improved Fusion Model. Next, we will improve the above fusion model to get better prediction results.

In this paper, we decided to use two ways to achieve data stabilization. One way is to take the logarithm of the data first and then make first-order difference to get the stationary time series; the other way is to directly make second-order difference to get the stationary time series.

The two methods will eventually get a stable time series. By establishing ARIMA models for these two series, we will get the predicted values of the two models. By averaging these two values, the result is the linear predicted value of the improved fusion model.

The residual sequences obtained by the two models are weighted and averaged to obtain a new residual sequence. Then, referring to the fusion model, the residual training set samples are generated by sliding, and the data are normalised to obtain the input matrix and test set of BPNN.

According to the BPNN method, the neural network is initialized, and the nonlinear residual prediction value of GDP is obtained by nonlinear prediction of residual sequence. The prediction value of the improved fusion model is simply added by the values obtained from linear and nonlinear parts. The flow chart of the improved fusion model is shown in Figure 3.

By adding the predicted values of the linear part and the nonlinear residual, we can get the final predicted value of the improved fusion model. Firstly, draw the fitting curve of the improved fusion model, as shown in Figure 4.

It can be seen from Figure 4 that the real data are almost all on the fitting curve of the model, and the growth form of GDP in H province is vividly expressed by the fitting curve in the figure, and the fitting effect has been greatly improved compared with the previous fusion model.

4. Analysis and Discussion

4.1. Prediction Error Analysis. Both linear and nonlinear trends can be found in historical data on per capita GNP.

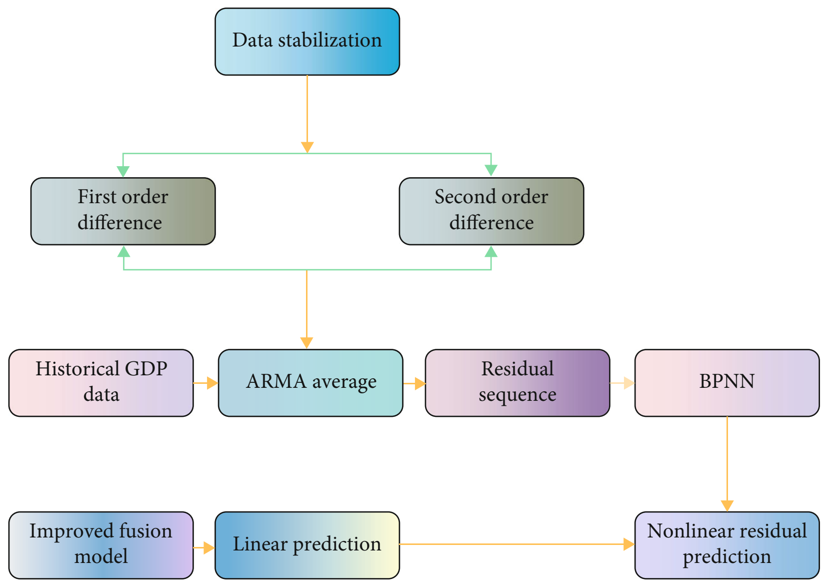

FIGURE 3: Flow chart of improved fusion model modeling based on.

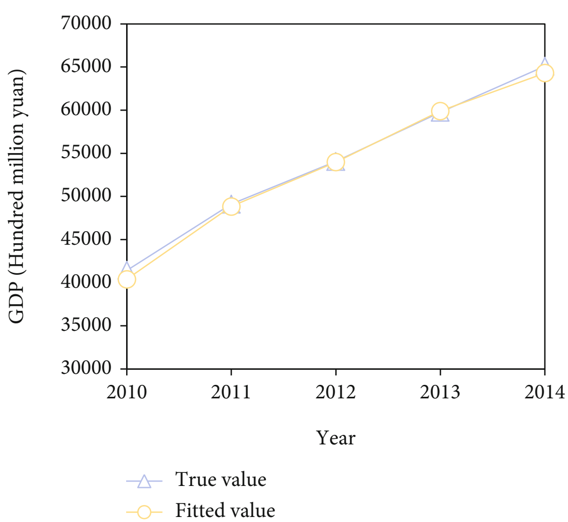

FIGURE 4: Fusion model fitting curve.

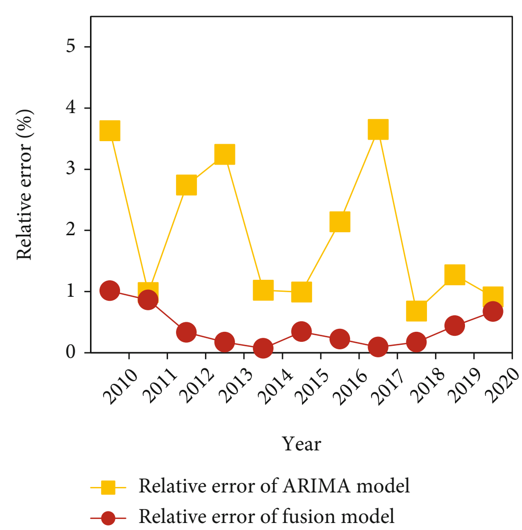

FIGURE 5: GDP forecast data.

Using BPNN and ARIMA models alone may result in excessive errors. As a result, the ARIMA model can be used to predict the ARIMA model error first, and then, BPNN can be used to predict the ARIMA model error second. Finally, by combining the ARIMA and BPNN predicted results, the fusion prediction model's predicted value can be calculated.

The optimized L-M learning algorithm is adopted, and the maximum number of trainings is set to 1000. The error data is normalised and loaded into BPNN, and the GDP forecast data of H province as shown in Figure 5 is obtained.

It can be seen from Figure 5 that the relative error of GDP predicted by the ARIMA model in 2017 is up to 3.65%, while the relative error of the corresponding ARIMA-BPNN fusion prediction in 2017 is only 0.09%. At the same time, we can see that the maximum relative error of the ARIMA-BPNN fusion model is 1.01% in 2010. It is much smaller than the maximum of 3.63% under the ARIMA model alone.

The average relative error of the whole model is obviously much better than that of fusion prediction. The average relative error of ARIMA alone model is 2.14%, while the average relative error of the ARIMA-BPNN fusion model is only 0.614%. Therefore, it is obvious that the ARIMA-BPNN fusion model is effective in forecasting GDP.

The ARIMA model and the modified network model are fused by the method of equal weight fusion. The calculation results are shown in Figure 6. According to Figure 6, the MAPE (mean absolute percentage error) fitted by the equal weight fusion model is 1.13%, and the prediction accuracy calculated by formula is 98.66%. Its value is better than the ARIMA model and the modified neural network model.

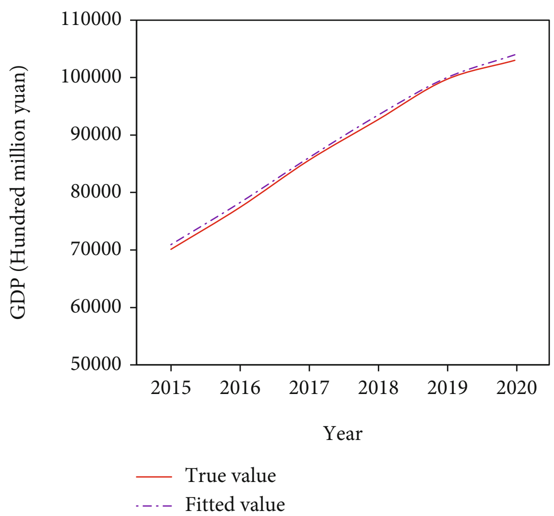

Figure 6: Equal weight fusion fitting results.

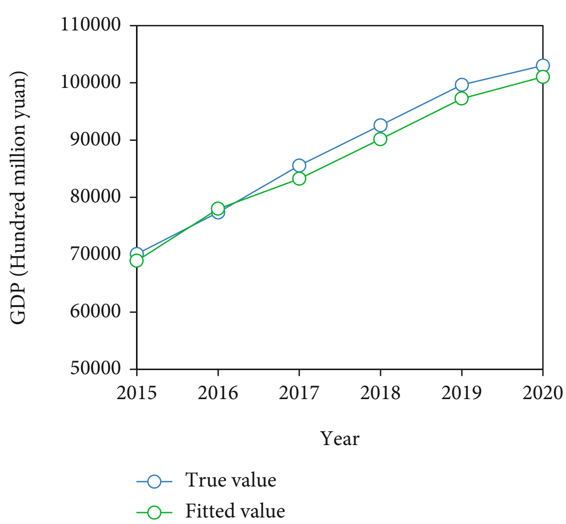

Figure 7: Simple weighted fusion fitting results.

The ARIMA model and the modified neural network model are given 1/3 and 2/3 weights, respectively. The calculation results are shown in Figure 7.

The average MAPE of the simple weighted fusion model is not only smaller than that of the ARIMA model and the modified neural network model but also smaller than that of the equal weight fusion model, and its prediction accuracy is 98.73% through formula calculation.

According to the formula, ARIMA and BPNN are given weights of 0.335 and 0.685, respectively, to obtain the fusion model. Then, according to the fusion model, predict the year from 2015 to 2020, and calculate the relative error of prediction. The result is shown in Figure 8.

It can be seen from the results in Figure 8 that the MAPE of the error sum of square reciprocal method is 1.00%, which is smaller than that of the equal weight fusion model but larger than that of the simple weighted fusion model. The prediction accuracy is 98.71%.

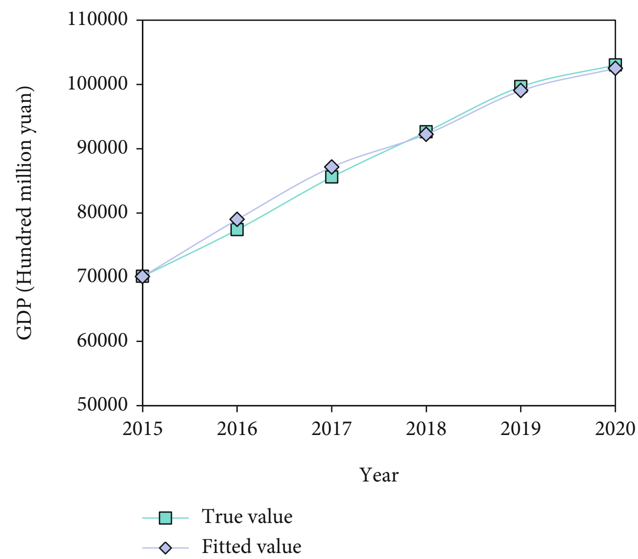

Figure 8: Fitting results by inverse square method of prediction error.

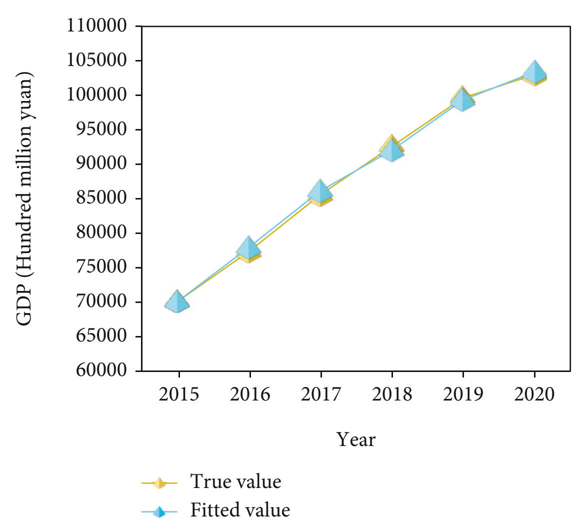

Figure 9: Error mean square reciprocal method model fitting results.

According to the formula, ARIMA and BPNN are given weights of 0.439 and 0.586, respectively, to obtain the fusion model. Then, according to the fusion model, 2015-2020 is predicted, and the calculated prediction relative error is shown in Figure 9.

It can be seen from the results in Figure 9 that the MAPE of error variance mean square reciprocal method is 0.89% smaller than that of other fusion models, and the prediction accuracy calculated by formula is 98.82%.

Comparing the MAPEs of four fusion models, we can see that the MAPE of the mean square reciprocal of error variance is the smallest. From the perspective of effectiveness evaluation, it can be concluded that the mean square reciprocal of error variance has the best effectiveness.

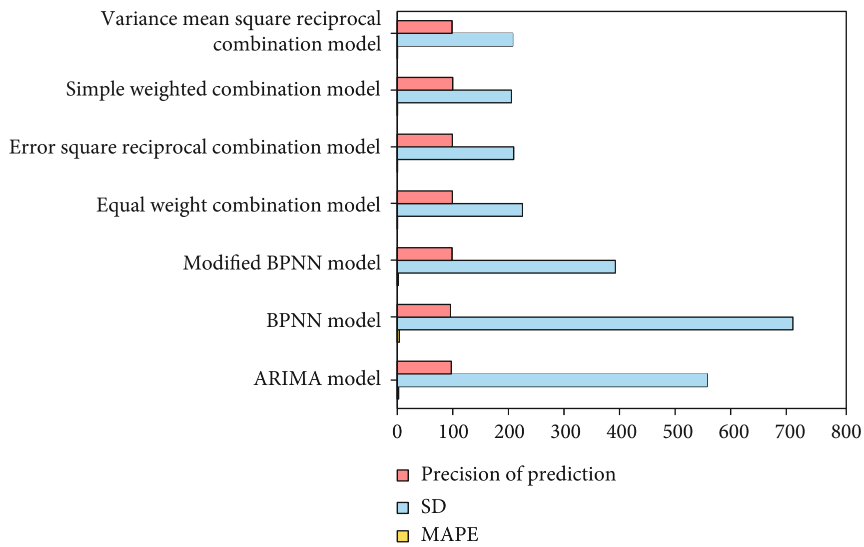

Figure 10: Results of different model evaluation criteria.

4.2. Model Comparison. A function curve is fitted to reflect the change law of the predicted data based on historical data. The predicted values at the required time points are estimated using this fitted curve. Exponential, curtain function, polynomial, logarithmic, and curve fitting models are examples of fitting models. This method has the advantages of being simple to use and implement, but it is only appropriate for data with a stable change law. The prediction error may be large if the data is fluctuating.

Repeated comprehensive analysis, induction and mining of the information of the hidden laws of the known data, and then mining the hidden information of the unknown laws according to the known data, the whole mining process is carried out in a certain closed area, and the random quantity is the grey quantity, which makes the system gradually "whitened" in the analysis and research process, and the prediction application of neural network belongs to the grey prediction category.

The prediction results of different models are compared with MAPE and SD (standard deviation) of prediction error and prediction accuracy, and the results are shown in Figure 10.

It can be seen from Figure 10 that the MAPE of the ARIMA model is 2.80%, and the SD of the prediction error is 556.809. Improved BPNNMAPE is 1.88%, and SD of the prediction error is 386.721. It can be seen from Figure 10 that MAPE of the ARIMA model is 2.80% and SD of the prediction error is 556.809. Improved BPNNMAPE is 1.88%, and SD of the prediction error is 386.721. It shows that the fitting effect of these two separate models is better than that of BPNN. The fitting effect of the single model is better than that of BPNN.

From the fusion prediction model, the MAPE of equal weight fusion model is 1.17%, which is smaller than that of the single model. The weighted fusion model has the Thayer unequal coefficient, MAPE, and SD of the prediction error, which is only larger than the error variance mean square reciprocal model fusion model.

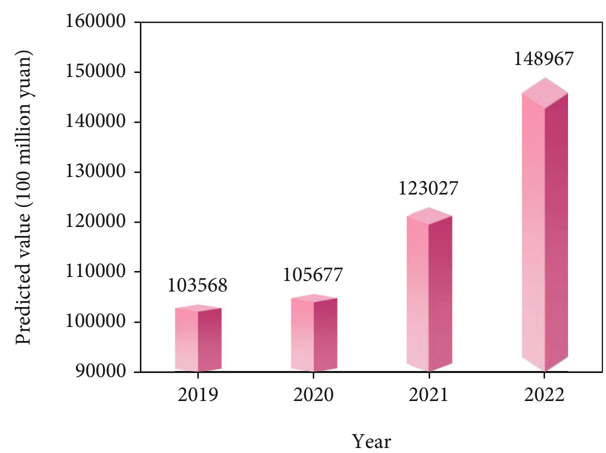

Figure 11: H province's forecast value for the next 4 years.

It can be seen from the above analysis that the fusion model can improve the accuracy of the model to a certain extent. When fusing models, the accuracy of fusion models is different depending on the way of weighting. Therefore, when fusing a single model, we should consider it from different aspects to get the optimal model. Finally, according to the model comparison and analysis, the optimal fusion model in this paper is the error variance mean square reciprocal fusion model.

4.3. Fusion Model GDP Forecast. The predicted values of linear and nonlinear parts of the improved fusion model are added to get the predicted value of GDP of the improved fusion model. The GDP of the first year predicted by the improved fusion model is taken as the GDP of H province in 2019, and then, the established ARIMA model is used to predict the GDP of H province from 2020 to 2022. The predicted results are shown in Figure 11.

It can be seen from Figure 11 that with the increase of time, the GDP of H province is constantly increasing, so is the economy, and the people's living standard is constantly improving.

Understanding the national economy by scientifically analyzing past GDP data and mastering its development trends and changes is beneficial for social workers. Based on these two points, this paper uses the GDP of H province as the research object to develop various models and compare them to find the best model for predicting GDP. After H province, the research findings can be used as a reference for economic development and provide a reasonable basis for relevant departments to formulate economic policies.

5. Conclusion

When forecasting data series, various single forecasting models may not fully comprehend the data information due to their own limitations, which may affect the forecasting results. The ARIMA-BPNN fusion prediction model is created by combining the traditional ARIMA model with the BPNN model in order to improve the model's prediction accuracy. The effectiveness of this forecasting method is tested using real-world examples. Using the change forecast to forecast the GDP of H province not only effectively captures the series' correlation but also depicts the nonlinear relationship of the economic series. The forecast value of the mixed model is better than that of the single time series model, based on the forecast results. The improved combination model has a better short-term prediction effect than the ARIMA model, and the ARIMA model has a better long-term prediction effect than the improved combination model. The combined model's prediction effect is lower than that of the ARIMA model, and the BPNN model's prediction accuracy is lower than that of other models. It also has some utility in general GDP forecasting issues. When forecasting data series, various single forecasting models may not fully comprehend the data information due to limitations imposed by their own conditions, which may have an impact on forecasting results. Single forecasting models can be fused in a specific way to improve forecasting accuracy. In this paper, a fusion forecasting model is developed that combines the ARIMA time series model with the BPNN algorithm, and the efficacy of this forecasting method is empirically assessed using relevant examples. ARIMA-BPNN mixed forecast is used to forecast the GDP of H province, which effectively captures the correlation of the series while also depicting the nonlinear relationship of the economic series. The mixed model's forecast value is better than that of the single time series model, according to the forecast results. The mixed model has a good prediction effect on GDP in the province of H, as well as a certain use value for general prediction problems.

GDP analysis and forecasting is a difficult task because there are many factors that influence GDP, and the mechanisms by which each factor influences GDP are relatively complex. More factors can be considered in future research, as this paper only considers the value of GDP. Due to a lack of time and energy, as well as numerous deficiencies in my knowledge, the methods that need to be strengthened in my knowledge are limited, so I was unable to apply more methods in this paper, which is also an area that requires future improvement.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The author does not have any possible conflicts of interest.

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