

Retraction

Retracted: Economic Growth Prediction Algorithm of Coastal Area Based on Impulse Response Function

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1].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] Q. Rong-Shan, D. Ding, and H. Li-Min, "Economic Growth Prediction Algorithm of Coastal Area Based on Impulse Response Function," *Security and Communication Networks*, vol. 2021, Article ID 3864188, 9 pages, 2021.

Research Article

Economic Growth Prediction Algorithm of Coastal Area Based on Impulse Response Function

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In order to solve the problems of low accuracy and long prediction time of traditional economic growth prediction algorithms in coastal areas, an algorithm based on impulse response function was designed to analyze economic growth prediction in coastal areas. Crawler technology is used to capture the economic data of coastal areas and normalize the captured data. Based on the processed data, the impulse response function is used to analyze the relationship between different economic variables, so as to build the PSO-LSTM model, which is used to predict the economic growth trend of coastal areas. The experimental results show that, compared with the experimental comparison algorithm, the prediction accuracy of the algorithm designed in this paper is always above 97%, and the prediction time is always below 1 s, which has certain practical significance.

1. Introduction

Occupying 70 percent of China's total area, the ocean is a treasure house of human resources and a spatial support for human survival and development. Life originated in the ocean, and human development will depend on it. On the one hand, the resources on the land of the region can no longer support the continued development of the economy and society; on the other hand, the space on the land determines that human beings must also go to the ocean [1]. Therefore, the 21st century is the century of the ocean, and coastal countries have turned their eyes to the ocean to seek the fulcrum of future development. Countries around the world have begun to develop and utilize Marine resources and vigorously develop the ocean, and they are constantly strengthening the research, development, and utilization of the ocean and have achieved fruitful results. Nowadays, in order to maintain the economic vitality of coastal areas, scientific and technological innovation is closely combined with the economy of coastal areas to fully solve the problem of slow economic development in coastal areas, improve the independent innovation ability of coastal areas, promote the

adjustment and transformation of economic structure, and effectively support the economic growth and sound and rapid development of coastal areas [2].

At present, some progress has been made in the research on the prediction algorithm of regional economic growth. For example, [3] proposed a prediction algorithm of macroeconomic indicators based on correlation analysis. Firstly, a large number of macroeconomic indicators were pre-processed by interpolation and classification methods to obtain time series data with consistent frequency. Then, the correlation analysis was carried out for the pretreated indexes, and the set of associated indexes with the greatest comprehensive influence on the specified target indexes was automatically selected through the index selection mechanism. Finally, the prediction model such as multiple regression analysis and back propagation (BP) neural network is combined to predict the target index, and the contribution degree of each associated index to the target index is calculated. However, the prediction accuracy of this method is low. Reference [4] proposed a GMDH based macroeconomic short-term prediction algorithm. This method compares traditional macroeconomic short-term

forecasting methods. It is usually based on quantitative or qualitative forecasting models. The quantitative features are both qualitative and GMDH algorithms. The hybrid regression mathematical model based on the GMDH forecasting model is used for macroeconomic short-term forecasting. The results are similar to traditional GMDH. The model is consistent. In order to verify the advantages of this algorithm, it is found in the practical application that this method has the problem of long prediction time and has a big gap with the ideal application effect. Reference [5] is put forward based on the optimization of macroeconomic forecasting algorithm of wavelet neural network; wavelet neural network model is adopted to improve the macroeconomic forecasting, used in the process of the intelligent algorithm of wolves to optimize the weights of wavelet neural network model, and adopts the normalization after some provinces economic data for the proposed model of the training. A good model can be used for macroeconomic forecasting to achieve relevant forecast results. However, the prediction accuracy of this method is low, and there is a big gap between it and the ideal application effect. Reference [6] uses data mining technology based on energy minimization technology to complete the logical mining task. These empirical results provide useful insights for decision-making and policy implementation, including the development of strategies to help the industry cope with ongoing price volatility, thus enabling the Malaysian palm oil industry to continue to dominate the international market. In recent years, machine learning algorithms have been successfully used to harness the potential of identifying hidden patterns in financial market behavior, and, as such, it has become a land of opportunity for financial applications such as algorithmic trading. Reference [7] proposed a statistical arbitrage trading strategy, which contained two key elements: a regression algorithm integration for asset return prediction and a dynamic asset selection.

In order to solve the problems existing in the traditional methods, this paper proposes an algorithm for economic growth prediction in coastal areas based on impulse response function.

Our contribution is threefold:

- (1) In order to solve the problems of low accuracy and long prediction time of traditional economic growth prediction algorithms in coastal areas, an algorithm based on impulse response function was designed to analyze economic growth prediction in coastal areas.
- (2) Crawler technology is used to capture the economic data of coastal areas and normalize the captured data. Based on the processed data, the impulse response function is used to analyze the relationship between different economic variables, so as to build the PSO-LSTM model, which is used to predict the economic growth trend of coastal areas.
- (3) The experimental results show that, compared with the experimental comparison algorithm, the prediction accuracy of the algorithm designed in this

paper is always above 97%, and the prediction time is always below 1s, which has certain practical significance.

The remainder of this paper is organized as follows. Section 2 introduces the design of economic growth prediction algorithm in coastal areas. Section 3 discusses experiment and analysis. Section 4 presents the conclusions of the study.

2. Design of Economic Growth Prediction Algorithm in Coastal Areas

2.1. Analysis of Economic Variables Based on Impulse Response Function. Crawler technology is used to capture economic data of coastal areas and process the data. The specific process is shown in Figure 1.

Different features may use different dimensions, so the difference between different eigenvalues may be large. When algorithms such as distance calculation or gradient descent are involved, the prediction effect may be greatly affected if data processing is not performed on them. In order to eliminate the influence caused by different dimensions or different value ranges among features, data should be normalized in advance [8].

By linear transformation of the original data, the deviation normalization maps the data to the interval [0,1]. The calculation formula is as follows:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}. \quad (1)$$

The impulse response function is used to measure the influence trajectory of the impact of a standard deviation of the random disturbance term on the current and future values of other variables, and it can describe the dynamic interaction and effect between variables more intuitively [9]. The impulse response function method based on VAR model is used to study the long-term relationship between economic variables in coastal areas. VAR function is needed to further analyze the impulse response of the system relationship among variables. Through this analysis, it tries to find out the long-term response of various economic variables such as the opening index of producer services trade in the process of economic growth prediction in coastal areas to the pulse disturbance of economic growth in coastal areas and then determine the long-term relationship between all variables [10].

2.1.1. Vector Autoregression Model. The vector autoregression model (VAR) is used to analyze the relationship between economic variables in coastal areas. The general form of VAR(P) is as follows:

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + Bx_t + \varepsilon_t. \quad (2)$$

In the above equation, y_t is a k -dimensional endogenous variable, and x_t is a d -dimensional exogenous variable. A_1, A_2, \dots, A_p and B are the coefficient matrices to be

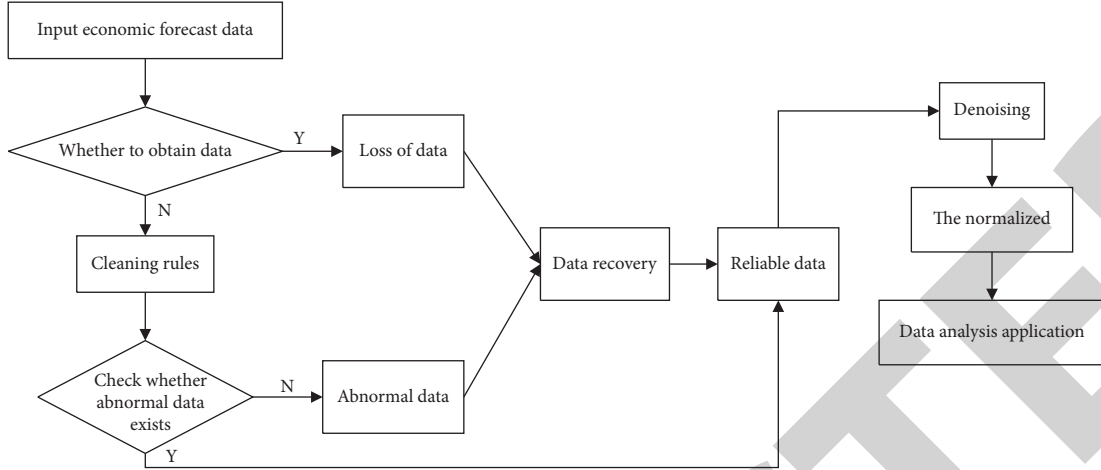


FIGURE 1: Data processing process.

estimated, and ε_t is the disturbance vector, which can be correlated synchronously with each other but not with their own lag values nor with the variables on the right-hand side of the equation [11]. In this way, the OLS method can be used to estimate each equation, and the obtained parameter estimators are consistent.

2.1.2. Impulse Response Function and Prediction Variance Decomposition. On the basis of the vector autoregression model, the model can be further analyzed by using impulse response function and prediction variance decomposition. The impulse response function describes the response of an endogenous variable to the impact of a unit change from another endogenous variable and provides the positive and negative directions, adjustment time delay, stability process, and other information of the response generated by the impact of the system. Cholesky decomposition method proposed by Sims (1980) is the most commonly used method [12]. From the point of view of the problem studied in this paper, the analysis results of impulse response function can describe the dynamic process of economic variable change in coastal areas. Take VAR(2) model as an example to illustrate the basic idea of impulse response function.

$$\begin{cases} x_t = a_1 x_{t-1} + a_2 x_{t-2} + b_1 y_{t-1} + b_2 y_{t-2} + \varepsilon_{1t}, \\ y_t = c_1 x_{t-1} + c_2 x_{t-2} + d_1 y_{t-1} + d_2 y_{t-2} + \varepsilon_{2t}. \end{cases} \quad (3)$$

Assume that the above system is active from $t = 0$. Let $x_1 = x_2 = y_1 = y_2 = 0$, and the disturbance terms $\varepsilon_{10} = 0$ and $\varepsilon_{20} = 0$ in phase 0, and all the others are 0. Then, the perturbation given at the initial stage will be transferred continuously in the system. By iterative calculation, $x_0, x_1, x_2, x_3, \dots, x_n$ can be obtained as the response function of y caused by the impulse of x , and $y_0, y_1, y_2, y_3, \dots, y_n$ can also be obtained as the response function of y caused by the impulse of x . When the pulse of phase 0 is $\varepsilon_{10} = 0$ and $\varepsilon_{20} = 0$, the response functions of x and y caused by the pulse of y can be obtained. The above impulse response process can clearly capture the effects of various factors on economic growth in coastal areas.

2.1.3. Variance Decomposition Theory. Based on the representation form of VMA(∞), Sims proposed a variance decomposition method to quantitatively grasp the influence relationship among economic variables in coastal areas.

$$y_{it} = \sum_{j=1}^k c_{ij}^{(0)} \varepsilon_{jt} + c_{ij}^{(1)} \varepsilon_{jt-1} + c_{ij}^{(2)} \varepsilon_{jt-2} + \dots + c_{ij}^{(n)} \varepsilon_{jt-n}. \quad (4)$$

The sum of the effects of the j -th perturbation ε_j on y_t from infinity to the present is in each bracket. Calculate its variance [13], and assume that sequence ε_t is independent; then

$$E \left[\left(c_{ij}^{(0)} \varepsilon_{jt} + c_{ij}^{(1)} \varepsilon_{jt-1} + c_{ij}^{(2)} \varepsilon_{jt-2} + \dots + c_{ij}^{(n)} \varepsilon_{jt-n} \right)^2 \right] = \sum_{q=0}^{\infty} \left(c_{ij}^{(q)} \right)^2 \delta_{ij}. \quad (5)$$

This is the result that the effect of the j -th disturbance term on the i -th variable from infinity to the present time point is evaluated by variance [14]. In addition, it is assumed that the covariance matrix of the disturbance term vector is a diagonal matrix, and then the variance of y_i is the simple sum of k terms of the above variances:

$$\text{VAR}(y_{it}) = \sum_{j=0}^k \left\{ \sum_{q=0}^{\infty} \left(c_{ij}^{(q)} \right)^2 \delta_{ij} \right\}. \quad (6)$$

The variance of y_i can be decomposed into k uncorrelated influences. Therefore, in order to determine how much influence each disturbance term has on the variance of y_i , the following scale is defined:

$$\text{RVC}_{j \rightarrow i}(\infty) = \frac{\sum_{q=0}^{\infty} \left(c_{ij}^{(q)} \right)^2 \delta_{ij}}{\text{VAR}(y_{it})} = \frac{\sum_{q=0}^{\infty} \left(c_{ij}^{(q)} \right)^2 \delta_{ij}}{\sum_{i=0}^k \left\{ \sum_{q=0}^{\infty} \left(c_{ij}^{(q)} \right)^2 \delta_{ij} \right\}}, \quad (7)$$

where RAC is the contribution of relative variance; that is, the influence of the j -th variable on the i -th variable is observed according to the relative contribution of the j -th

variable based on the variance of impact to the variance of y_i [15]. In fact, it is impossible to evaluate the $c_{ij}^{(q)}$ sum of $s = \infty$. If the model meets the condition of stationary direction, $c_{ij}^{(q)}$ decreases geometrically with the increase of q . Therefore, only a limited number of s terms are needed to complete the analysis of the relationship between various economic variables in coastal areas.

2.2. Prediction Based on the PSO-LSTM Model. Based on the processed data, the relationship between different economic variables was analyzed through the above process, and then the PSO-LSTM model was built to predict the economic growth trend of coastal areas.

Long short-term memory (LSTM) network is a variant of RNN. RNN can only have short-term memory because of the possibility of gradient disappearance. LSTM network solves the problem of gradient disappearance to a certain extent by combining short-term memory and long-term memory through gate control. You can learn to rely on information for a long time. The schematic diagram of LSTM circulation module is shown in Figure 2.

The key to LSTM is the addition of a memory cell inside the hidden layer for storing historical information. In addition, three gates, input gate, forget gate, and output gate are added to each neural unit of the hidden layer in order to update and maintain historical information. The structure of a single LSTM node is shown in Figure 3.

The specific calculation formula for each layer of LSTM is as follows.

The calculation formula of forgetting gate is as follows:

$$f_t = \sigma(W_f * [h_{t-1}, x_t]). \quad (8)$$

The calculation formula of the input gate is as follows:

$$\begin{aligned} i_t &= \sigma(W_i * [h_{t-1}, x_t] + b_i), \\ \tilde{C}_t &= \tanh(W_c * [h_{t-1}, x_t] + b_c). \end{aligned} \quad (9)$$

The calculation formula of update gate is as follows:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t. \quad (10)$$

The calculation formula of the output gate is as follows:

$$\begin{aligned} O_t &= \sigma(W_o * [h_{t-1}, x_t] + b_o), \\ h_t &= o_t * \tanh(C_t). \end{aligned} \quad (11)$$

The performance of the experimental model is closely related to the construction of the training set and test set. Clean and tidy input data, reasonable feature selection, and the most suitable algorithm model ensure that the model can achieve the expected experimental results [16, 17]. The prediction task of the prediction algorithm designed in this paper is a process of supervised learning, so the data is divided into two parts, test set and training set, when using the LSTM model for the prediction experiment. The prediction model in this paper can be simply designed as the structure shown in Figure 4.

Aiming at the problem that the LSTM network model cannot accurately obtain the initial connection weight and

threshold, particle swarm optimization (PSO) is used to optimize the initial connection weight and threshold of the LSTM model, so as to better solve the problem of economic development prediction in coastal areas. The optimal initial weight and threshold obtained by particle swarm optimization algorithm are used to construct the PSO-LSTM model, and the specific model implementation process is shown as follows.

PSO is a swarm intelligence optimization algorithm inspired by bird predation process. In PSO, the potential solution to each optimization problem is treated as a particle, like a bird in a flock of birds. Each particle has a speed that determines its direction and distance, as well as a fitness value, and then all the particles look for the optimal value in the solution space based on the current optimal particle.

Suppose that, in a D -dimensional search space, the number of particles is N , and a particle X_i in the particle swarm can be expressed as

$$X_i = [x_{i1}, x_{i2}, \dots, x_{iN}], \quad i = 1, 2, \dots, N. \quad (12)$$

The velocity of a particle X_i in the particle swarm can be expressed as

$$V_i = [v_{i1}, v_{i2}, \dots, v_{iN}], \quad i = 1, 2, \dots, N. \quad (13)$$

The optimal position found by a single particle is called the individual extreme value, which is represented by P_{best} . The optimal position found by the entire particle swarm is called the global extreme value, which is represented by g_{best} . After that, the particle is updated according to the two following formulas:

$$\begin{aligned} V'_i &= \omega V_i + c_1 * rand(0, 1) * (P_{best} - X_i) \\ &\quad + c_2 * rand(0, 1) * (g_{best} - X_i), \end{aligned} \quad (14)$$

$$X'_i = X_i + V'_i. \quad (15)$$

Among them, c_1 and c_2 represent the learning factor, usually taking $c_1 = c_2 = 2$; ω represents the inertia factor, larger ω means strong global search ability and weak local search ability, and smaller ω means strong local search ability and weak global search ability; $rand(0, 1)$ represents a random number in the range $[0, 1]$.

PSO has fewer parameters to adjust, is easy to realize, and has strong universality by using real number solution. At present, PSO has been widely used in pattern recognition, image processing, neural network training, power system design and decision-making, and scheduling related industries.

Therefore, this paper uses the algorithm to improve the LSTM model built above and then builds the PSO-LSTM model, which is used to forecast the economic development of coastal areas. The PSO-LSTM model's building process is shown in Figure 5.

The steps of economic growth prediction algorithm in coastal areas are shown below.

Step 1. Initialize the LSTM model and determine the model parameters.

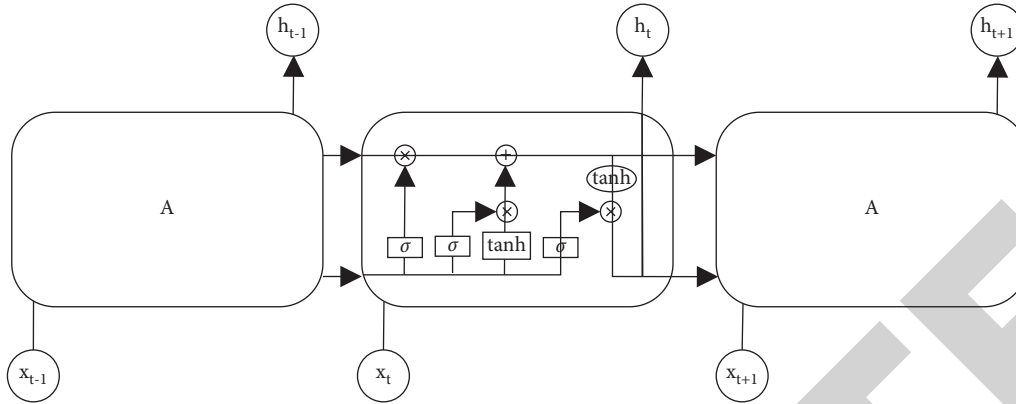


FIGURE 2: Schematic diagram of the LSTM circulation module.

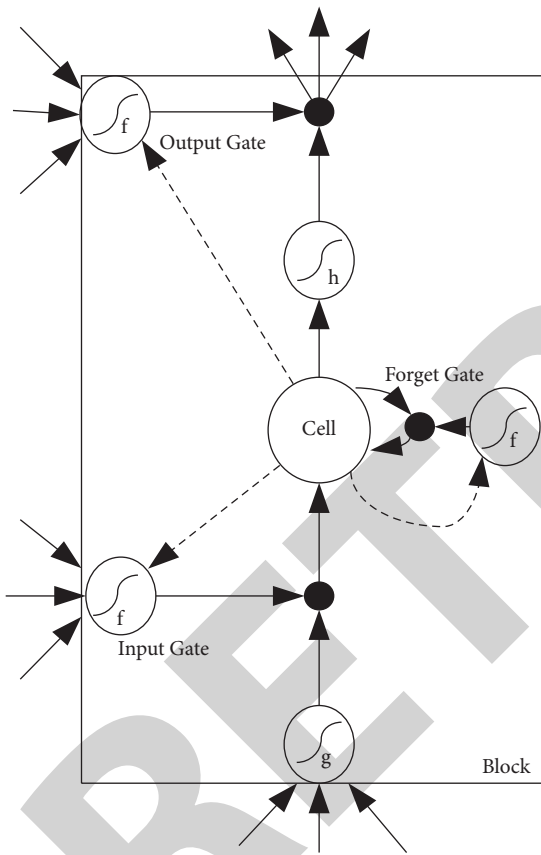


FIGURE 3: Schematic diagram of one LSTM cell node structure.

Step 2. Data processing. In this paper, the maximum-minimum method is used to normalize economic data in coastal areas, so that the range of processed data falls within $[0, 1]$.

Step 3. Initialize PSO parameters.

Step 4. Initialize the velocity and position of the particle.

Step 5. Determine the particle fitness function:

$$f(x_i) = \frac{1}{N} \sum_{j=1}^J (\hat{y}_i^{train} - y_i^{train}), \quad (16)$$

where y_i^{train} and \hat{y}_i^{train} , respectively, represent the expected output and actual output of the training set.

Step 6. Calculate the fitness fit_{x_i} corresponding to each particle X_i and compare fit_{x_i} with individual extreme value P_{best} . If $fit_{x_i} < P_{best}$, replace P_{best} with fit_{x_i} to complete the update of P_{best} .

Step 7. Compare the best fitness (individual extreme) P_{best} of each particle with the global extreme value g_{best} . If $P_{best} < g_{best}$, replace g_{best} with P_{best} to complete the update of g_{best} .

Step 8. Update the velocity and position of the particle; calculate the fitness of the new particle, and find the individual extreme value and global extreme value of the new particle.

Step 9. After satisfying the termination condition of PSO algorithm (usually the maximum number of iterations or the minimum fitness value), the optimal particles are input into the LSTM model as its initial weight and threshold, and the PSO-LSTM model is trained.

Step 10. Use the trained model to forecast economic growth in coastal areas and get accurate prediction results.

3. Experimental Design and Result Analysis

3.1. Experimental Scheme Design. In order to test the practical application effect of the prediction algorithm of economic growth in coastal areas based on impulse response function, the experimental design is carried out. The specific experimental environment is shown in Table 1.

The data used this time came from a coastal area, and the data set was from the data released on the official website of the National Bureau of Statistics. The collected data were cleaned and repaired, so as to improve the scientificity and accuracy of the simulation experiment results. The data

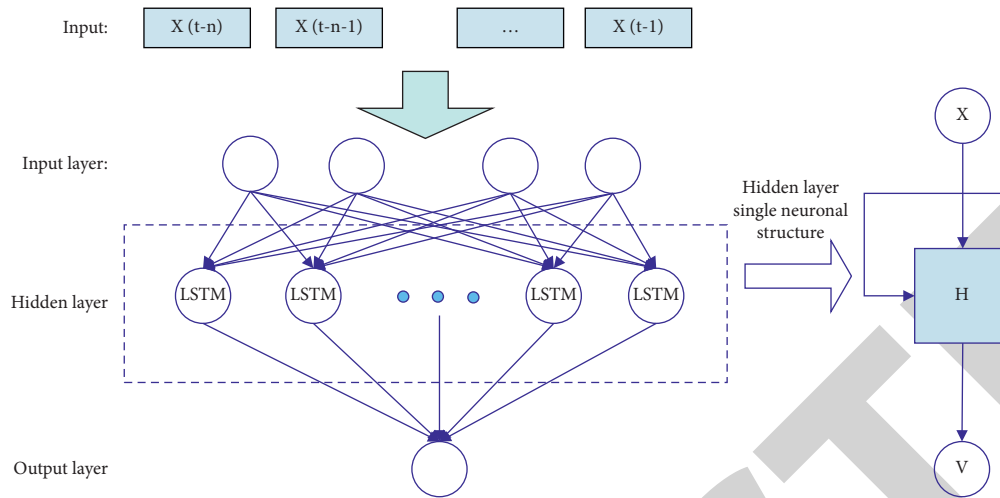


FIGURE 4: Structure of the prediction model.

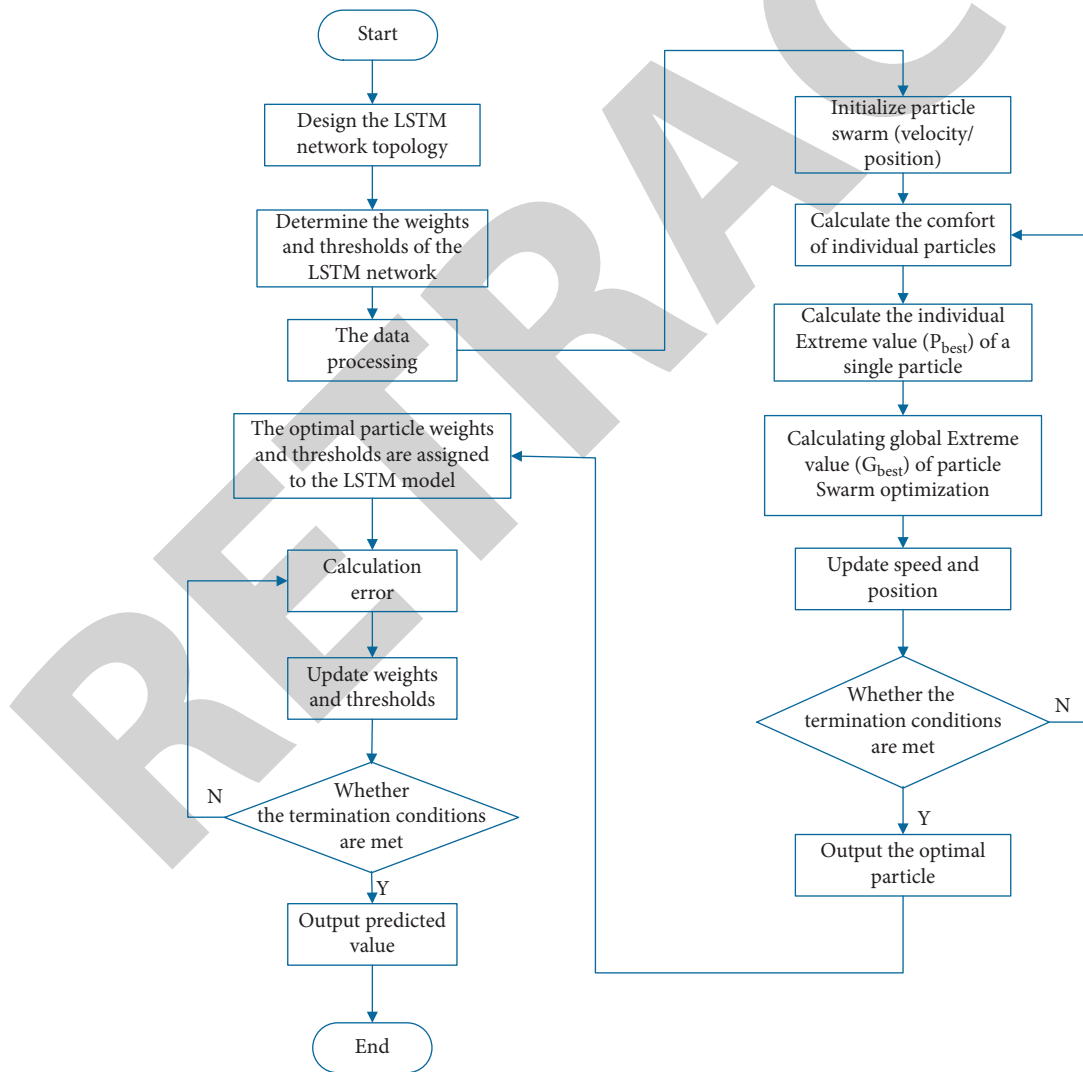


FIGURE 5: PSO-LSTM model's building process.

TABLE 1: Experimental environment.

Operating system	Windows 10 64-bit
Database	MySQL-5.6.25
JDK	JDK 1.8.0-71
Server	Tomcat-8.0.23
Development of language	Java
Browser	Google Chrome
Simulation software	MATLAB 7.2

included historical data on 39 economic indicators from January 2010 to October 2020. Among them, the time unit of indicators such as business climate index, entrepreneur confidence index, and national tax revenue is quarterly, while the time unit of other indicators is monthly. Introduction of economic forecast data set is shown in Table 2.

3.2. Analysis of Impulse Response Function. The impulse response function method based on VAR model is used to study the long-term relationship between variables, and the impact response path between the import and export of service trade and economic growth is obtained. Impulse response can reflect the process of how an endogenous variable influences other variables through the model when it changes and finally returns to itself. The impulse response is analyzed using Eviews 7.0, and the results are shown in Figure 6.

As can be seen from Figure 6, GDP growth rate has a certain volatility to its own standard deviation disturbance, showing a weak negative effect in the third, sixth, seventh, and ninth periods, but the cumulative impact is 0.080346, showing a positive effect. The disturbance of GDP growth rate to the standard deviation of the growth rate of service trade export also has certain fluctuation, but the overall effect is positive. The cumulative effect is 0.051226, indicating that the growth rate of service trade export has a positive effect on economic growth in the long run. The response of GDP growth rate to the disturbance of standard deviation of the growth rate of service trade import fluctuates greatly, and the positive effect and negative effect appear alternately. The cumulative effect is 0.0207, indicating that the growth rate of service trade import has a weak negative effect on economic growth in the long run. In general, the impact of the growth rate of service trade import and export on economic growth showed a gradually decreasing trend. The response of service trade exports to one standard deviation's information is shown in Figure 7.

As can be seen from Figure 7, the impact of export growth rate of service trade on its own standard deviation shows a highly positive effect in the first period, and no significant effect is shown in the subsequent periods, but its cumulative effect is 0.090504, showing a highly positive effect. The impact response of service trade export growth rate on GDP growth rate is positive in the first period, and it becomes weakly negative in the subsequent periods. The cumulative effect is 0.029412, indicating that economic growth has a weak inhibition on the increase of service trade export growth rate. The impact response of service trade import growth rate to export growth rate is 0 in the initial

TABLE 2: Introduction of economic forecast data set.

Index name	The dimension	Number of training samples	Number of test samples
GDP	20	111 + 19	111 + 19
CPI	20	111 + 19	111 + 19

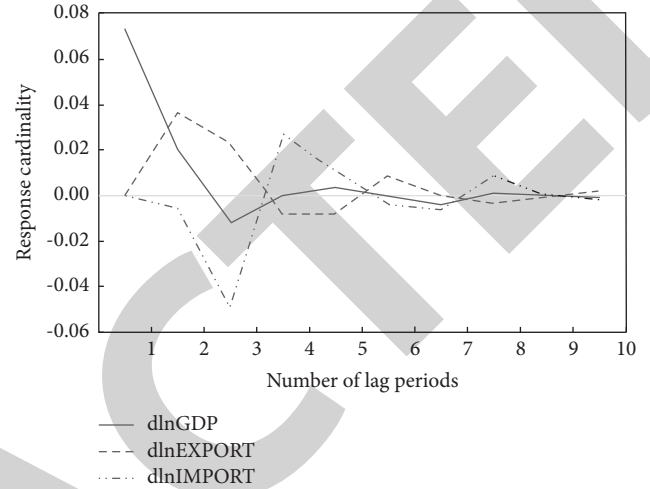


FIGURE 6: The influence of economic growth on information of one standard deviation.

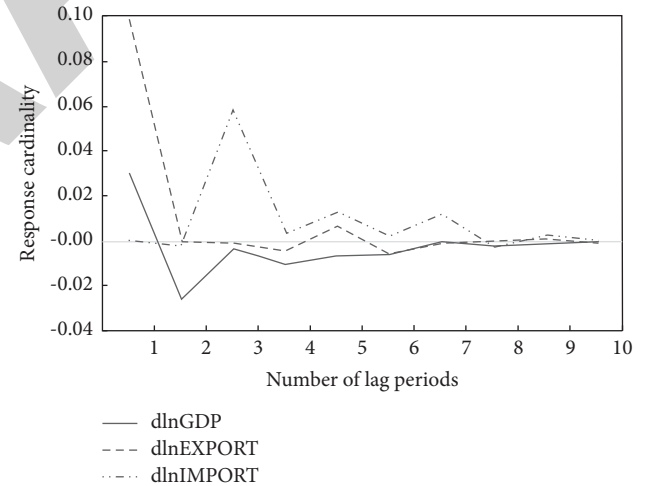


FIGURE 7: The response of service trade exports to one standard deviation's information.

stage, and it fluctuates below the horizontal axis in the second and eighth stages, which is a weakly negative effect, and its cumulative effect is 0.0854105, which is generally positive. Its economic meaning is that the growth rate of service trade import will promote the growth rate of export on the whole. Response results of service trade import standard information are shown in Figure 8.

The impact response of the import growth rate of service trade to its own standard deviation has a certain volatility. In the first period, it shows a highly positive effect and then a little fluctuation, but the overall performance is a highly positive effect. The impact response of economic growth rate

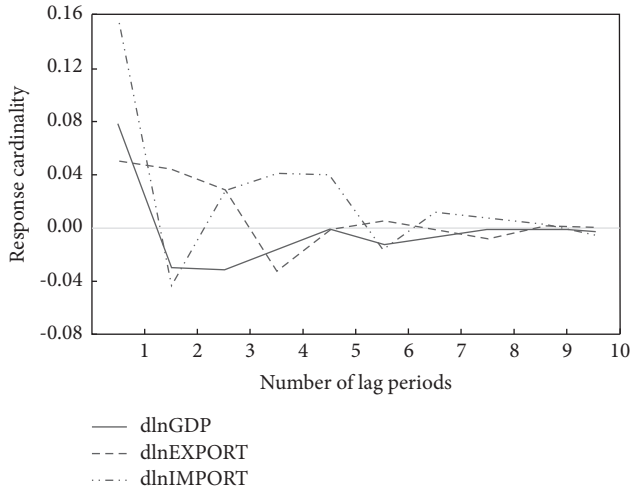


FIGURE 8: Response results of service trade import standard information.

to the standard deviation of service trade import growth rate shows a highly positive effect in the first period and starts to decline in the second period and continues to be negative. Its economic meaning is the impact of the economic growth rate of service trade import growth rate; there is a lag in the initial phase which will promote the increase of the import growth rate; later, its inhibition effect will gradually appear, showing that the service trade export growth to the impact of the import growth rate also has a certain volatility, and the basic trend of positive and negative effects appears alternately. The cumulative effect is 0.089771, which is a positive effect.

3.3. Analysis of Experimental Comparison Results. The prediction algorithm based on correlation analysis, the prediction algorithm based on GMDH, and the prediction algorithm based on impulse response function designed in this paper are taken as the experimental comparison method. The prediction accuracies of different algorithms are compared to verify the prediction effect of this algorithm. The specific comparison results are shown in Figure 9.

Through the analysis of the results in Figure 9, it can be seen that the prediction accuracy of the prediction algorithm based on correlation analysis varies between 55% and 84%, and that of the prediction algorithm based on GMDH varies between 62% and 87%. Compared with the two algorithms, the prediction accuracy of the prediction algorithm based on impulse response function designed in this paper is always above 97%. It shows that this method can be used to accurately predict the economic growth in coastal areas, and the practical application effect is better.

The prediction algorithm based on correlation analysis, the prediction algorithm based on GMDH, and the prediction algorithm based on impulse response function designed in this paper are taken as the experimental comparison method. The prediction efficiency of the algorithm is verified by comparing the prediction times of different algorithms. The specific comparison results are shown in Figure 10.

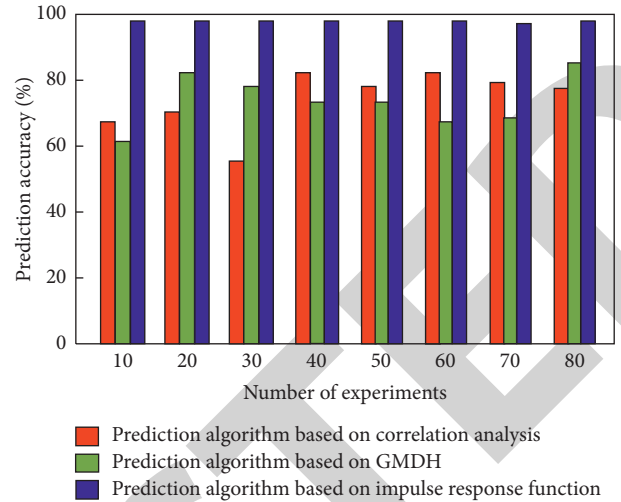


FIGURE 9: Comparison results of prediction accuracy.

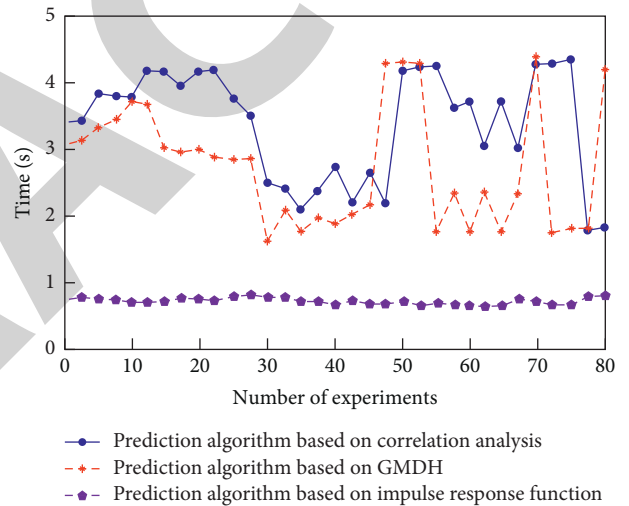


FIGURE 10: Prediction time comparison results.

From the analysis of the data in Figure 10, it can be seen that the prediction time of the prediction algorithm based on correlation analysis varies between 1.7 s and 4.3 s, and that of the prediction algorithm based on GMDH varies between 1.6 s and 4.2 s. Compared with the two algorithms, the prediction time of the prediction algorithm based on impulse response function designed in this paper always stays below 1 s. It is shown that this method can realize the rapid forecast of economic growth in coastal areas, with higher prediction efficiency and better practical application effect.

4. Conclusion

Technological progress and innovation are the key to promoting the rapid implementation of the coastal area economic development strategy. Therefore, effective implementation of the coastal area economic development strategy is conducive to the development of circular economy outside the region, creating new economic development strategic points and encouraging coastal areas to get

rid of traditional development paths. Relying on this, we foster new industrial growth points for regional development. It is of great practical significance to promote the coordinated development of regional economy, enhance the overall competitiveness, and then drive the structural adjustment and industrial upgrading for the comprehensive development of the economic society in coastal areas. Therefore, this paper puts forward a prediction algorithm of economic growth in coastal areas based on impulse response function. The experimental results show that the impact of the growth rate of import and export of service trade on economic growth shows a gradually decreasing trend, which will promote the growth rate of export on the whole, and the impact of economic growth on the growth of service trade imports shows an alternating trend of positive and negative effects, which is a positive effect. Moreover, compared with the experimental comparison algorithm, the prediction accuracy of the algorithm designed in this paper is always above 97%, and the prediction time is always below 1 s, which can fully solve the problems existing in the traditional method and has a certain practical significance.

Data Availability

The 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.

Acknowledgments

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