Research Article

GDP Economic Forecasting Model Based on Improved RBF Neural Network

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Among the existing GDP forecasting methods, time series forecasting and regression model forecasting are the two most commonly used forecasting methods. However, traditional macroeconomic forecasting models are unable to accurately achieve optimal forecasts of highly complex nonlinear dynamic macroeconomic systems due to the influence of multiple confounding factors. In order to solve the above problems, a GDP economic forecasting model based on an improved RBF neural network is proposed. First, the main traditional GDP forecasting methods are analyzed. Then, RBF neural networks are used to solve the problem that traditional forecasting technology methods cannot handle multi-factor complex nonlinearities well. Second, to further improve the convergence speed and accuracy of the RBF neural network learning algorithm, the Shuffled Frog Leaping Algorithm with global search capability and high practicality is fused into the RBF network training. Finally, the improved RBF neural network is used to build a GDP economic forecasting model. The performance of the Shuffled Frog Leaping Algorithm and the improved RBF neural network was tested using the approximation of Hermit polynomials and the Iris classification problem as simulation examples. The experimental results show that the improved RBF neural network-based GDP economic forecasting model achieves more accurate forecasting accuracy than other forecasting methods.

1. Introduction

Economic globalization is an important feature of economic development in today’s world. An important indicator in the economic sphere—gross domestic product (GDP)—has also become a growing concern, and is an important economic indicator of a country’s economic situation, providing an important basis for the health of the economy. GDP is the market value of all final goods and services produced within a country in a given period, and GDP growth is an important economic indicator of the health of a country’s economy [1–6]. The famous American economist and Nobel Prize winner Paul Anthony called GDP “one of the greatest inventions of the century.” In-depth research and analysis of GDP are of great importance to macroeconomic regulation and the formulation of economic policies.

Macroeconomics is the study of the entire national economic activity. The development and changes in macroeconomics are influenced by a variety of factors. These factors are interlinked and interact with each other, making the process of macroeconomic development trendy, cyclical, open, and nonlinear. With the development of economic statistics, econometrics, and other related techniques, forecasting has become an emerging practical and comprehensive discipline. Forecasting is to rely on historical information and the current situation and to explore the laws of the evolution of things according to certain theories, so as to form hypotheses and judgments. The past and present operation of the macroeconomic system is the basis for forecasting [7–9]. In macroeconomic forecasting, the traditional methods are mainly time series analysis and multiple regression methods.

The historical data collected in macroeconomic forecasting is generally time series data. Time series refers to the sequence formed by sorting the data of the same statistical variables according to the time sequence of occurrence. The purpose of studying time series is to discover the intrinsic links between data through the analysis of historical data, so
that future data can be predicted. Most of the modeling and forecasting of time series use statistical regression models for continuous time series. Another analytical method that is more widely used is Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA). For non-stationary time series, the series is made stationary by differencing several times and then the series is represented as a combination of white noise and moving average [10–13]. Another mainstream forecasting method is multiple regression, also known as the Vector Autoregressive (VAR) method, which is a statistically based model that constructs a model from a function of the lagged values of all the endogenous variables in the system. VAR does not require any implementation constraints and has been widely used in economic forecasting in recent years.

The above traditional methods are the dominant approaches in the field of economic forecasting. Both methods use linear models to simulate real-life complex systems in order to make forecasts, and therefore often do not give a good result when dealing with complex non-linear systems [14]. A large number of researchers have noticed the limitations of linear models and have therefore turned their attention to non-linear models. At the beginning of the research on non-linear models, people still habitually rely on the traditional ideas of model research. The general idea of traditional forecasting methods is to set up a model by observing and analyzing the changes in the system, then to test the model for estimation and finally to select the best model. However, economic historical data usually has very complex non-linear time-series data and forecasting using traditional methods often faces many problems [15–17]. Traditional methods focus on the analysis of causality and the relationship between time series of the data. In the actual forecasting process, such methods lose the amount of information due to problems such as multicollinearity and error series, making the forecasting accuracy unsatisfactory. In fact GDP is influenced by multiple factors and the relationships between various factors are complex, presenting complex time series and non-linearity, which makes GDP forecasting very difficult.

In the face of unsolvable complex non-linear problems, people have started to look beyond traditional methods to find new ways of research. The human brain can handle a variety of complex non-linear problems very quickly, and researchers have been inspired by the idea of how to simulate the human brain to deal with complex non-linear problems. An artificial neural network (ANN) is an intelligent bionic model that mimics the function of neurons in the brain [18–21], and is a non-linear complex network system consisting of a large number of interconnected neurons. There are various learning algorithms for ANNs, but backpropagation (BP) is the most widely used weight correction algorithm for neural networks. ANNs have proven to be very effective in building predictive models, automatically learning from previous experience in a sample of data without the need for complex query and representation processes.

Currently, research on neural network-based forecasting has focused on time series forecasting and regression forecasting. Doucoure et al. [22] collected real-time series data and removed the most recent data in each series from the sample. These latest data were then predicted with reference to each prediction model. Finally, the obtained prediction results were compared with the real data. The results show that ANN has higher performance than ARMA. Wu and Lee [23] used a support vector machine based on principal component analysis to forecast regional economies. Haoret al [24] applied BP neural networks to CPI forecasting. Wang et al. [25] proposed a GDP forecasting model based on principal component analysis and Bayesian regularised BP neural networks. In addition, ANNs are also heavily applied to stock prices, stock market indices, exchange rates, commodity price forecasting, early warning of financial conditions, traffic flow forecasting, etc. Numerous research results have shown that ANN can be successfully applied to macroeconomic forecasting.

The advent of radial basis function (RBF) neural networks has brought new life to the research and application of ANNs [26–28]. The structure of RBF neural networks is similar to that of multilayer forward neural networks, but it is a three-layer feedforward network with a single hidden layer. BP networks are typically global approximation networks, whereas RBF networks can determine the appropriate network topology for the problem, learn quickly, and do not suffer from local minima. The research and application of RBF neural networks is also gaining importance. Due to the advantages of RBF neural networks, they are beginning to replace BP networks in an increasing number of fields.

Therefore, this study proposes an economic forecasting model for GDP based on an improved RBF neural network. In this study, a GDP forecasting model is built using a RBF neural network optimized by the Shuffled Frog Leaping Algorithm (SFLA). When training the network, a normalization process was used to preprocess the input and output data of the neural network to ensure that the data were of the same order of magnitude, and the forecasting results were compared with the traditional forecasting model. The experimental results show that the improved RBF neural network has better application in GDP forecasting. The main objective of this study is to use the improved RBF neural network as an alternative to traditional GDP forecasting methods (time series forecasting and regression model forecasting) in order to solve the problem of optimal forecasting of highly complex nonlinear dynamic macro-economic systems.

The main innovations and contributions of this paper include:

1. RBF neural networks are used to solve the problem of complex nonlinearities of multiple factors that cannot be well handled by traditional prediction technology methods.

2. To further improve the convergence speed and accuracy of the RBF neural network learning algorithm, SFLA, which has global search capability and high practicability, is fused into the RBF network training.
The rest of the study is organized as follows: In Section 2, the problems with the main traditional GDP forecasting methods are studied in detail, while Section 3 provides the Improved RBF neural network. Section 4 provides the economic forecasting model for GDP based on SFLA-RBF neural network. Section 5 provides the experimental results and analysis. Finally, the paper is concluded in Section 6.

2. Problems with the Main Traditional GDP Forecasting Methods

Forecasting is the advanced estimation of things that have not yet occurred and is a comprehensive study of the interconnections of things. Economic forecasting methods can be divided into two main categories: qualitative forecasting and quantitative forecasting. The former is based on human experience and subjective judgment to obtain forecasts directly, while the latter is based on historical data to build mathematical models and then make quantitative forecasts. Among the classical quantitative forecasting methods are regression forecasting analysis, econometric model forecasting and random time series forecasting. In terms of the timing of forecasts, they can be divided into long-term forecasts, medium-term forecasts, and short-term forecasts.

2.1. Stochastic Time Series Forecasting. Time series analysis refers to the processing of data analysis of data series arranged in chronological order. ARMA is widely used in forecasting in the economic field. In terms of short-term forecasting, ARMA can achieve a high level of forecasting accuracy. In general, the ARMA model is defined as follows:

\[ x_t = \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \cdots + \varphi_p x_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \cdots - \theta_q \epsilon_{t-q}, \]

where \( p \) is the autoregressive order, \( q \) is the moving average order, \( \varphi \) is the autoregressive average coefficient, and \( \varphi \) is the sliding average coefficient. If we use the backward shift operator, we can obtain the new equation given as follows:

\[ \varphi(B)x_t = \theta(B)\epsilon_t, \]

where \( e_t \) is a random interference error term, and \( B \) is a white noise sequence with mean value of 0.

The main contribution of the ARMA model is the discovery that the more pronounced changes in the economic time series are predictable and that such changes are derived from a particular type of non-linear dependence. From a forecasting point of view, the use of ARMA models not only improves the accuracy of the forecast values compared to ordinary least squares, but also the reliability of the forecast values is known. When the variance is large, the confidence interval for the predicted value is larger and therefore less reliable. Conversely, the reliability of the predicted values is better. Using this property, ARMA models are of great practical value when performing risk analysis on stocks, bonds, futures and options etc.

2.2. Regression Model Predictions. A regression model, also known as a causal model, is used to make forecasts based on the historical values of variables and the historical values of other relevant variables. The regression analysis has a very wide range of applicability, not only for micro-forecasting but also for macro-forecasting. Regression analysis methods are not only suitable for short-term forecasting but also for long-term forecasting. Linear regression models are the simplest econometric models.

\[ Y_i = \beta_0 + \beta_1 X_i + u_i, \quad (i = 1, 2, \ldots, n), \]

where \( Y_i \) is the explanatory variable, \( X_i \) is the explanatory variable, \( \beta \) is the theoretical parameter, and \( u_i \) is the random perturbation term. Perturbation terms arise for two main reasons: (1) the stochastic nature of objective phenomena. The stochastic nature of human behavior, the stochastic nature of the social environment, and the stochastic nature of the natural environment dictate the need to introduce perturbation terms into the regression model. (2) Measurement error. When collecting and collating data, some subjective or objective measurement error always arises, resulting in the observed values of some variables not being equal to the actual values.

The assumptions of the regression model require that the explanatory variables are independent of the random error term.

\[ E(u_i) = 0, \]
\[ \text{Cov}(u_i, X_i) = 0, \]
\[ \text{Cov}(u_i, u_j) = 0 (i \neq j), \]
\[ \text{Var}(u_i) = \sigma_u^2. \]

The estimation of the regression model parameters is achieved through ordinary least squares estimation. The least squares estimate is a linear function of the observed \( Y \) variable with a mean equal to the true value of the overall regression parameters.

2.3. Evaluation of Traditional GDP Forecasting Methods. Time series forecasting has the advantages of being simple, intuitive and easy to understand, and can easily remove interfering components from the data series. However, there are two problems with time series forecasting: firstly, when there are many forecast items, a large amount of data needs to be stored. Secondly, the most recent observations contain more information than earlier observations and should have a larger weight. In addition, many studies have shown that the prediction accuracy of time series forecasting is low. Time series forecasting assumes that changes in the predictor are only time-dependent. However, in fact, the forecasting object has a close and complex relationship with external factors. Time series forecasting is generally used for short-term forecasting as it relies heavily on the principle of inertia. The disadvantage of time series forecasting is that it is less able to identify changes in the forecast object.
Regression forecasting is a forecasting method based on the principle of correlation. As the forecast object is influenced by certain factors, changes in these factors will lead to changes in the forecast object. The basic idea of regression forecasting is to analyze and study the interrelationship between the forecast object and the relevant factors. As regression analysis has a more rigorous theoretical basis and more mature calculation and analysis methods, the regression forecasting method is more theoretical. Regression forecasting models can obtain relatively accurate forecasting results. In fact, there is a complex intrinsic relationship between the prediction object and the relevant factors. The correlation is a common socio-economic phenomenon and therefore regression forecasting is widely used. The disadvantage of regression forecasting is that the selection of correlates often depends on the knowledge and experience of the forecaster. Although some of the variables have a strong correlation with the predictor variables, they may actually have no effect on the outcome of the prediction.

3. Improved RBF Neural Network

3.1. Principle of RBF Neural Networks. In the study, the economic data are processed using the RBF neural network model. In the RBF neural network model, let the input samples be \( X_k = (x_{k1}, x_{k2}, \ldots, x_{kn}) \), \( k = 1, 2, \ldots, m \), where \( m \) and \( n \) represent the total number of samples and the total number of features of one sample respectively. In general, the number of neurons and the number of features in the input layer are equal. The number of neurons in the input layer is generally smaller than the total number of features after the sample features have been filtered [29]. The output of the \( k \)-th sample after the model is \( Y_k = (y_{1k}, y_{2k}, \ldots, y_{nk}) \), and \( n \) is the number of neurons in the output layer. A diagram of the radial basis function in the plane is shown in Figure 1.

An RBF network is usually a three-layer feedforward network with the structure shown in Figure 2. First, the input samples are adjusted by the weighting coefficients to give the values of the first hidden layer [30].

\[
S_{ij} = \sum_{i=1}^{n} W_{ij} x_i - \theta_{ij}, \quad j = 1, 2, \ldots, p. \tag{5}
\]

The values of the first implied layer need to be feature transformed.

\[
b_{ij} = \exp \left( -\frac{\| x_i - \theta_{ij} \|^2}{2\sigma^2} \right), \tag{6}
\]

where \( \sigma \) is a real number greater than 0 and \( \theta_{ij} \) is the \( j \)-th hidden layer centroid. The feature transformation function selected for the RBF neural network is the Gaussian function. The first hidden layer is used as input, and the values of the second hidden layer are obtained after adjustment of the weight coefficients.

\[\begin{align*}
S_{2j} &= \left( \sum_{i=1}^{m} W_{2ij} x_i + \theta_{1j} \right) + \sum_{i=1}^{p} W_{ij} b_{ij} - \theta_{2j}. \tag{7}
\end{align*}\]

The output after all implied layers requires additional weights \( V_{jt} \).

\[
L_t = \sum_{j=1}^{p} V_{jt} b_{2j}. \tag{9}
\]

The Gaussian function is solved to obtain the output of the whole model [31].

\[
C_t = \exp \left( -\frac{\| \sum_{j=1}^{p} V_{jt} b_{2j} - \theta_{2j} \|^2}{2\sigma^2} \right). \tag{10}
\]

The error results for the \( k \)-th sample are shown as follows:

\[
E_k = \frac{\sum_{t=1}^{q} (y^k_t - C^k_t)}{2}. \tag{11}
\]

The errors for all samples are shown as follows:

\[
E = \sum_{k=1}^{m} \frac{d_{jk}}{2}, \Delta V_{jt} = -\frac{\partial E_k}{\partial V_{jt}}. \tag{12}
\]

Solve for the weights between the implied and output layers [32].

\[
\Delta W_{jt} = \alpha d_{jk} b_{jt}, \quad j = 1, 2, \ldots, n; k = 1, 2, \ldots, m, \tag{13}
\]

where, \( \alpha \) is the learning speed and \( d_{jk} = (y^k_j - C^k_j)(1 - C^k_j) \).
3.2. Improved RBF Based on SFLA. There are two main ways to optimize the RBF neural network: firstly, by continuously optimizing the weights of the layers in the RBF neural network through the algorithm. By optimizing the weights, the output of the RBF neural network is brought closer to the actual result; secondly, the number of nodes and the distribution of nodes in the RBF neural network are continuously adjusted by the algorithm, so that the output of the RBF neural network is brought closer to the actual result. In practice, it is also possible to use a mixture of these two approaches to be able to obtain the global optimal solution.

In this study, SFLA is used to optimize the RBF neural network weights. The structure of the network model is generated based on the initial weights and random pre-defined nodes. Multiple weights are used as the input set for SFLA and the network structure model with the smaller error function is selected for optimization.

To further improve the prediction accuracy, SFLA was chosen to optimize the weight parameters of the RBF neural network. Let there be P frogs in the pond forming a frog population, denoted as \( X^p = [x^p_1, x^p_2, \ldots, x^p_P] \). The Root Mean Square Error (RMSE) of GDP prediction was chosen as the fitness function and the fitness of all frogs was calculated. The frog with the highest fitness is recorded as \( x^g \). Firstly, \( P \) frogs were randomly divided into \( M \) groups, and then the search for the maximum amount of food was conducted within each of the \( M \) groups.

\[
\begin{align*}
    d_i &= \text{rand} \times (X^k_b - X^k_w), \\
    X^k_{w,\text{new}} &= X^k_{w,\text{old}} + d_i,
\end{align*}
\]

where \( X^k_b \) is the best individual in the \( k \) group, \( X^k_{w,\text{old}} \) is the worst individual before and after the move in the \( k \) group, \( X^k_{w,\text{new}} \) is the worst individual after the move in the \( k \) group, rand is a random number, and \( d_i \) is the move step.

The main steps of SFLA are shown as follows:

Step 1: SFLA applies the results after the \( t \)-th iteration during the \( (t+1) \)-th computational iteration, moving the frog \( X^i_b(t) \) with the larger RMSE continuously closer to the frog \( X^i_w(t) \) with the smaller RMSE.

\[
\begin{align*}
    \Delta_w(t) &= \text{rand} (X^i_b(t) - x(t)), \\
    X^i_w(t+1) &= X^i_w(t) \Delta_w(t), R_{\text{min}} = \Delta_w(t) \leq R_{\text{max}}.
\end{align*}
\]

Step 2: If the value of \( X^i_w(t+1) \) solved at time \( t+1 \) is larger than \( X^i_w(t) \) (with better fitness), then replace \( X^i_w(t) \) with \( X^i_w(t+1) \). For the frog movement step problem, a step factor \( C \) can be introduced. For the \( k \) frog, the distance of the \( i \) movement is calculated as follows:

\[
d_i = \text{rand} \times (X^k_b - X^k_{w}) \times C. \tag{16}
\]

In this regard, the step factor is updated as shown as follows:

\[
C = C_{\text{min}} + i_{\text{now}} \times G_{\text{global}} \times (C_{\text{max}} - C_{\text{min}}). \tag{17}
\]

Where \( C_{\text{min}} \) is the minimum movement step of the frog in the current population and \( C_{\text{max}} \) is the maximum movement step of the frog in the current population. These two variables can be set as appropriate. \( G_{\text{global}} \) is the sum of the fitness values of all frogs in the population, and \( i_{\text{now}} \) is the number of times the frog has moved at the current moment [33].

Step 3: When the fitness values of all frogs in the population are close to \( X^i_b(t) \) and the error is within the set threshold, the iteration of the algorithm stops. The distribution of all frogs at the current moment is output, which is the optimal solution.

After the optimal weight solution is obtained, the GDP prediction model of RBF neural network can be determined. The process of finding the optimal individual by SFLA is the process of solving for the optimal solution of the RBF neural network weights. The optimal result of the SFLA training is the optimal RBF neural network structure model.
4. Economic Forecasting Model for GDP Based on SFLA-RBF Neural Network

4.1. GDP Sample Data Processing. We selected the five most influential indicators on GDP: employed population F1, fixed asset investment F2, fiscal expenditure F3, total foreign trade exports F4, and total retail sales of social consumer goods F5 as the initial variables, as shown in Table 1. These five indicators were preprocessed as input variables for the SFLA-RBF neural network.

Therefore, before using neural networks for GDP forecasting, the raw data is normalized to avoid the effect of overloading the raw data.

$$y = \frac{x - \min}{\max - \min}$$  \hspace{1cm} (18)

where max and min are the maximum and minimum values in the sample data respectively, x is the original sample data and y is the transformed value. This not only avoids the input data falling into the saturation region, but also maintains the original characteristics of the data. When the neural network has finished processing, the inverse normalization operation is done. The normalized data is shown in Table 2.

$$y = x \ast (\max - \min) + \min.$$  \hspace{1cm} (19)

4.2. Implementation of the GDP Economic Forecasting Model. The flow of the SFLA-RBF neural network-based GDP economic forecasting model is shown as follows:

Step 1: Input of the normalized data GDP sample data, followed by initialization and vectorization.

Step 2: random generation of RBF neural network weights.

Step 3: Treat the weights randomly generated in step 2 above as separate individuals and set the fitness function to find $J_{ce}$.

Step 4: Iteration and migration process according to the SFLA algorithm and determine whether the cut-off condition is met, if so skip to the next step, otherwise continue the iterative operation.

Step 5: Arrange the $J_{ce}$ values in descending order to obtain the weighted global optimal solution for the RBF network.

Step 6: The optimized RBF neural network structure model is obtained, which can effectively achieve accurate GDP prediction.

5. Experimental Results and Analysis

5.1. Experimental Setup. In this study, the neural network toolbox of MATLAB 7.0 software was selected for modeling. The GDP data from 1997 to 2016 was selected as the sample object for the experiment. The experimental data were mainly obtained from the website of the National Bureau of Statistics (http://www.stats.gov.cn/). In this experiment, 14 sets of data from 1997 to 2010 were used as training samples, and 4 sets of data from 2011th to 2014 were used as test samples to test the prediction performance of the SFLA-RBF neural network model.

The parameters of the RBF neural network: initial learning rate of 0.015, number of iterations epochs of 1000, selection target of 0.0001. Parameters of the SFLA algorithm:
population size of 64, number of population selections of 40, initial weight of 0.9, step size factor of 2. In the experiment, the model was first trained with 14 sets of data, and 4 sets of data were input into the model after the training was completed to obtain the prediction output of the model. The predicted output of the model was obtained.

5.2. Simulation Example of SFLA-RBF Neural Network Model. First, the same RBF neural network is optimized by using the PSO algorithm [34] and the SFLA algorithm to optimize the weight parameters for the approximation of the Hermit polynomials, respectively.

\[ f(x) = 1.1 \left(1 - x^2\right) \exp\left(-\frac{x^2}{2}\right). \]  
(20)

The RBF network structure is 1-5-1. The simulation results at 200 iterations are shown in Figure 3. The convergence curves of the objective function values are shown in Figure 4. It can be seen that compared to the PSO-RBF algorithm, the SFLA-RBF approximation is better and almost coincides with the original function.

The simulation experiments were then programmed in MATLAB to classify the Iris problem using a three-layer RBF network. The RBF network structure was 4-6-3. The RBF neural network was trained using the PSO algorithm, the BP algorithm and the SFLA algorithm respectively. The trained neural network was then tested with samples from the test set, and the results are shown in Figure 5. It can be seen that SFLA-RBF has the fastest convergence speed and the smallest error, which is significantly better than the other two models.

5.3. Comparison of GDP Forecast Results. First, we confirmed the non-smoothness of the normalized GDP data series (Table 2) by examining the autocorrelogram, as shown in Figures 6 and 7.
It can be seen that the normalized GDP data series is non-stationary. Stochastic time series forecasting, regression model forecasting, RBF neural network, and SFLA-RBF neural network were used for GDP forecasting respectively. The RMSE was chosen as the criterion for the accuracy of the network predictions. In the simulation process, the RBF neural network structure was set differently to verify its performance in order to fully validate the impact of SFLA-RBF on the prediction accuracy, and the simulation comparison results are shown in Table 3.

![Figure 7: Autocorrelation coefficient for GDP data series.](image)

| Year | Number of hidden layer neurons | Stochastic time series forecasting RMSE | Regression model prediction RMSE | RBF RMSE | SFLA-RBF RMSE |
|------|--------------------------------|----------------------------------------|---------------------------------|-----------|---------------|
| 2011 | 5                              | 0.0874                                 | 0.0802                          | 0.0771    | 0.0703        |
|      | 10                             | 0.0821                                 | 0.0721                          | 0.0634    | 0.0535        |
|      | 20                             | 0.0751                                 | 0.0649                          | 0.0674    | 0.0598        |
|      | 30                             | 0.0733                                 | 0.0678                          | 0.0662    | 0.0572        |
| 2012 | 5                              | 0.0892                                 | 0.0801                          | 0.0762    | 0.0711        |
|      | 10                             | 0.0674                                 | 0.0660                          | 0.0644    | 0.0578        |
|      | 20                             | 0.0848                                 | 0.0797                          | 0.0707    | 0.0604        |
|      | 30                             | 0.0736                                 | 0.0676                          | 0.0668    | 0.0612        |
| 2013 | 5                              | 0.0928                                 | 0.0871                          | 0.0792    | 0.0751        |
|      | 10                             | 0.0759                                 | 0.0743                          | 0.0653    | 0.0577        |
|      | 20                             | 0.0771                                 | 0.0725                          | 0.0691    | 0.0614        |
|      | 30                             | 0.0691                                 | 0.0691                          | 0.0688    | 0.0607        |
| 2014 | 5                              | 0.0920                                 | 0.0855                          | 0.0817    | 0.0773        |
|      | 10                             | 0.0760                                 | 0.0705                          | 0.0672    | 0.0549        |
|      | 20                             | 0.0869                                 | 0.0776                          | 0.073     | 0.0618        |
|      | 30                             | 0.0847                                 | 0.0784                          | 0.0691    | 0.0592        |

It can be seen that the normalized GDP data series is non-stationary. Stochastic time series forecasting, regression model forecasting, RBF neural network, and SFLA-RBF neural network were used for GDP forecasting respectively. The RMSE was chosen as the criterion for the accuracy of the network predictions. In the simulation process, the RBF neural network structure was set differently to verify its performance in order to fully validate the impact of SFLA-RBF on the prediction accuracy, and the simulation comparison results are shown in Table 3.

It can be seen that the RMSE of GDP prediction based on SFLA-RBF is lower for the same neural network size, indicating a higher prediction accuracy. In particular, when the number of hidden layers is 10, the prediction results of SFLA-RBF all exhibit lower RMSE, which can obtain more satisfactory prediction results. Therefore, in practice, a suitable neural network size can be chosen to accomplish GDP economic forecasting.

5.4. Effect of SFLA Parameters on GDP Forecasting Performance. In order to further validate the optimization performance of SFLA on RBF neural networks, the main parameters of SFLA were set differently. The number of groups, move steps, and number of iterations within groups were mainly simulated to verify the effect of different parameters on the prediction accuracy. The number of hidden layer neurons of the RBF neural network was set to 10 and...
after 10 predictions. The maximum, mean, and minimum values of its predicted RMSE were solved as shown in Table 4. It can be seen that when the number of groups belongs to [10, 20, 30, 40, 50] and the step size [1, 3, 5], the RMSE does not exceed 0.7, and the maximum and minimum values do not deviate much from the mean value, so the algorithm is relatively stable. In practice, the SFLA parameters can be fine-tuned by changing the main parameters several times in order to achieve better prediction results.

The number of groups and step size were fixed at 30 and 3, and the number of different iterations was adjusted to verify their effect on prediction accuracy as shown in Table 5. It can be concluded that as the number of iterations in the group increases, the maximum, minimum and mean values of RMSE slowly decrease. However, when the number of iterations is 40 and 50, the minimum and average values of RMSE for both do not change. In addition, the maximum value also remained almost unchanged and reached stability, and did not keep decreasing as the number of iterations increased. Therefore, the number of iterations should be set reasonably. If the number of iterations is increased, the prediction time will definitely increase. The number of iterations in a group should be set at a reasonable level according to the actual situation.

### 6. Conclusion

In order to solve the problem of optimal forecasting of high-complexity nonlinear dynamic macroeconomic systems, a GDP economic forecasting model based on an improved RBF neural network is proposed in this paper. In this paper, a GDP forecasting model is developed using an SFLA-optimised RBF neural network. When training the network, a normalization process is used to pre-process the input and output data of the neural network to ensure that the data are of the same order of magnitude, and the prediction results are compared with the traditional prediction model. The experimental results show that the improved RBF neural network has better application value in GDP prediction. When the number of hidden layers is 10, the prediction results of SFLA-RBF all exhibit lower RMSE, which leads to more desirable prediction results. Follow-up studies will further adjust the SFLA parameters to improve the time efficiency of GDP prediction.

### Data Availability

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

### Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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| Grouping | Step length | Maximum value | Minimum value | Average |
|----------|-------------|---------------|---------------|---------|
| 10       | 1           | 0.0611        | 0.0579        | 0.0591  |
|          | 3           | 0.0591        | 0.0572        | 0.0588  |
|          | 5           | 0.0620        | 0.0601        | 0.0612  |
| 20       | 1           | 0.0594        | 0.0569        | 0.0577  |
|          | 3           | 0.0553        | 0.0534        | 0.0542  |
|          | 5           | 0.0617        | 0.0577        | 0.0593  |
| 30       | 1           | 0.0532        | 0.0502        | 0.0513  |
|          | 3           | 0.0507        | 0.0483        | 0.0499  |
|          | 5           | 0.0569        | 0.0529        | 0.0537  |
| 40       | 1           | 0.0604        | 0.0571        | 0.0582  |
|          | 3           | 0.0591        | 0.0559        | 0.0573  |
|          | 5           | 0.0642        | 0.0616        | 0.0627  |
| 50       | 1           | 0.0607        | 0.0581        | 0.0593  |
|          | 3           | 0.0588        | 0.0564        | 0.0579  |
|          | 5           | 0.0651        | 0.0617        | 0.0632  |

| Number of iterations within a group | Maximum value | RMSE | Minimum value | Average |
|-------------------------------------|---------------|------|---------------|---------|
| 10                                  | 0.0578        |      | 0.0561        | 0.0573  |
| 20                                  | 0.0557        |      | 0.0531        | 0.0539  |
| 30                                  | 0.0541        |      | 0.0527        | 0.0513  |
| 40                                  | 0.0509        |      | 0.0482        | 0.0501  |
| 50                                  | 0.0508        |      | 0.0482        | 0.0501  |
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