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Retraction

Retracted: Economic Forecasting Model Based on Chaos Simulated Annealing Neural Network

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets 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 own 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. Zhang and Y. Mu, "Economic Forecasting Model Based on Chaos Simulated Annealing Neural Network," *Mathematical Problems in Engineering*, vol. 2022, Article ID 9005833, 10 pages, 2022.

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Research Article

Economic Forecasting Model Based on Chaos Simulated Annealing Neural Network

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In view of the prototype of the traditional chaotic network model, a neural network model with continuously updated chaotic noise is innovatively improved. This model has the advantages of two network models. On this basis, a logic graph is proposed, which can replace the chaotic noise generated by the running process of the model function. Models with these advantages can innovatively solve problems such as constrained optimization with dimensions larger than three, high discreteness, and weak linear relationship between convex and concave. Simulation results can be confirmed that the algorithm of this model is very close to the predicted value. This neural network model is an improved model with strong applicability and can be applied to optimization problems of economic systems or other industrial systems. In order to effectively alleviate the predictive control problem of nonlinear research objects, we propose a control method based on chaotic neural network in this study. Taking the economic model as the nonlinear object, establishing the basic structure of the chaotic neural network model, reconstructing the time and space structure, and obtaining the optimal solution of time continuation and embedding dimension through information entropy and pseudonearest neighbor, then the chaotic properties of nonlinear objects and the topology of chaotic neural networks are determined. In the simulation, test samples and experimental samples are established, and the predicted and true values are compared. The prediction results of the model established by this method in this study prove the effectiveness of the method. The training time of the chaotic neural network will not fall into a local minimum, thereby reducing the training time and ensuring the accuracy of the prediction.

1. Introduction

As an intelligent information processing system, chaotic neural network is considered to be able to realize real-world computing and is widely used in the research of high-dimensional nonlinear system dynamics. With the development of technology and economy, the role of applied forecasting theories and methods has become increasingly prominent in the study of social and economic issues [1]. Traditional prediction has great limitations in dealing with complex nonlinear problems and is not enough to deal with complex natural and social phenomena. Since chaos theory is mainly used to solve and deal with nonlinear dynamic problems, and neural network also has unique and significant advantages in dealing with nonlinear problems, the combination of chaos theory and neural network is an effective method to analyze complex systems in the real world [2]. The state of social and economic development has also become the focus of attention in people's daily life. Economic growth leads to increased demand, and in order to maintain balance between market demand and supply, supply also needs to increase. Therefore, the production will increase, and capital and labor must be invested to increase production. The level of economic strength of the country is largely reflected in its various economic indicators. In order to formulate effective implementation policies and plans, the government and related research institutions must make accurate forecasts of the future macroeconomic trends of a country or region and then decide whether to stimulate or suppress the economic scale according to the forecast results

[3]. However, the future macroeconomic trend is affected by many factors in its internal and surrounding environment (the relationship between various factors is complex), and it is a nonlinear complex system that changes in real time. Traditional time-series analysis has problems such as multicollinearity and error series correlation in economic forecasting, which makes the forecasting accuracy unsatisfactory [4]. However, compared with traditional prediction methods, as a nonlinear and nonconvex linear complex network system, artificial neural network has parallel distributed information processing structure and adaptive information processing capability, which can effectively deal with high-complexity nonlinear network systems. For example, some studies used artificial neural networks to predict the economic impact of multihazard hurricane events [5]. Other studies use the BP algorithm to establish and train an artificial neural network economic forecasting model and forecast GDP. The model has strong generality and practicability, but the prediction accuracy is still unsatisfactory [6–9].

Therefore, this study proposes a macroeconomic forecasting method based on chaotic simulated annealing neural network. This method combines the chaos model on the basis of artificial neural network theory to realize the forecasting of macro-GDP economic forecast. At the same time, in order to obtain the best global optimal result, the chaotic annealing algorithm is used to optimize the weights of the model. The experimental results verify the feasibility and accuracy of the proposed prediction model [10, 11]. The chaotic simulated annealing neural network has richer chaotic dynamic characteristics and global search performance and can more accurately solve function optimization and TSP problems. At the same time, because the excitation function is more in line with the biological mechanism of real neurons, it can represent the frequency-amplitude relationship between neuron excitation and response and fully reflects the nonlinear dynamic characteristics of complex and variable brain activities, as shown in Figure 1 (the proportion of economic losses over the years) [12]. On the basis of the traditional Hopfield neural network (HNN), a self-feedback term with the characteristics of chaotic simulated annealing that decays with time is added to make it generate chaotic motion, so as to use the ergodicity and pseudorandomness of chaos for global optimization search. Therefore, the change of the chaotic characteristics in the chaotic simulated annealing neural network depends on the decay process of the self-feedback term [13]. The change of the self-feedback term is controlled by the self-feedback connection weight, and the annealing function determines the decay speed of the connection weight, which directly affects the accuracy of the global chaotic search in the early stage and the convergence speed in the later stage [14]. Therefore, the model method of using chaotic simulated annealing neural network in the process of economic forecasting can well avoid the model defects of the traditional network. In the prediction structure, the larger the sample size, the higher the accuracy of the prediction. Due to the lack of data, in the long-term forecast, and due to the changes in the forecast,

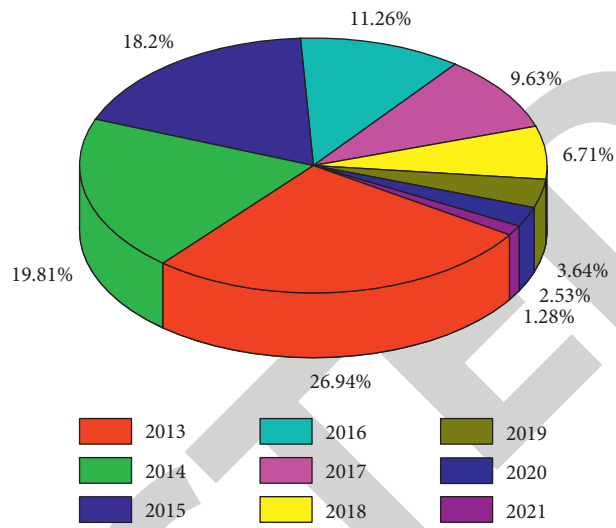

Figure 1: Percentage of economic losses over the years.

managers can take corresponding measures to avoid the appearance of anomalies, and the answers obtained are not necessarily accurate. There are many factors to consider when taking measures based on predicted data, and actual survey results are often more accurate than speculation based solely on data. In this study, a new chaotic network model is adopted to improve the deficiency of chaotic noise. This model can solve the constrained optimization problem with size greater than 3, the high discreteness problem, and the weak linear relationship between convex and concave problems. This is the biggest contribution and innovation of this model.

2. Macroeconomic Indicator Selection

This study shows three different indicators, which are GDP, GPI, and market economy. In macroeconomic economics, GDP and GPI are commonly used to measure the the comprehensive level of economic development of a country or region. Market economy, which is the most efficient and dynamic carrier of economic operation, refers to the economic form of allocating social resources through the market. In terms of the selection of predictive indicators of the model, most of the existing literature has the phenomenon that the selection of indicators is separated from the macroeconomic theory, which may lead to the problem of missing important indicators. At the same time, because China's economic growth has clear national characteristics, especially structural characteristics, it is quite different from other countries such as Europe and the United States [15]. If the characteristics of China's economy are ignored in the process of indicator selection, it will easily lead to an increase in GDP forecast errors. In view of this, this study makes two improvements on the basis of the existing research. First, a benchmark index system is constructed based on the chaotic annealing prediction model. Second, include expanded indicators that reflect China's national conditions to establish a scientific and reasonable macroeconomic indicator system to more accurately predict *GDP*.

Figure 2 shows that referring to the practice of existing articles, this study selects the following specific indicators [16]. (1) Quarterly real GDP growth rate is used to measure the growth rate of total output (Y) and is the core indicator of macroeconomic forecasting. (2) Quarterly industrial added value year-on-year growth rate (IVA) reflects the value of activities generated by various enterprises in the country at a certain point in time and reflects the contribution of production units or sectors to GDP, which is the GDP commonly used supplementary indicators [17]. (3) Quarterly actual growth rate of total retail sales of consumer goods (C) can reflect domestic consumption and play an important guiding role in judging the current macroeconomic development and future economic trends. (4) Quarterly actual fixed asset investment growth rate (I) chooses this index as the investment index because fixed asset investment is the most important part of investment, and it is an important basis for monitoring macroeconomic trends and macrocontrol. (5) The real interest rate of loans (r) reflects the indirect financing cost actually faced by the enterprise. At the same time, based on the availability of data, this study uses this index as the interest rate index of the model. (6) The current year-on-year growth rate (G) of quarterly general public budget expenditures is a more commonly used indicator of government purchases. (7) Quarterly nonfinancial sector leverage ratio (DEBT) reflects the debt burden in a certain period and will have an important impact on the level of economic output. This study uses this indicator as the current year-on-year growth rate of quarterly general public budget expenditure (G) supplementary indicator. (8) The year-on-year growth rate of export value in the quarter can better measure the degree of market openness. When the indicator increases, the export growth rate accelerates, indicating that the economic operation is under good condition. On the contrary, if the indicator decreases, the export growth rate decreases, indicating that the macroeconomy is sluggish and the growth rate slows down. (9) Consumer price index (CPI) is used in this study to measure the level of inflation. (10) Quarterly M_2 YoY growth rate (M_2) is a commonly used indicator of changes in the money supply [18, 19].

3. Establishment and Validation of the Model

3.1. Introduction to the Chaos Neural Network Model. There are two main types of chaotic neural network models: (1) a chaotic neuron model proposed by Aihara et al. on the basis of previous derivations and experiments; (2) a coupled chaotic oscillator proposed by Inoue et al. chaotic neural network model. Some scholars have carried out a lot of research work on the former model and proposed many improved models and algorithms. For example, Chen and Aihara proposed a transient chaotic neural network model. It introduces a self-feedback connection weight on the basis of chaotic neural network as a fractal parameter of network dynamics to control the convergence of the network, but to ensure the convergence of TCNN, many parameters need to be selected. Wang and Smith proposed a chaotic simulated annealing model with a decaying time step. The number of parameters to be selected for this model has been significantly reduced. Hayakawa et al. proposed a discrete continuous HNN model with chaotic noise and pointed out that it is more effective to add HNN to the chaotic time series correlated in a short time to find the global optimum [20].

Traditional simulated annealing algorithms usually set the initial temperature to a high value in order to adequately perform a random search of the solution space. As a module of data mining, the chaos neural network model can be used as a separate tool to discover some deep information distributed in the database and summarize the characteristics of each category. This approach will result in redundant iterations at high temperatures, which in turn reduces the efficiency of the algorithm. Therefore, the initial temperature T_0 needs to be set according to the Boolean function design. This study uses the chaos principle to set the initial temperature. For a Hopfield neural network, the key is to determine its weight coefficient under stable conditions. The probability of accepting a poor solution is P_0, and the following formula can be obtained [21]:

$$P_o = e^{Nf(f_o) - Nf(f_n)/T_o}. \tag{1}$$

Taking the logarithm of both sides, you can get a further calculation formula:

$$T_o = \frac{Nf(f_o) - Nf(f_n)}{\ln P_o}. \tag{2}$$

According to the chaos principle, N possible solutions are firstly searched, and the maximum and minimum values of the objective function values corresponding to these N possible solutions are recorded. The formula for calculating the initial temperature is [22]

$$T_o = \frac{\triangle C}{\ln P_o}. \tag{3}$$

3.2. Perturbation Strategy of the Algorithm. When the traditional simulated annealing algorithm searches for the optimal solution, due to the setting of the perturbation rule, the perturbed solution can only be compared with its adjacent solutions, which is easy to fall into the local optimal solution. Therefore, in order to prevent the above phenomenon from happening, this study improves the mutation strategy in the genetic algorithm according to the characteristics of the balanced Boolean function and applies it to the perturbation scheme in simulated annealing. The search space of the scheme in this study is a balanced Boolean function with high nonlinearity and low autocorrelation, so the following strategies are needed to ensure that the Boolean function after disturbance is still balanced: define a balanced Boolean function, and let a be the Boolean number of times that the true value of the function is exchanged; then, the value of $f(x_1)$ and the value of hair $f(x_2)$ are exchanged, and the number of exchanges is increased by 1; repeat the above exchange steps until the exchange.

When the number of changes is equal to, the perturbation ends.

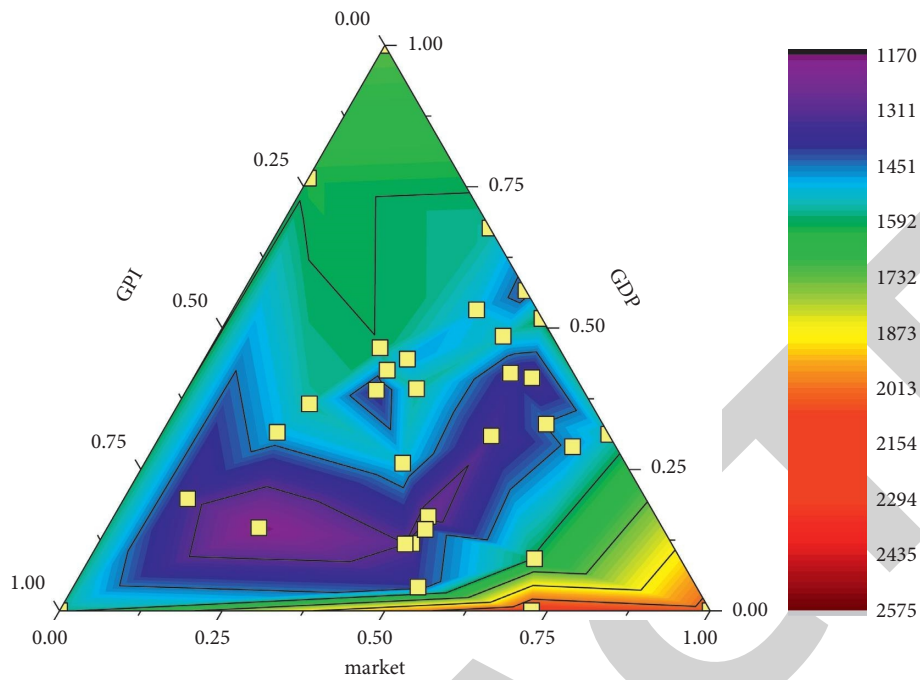

Figure 2: The influence of the changes of the three indicators with the number of industries.

As shown in Figure 3, the value of training error α is adaptively selected: the initial search should be carried out within a larger solution space so that more choices can be made, so the value at this time should be larger; when the algorithm search is carried out to a certain extent. The searched solution has gradually moved closer to the global optimal solution, and the search should be carried out in a small range of the neighborhood of the optimal solution, so the value of α should be small at this time. Therefore, the value of α is related to the current number of iterations, and the formula is [23]

$$\alpha = 1 - \left[\frac{k-1}{k}\right]^m, \tag{4}$$

where m is an integer and k is the current iteration number.

In this study, the idea of particles moving towards the current global best solution in swarm intelligence is combined with the simulated annealing algorithm, and a new learning strategy is proposed. The improved learning strategy is judging that if the solution is not accepted for a period of time during the search process, or a good solution is not generated, the best solution searched by the current algorithm is set as the initial solution of the next iteration. Make the next iteration continue with perturbation starting from the current best solution [24, 25].

3.3. Control Model for Discrete Nonlinear Dynamical Systems. We have the following discrete nonlinear dynamic system:

$$X_{t+1} = f(X_t, \mu). \tag{5}$$

where x represents the system state at time t, f represents the mapping transformation from R to itself, which is nonlinear,

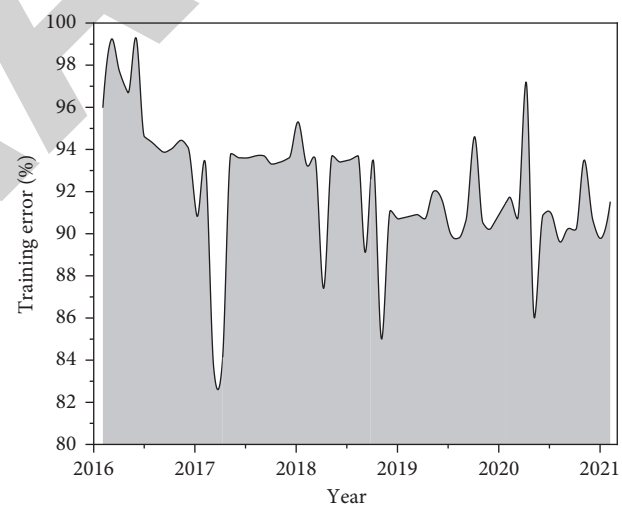

Figure 3: Training error correlation coefficient plot.

and $p \in R$ is the system parameter. So, the formula can be written in the following equivalent form [26]:

$$X_{t+1} - X_t = f(X_t, \mu) - X_t. \tag{6}$$

In this theory, the introduction of the control factor θ will show in regulating the stability of the equilibrium solution of the θ dynamic system. For purposes, we call θ the control stiffness.

The algorithm has clear ideas, simple principles, flexible use, and strong "robustness." The algorithm has asymptotic convergence, and its convergence to the optimal solution set is random. The slow decrease of the parameter (temperature) occurs asymptotically. Below, we give the algorithm steps of

this iterative method to determine the value of the control parameter θ in the system:

(1) The initial state of the system is given, the initial control parameter is simulated annealing initial temperature $T(0) = T$, the random iteration times P value of the optimal parameter 0 is searched, and $t = 0$.

(2) Automatically generate a satisfactory control parameter $\theta_0(t)$ according to the following process:

(i) If the number of iterations is less than P, turn to 2, otherwise turn to 3

(ii) Randomly generate a new day (t) in the (0,1) interval and then calculate the state deviation $X(t)$ of the controlled system

(iii) Accept or reject the judgment of the current control parameter Min(t); if $X(t) \geq 0$, accept θ.

In the above control algorithm, the equilibrium position of the system is generally not known in advance. Therefore, to judge the pros and cons of the control parameters, the relative errors of the adjacent two iterations can be compared. According to the above algorithm steps, the author wrote corresponding programs to simulate several chaotic systems. The results of the simulation experiments show that the control effect is very precise in the system.

4. Optimization Algorithm for Simulated Annealing Strategy

In order to better understand the operation mechanism of the chaotic neural network model with inverse trigonometric functions, now take a single neuron as an example to examine the dynamic behavior of the network [27]:

$$x(t) = \frac{1}{1 + e^{-y(t)/\varepsilon}}. \tag{7}$$

Next, we analyze the dynamic characteristics of the model through the inverted bifurcation diagram of neurons and the time evolution diagram of the maximum Lyapunov exponent. Take $\varepsilon = 1.02$, $y(1) = 0.557$, $t(1) = 0.5$, $c = 0.9$, $k = 0.9$, $I = 0.65$, and $\beta = 0.05$. The inverted bifurcation diagram and the maximum exponent diagram of the neuron in this environment are shown in Figure 4.

In Figure 4, as the parameter β increases, the chaotic dynamic characteristics of the network output $x(t)$ disappear faster; because the self-feedback connection weight $z(t)$ decays exponentially, it tends to 0. The convergence speed of is also accelerated with the increase of the parameter β.

From the analysis of the inverted bifurcation diagram and the maximum Lyapunov exponent spectrum above, the chaotic dynamic characteristics of the network are sensitively dependent on the self-feedback connection weight $z(t)$. The decreasing speed of $z(t)$ directly affects two important indicators for judging the optimization algorithm: accuracy and speed. As shown in Figure 5, we can see that, in the Fourier transient chaotic neural network model, with the decrease of the self-feedback connection term z, the influence of z on the network becomes smaller and smaller, and

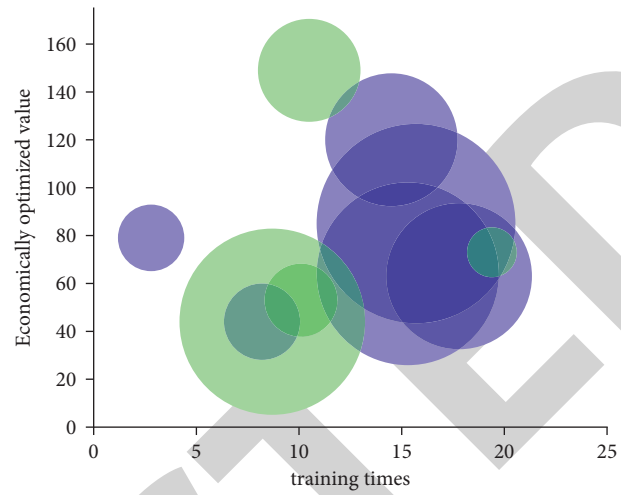

Figure 4: Schematic diagram of the training error circle.

the network gradually tends to a stable equilibrium point. This transition process is manifested in which the single neuron of the network is an inverted bifurcation process. Chaos is shown in the first half; when z drops to a certain level, the chaos disappears and turns to the convergence stage. When z drops very fast, it will directly enter the convergence process through a short search stage, so the speed of the algorithm is very fast. However, because the rich dynamic characteristics of chaos are not fully utilized, it is easy to fall into the local minimum value, and the accuracy is greatly reduced. Conversely, if the change in $z(t)$ is small, the accuracy can be improved at the expense of optimization speed [28, 29].

Through using the characteristics of chaotic dynamic search without affecting the convergence speed of the network, as shown in Figure 6, the idea of piecewise exponential simulated annealing strategy will be used to improve the chaotic neural network model with inverse trigonometric function. Usually, the bifurcation point at which the simulated annealing algorithm transfers from the search stage to the convergence stage is relatively stable, basically located near $z/2$. Therefore, this study replaces the formula in the original network model with the following piecewise exponential simulated annealing function [30]:

$$z_i(t+1) = (1 - \beta_1) z_i(t). \tag{8}$$

The value of $z(t)$ is large at the beginning, and the value of parameter β is small to take full advantage of the rich dynamic search characteristics of chaos. This enables the network output value to be traversed and searched in a large range. In this way, the algorithm can avoid falling into the defect of the local optimal value and obtain the global optimal solution. As the value of $z(t)$ decreases, the network output gradually converges to the bifurcation point, so a relatively large exponential decay can be used to reduce the convergence time. Through the above analysis, if the piecewise exponential annealing function is added to the chaotic neural network model with inverse trigonometric function. When $z(t) > z/2$, a relatively small exponential decay is used. Through this method, we can effectively use

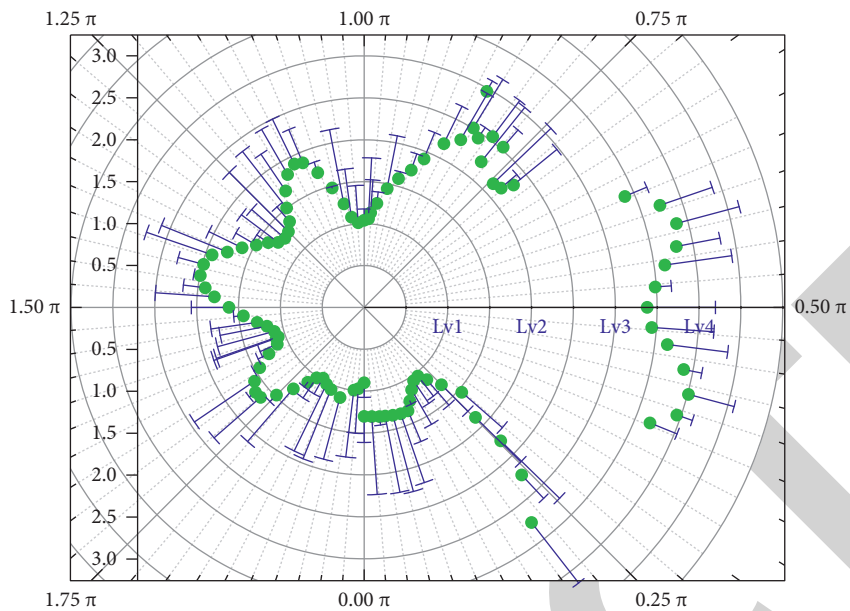

Figure 5: Comparison of experimental results of CPI prediction.

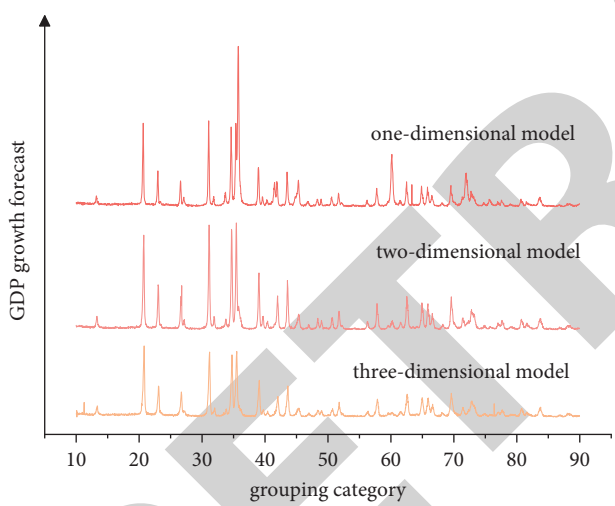

Figure 6: Prediction results of three models.

the chaotic dynamic motion to search so that the network will not fall into the trap of local optimization, which increases the possibility of obtaining the overall optimal solution of the combinatorial optimization problem in the model. In the convergence stage, a relatively large exponential decay is used to overcome the speed problem caused by the small exponential decay and reduce the convergence time. Therefore, based on this, a Fourier transient chaotic neural network based on piecewise exponential annealing is proposed.

5. Chaos Annealing Neural Network Modeling

Economic time-series data are affected by various factors such as various industries, has an obvious upward or downward trend, and presents the characteristics of nonlinear changes. Before establishing a forecast model, as shown in Figure 7, it needs to be stabilized to change linear data. Assuming that the economic time series is y_t, there is the following formula:

$$\ln y_t = a + bt. \tag{9}$$

The economic time-series data after preprocessing are

$$y_t' = \ln y_t - (a + bt). \tag{10}$$

The smoothed data are used to lay the foundation for subsequent analysis. Due to the chaotic nature of economic time-series data, the analysis of its chaotic nature and the reconstruction of phase space will reveal the hidden change laws of economic time-series data. Let the collected inter-economic series be $x(t)$, where $t = 0,1,2,\ldots,n$ reconstruct the economic time series with chaotic characteristics into the following formula:

$$X_t = (a_t, a_t + m, \ldots a_t + (n-1)m)^T, \tag{11}$$

where m is the delay time and n is the embedding dimension.

According to Takens theorem, as long as a reasonable delay time t and embedding dimension n are selected, this chaotic characteristics hidden in the economic time series can be accurately mined. Using the concept of information entropy, the correlation of 2 variables is calculated to determine the delay time τ. First, define two time series, $X \sim x(t)$ and $Q \sim x(t+m)$, that is, the delay time of the time series is t. Then, the corresponding average information components are obtained as

$$H(X) = -\sum_{i=1}^{n} \mathrm{PLX}(x_i)\log_2 P_X(x_i). \tag{12}$$

Figure 8 shows GDP out-of-sample prediction results of the chaotic annealing neural network model. For a

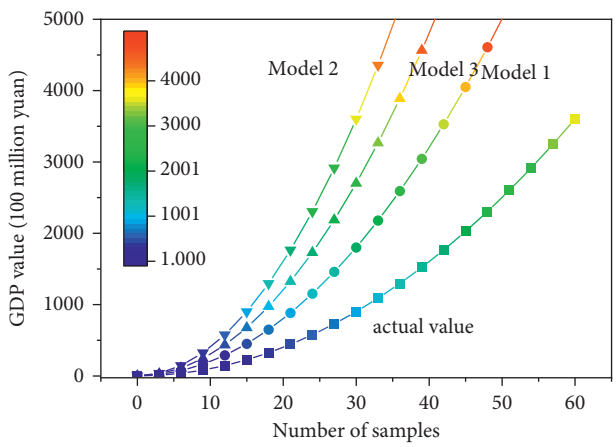

Figure 7: Three models and real GDP calculations.

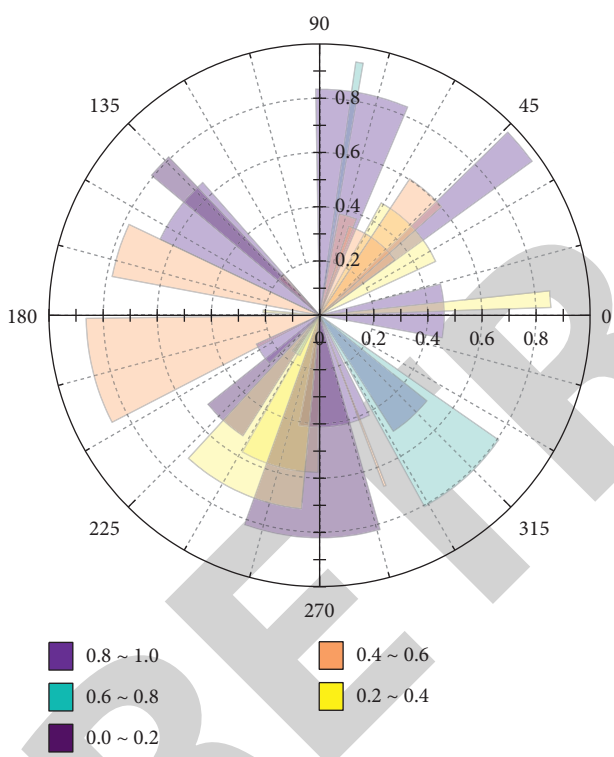

Figure 8: GDP out-of-sample prediction results of the chaotic annealing neural network model.

specific time series, it can be transformed into an m-dimensional phase space. The saturation dimension is large enough to describe the original system more clearly. The pseudonearest neighbor method is used to complete the establishment of the saturation embedding dimension m.

Considering the problem of optimizing the neural network, the traversal search mechanism of the chaotic neural network is used so that the data will not take the local minimum value during the training process. As shown in Figure 9, according to the topology of the model, the following model is studied:

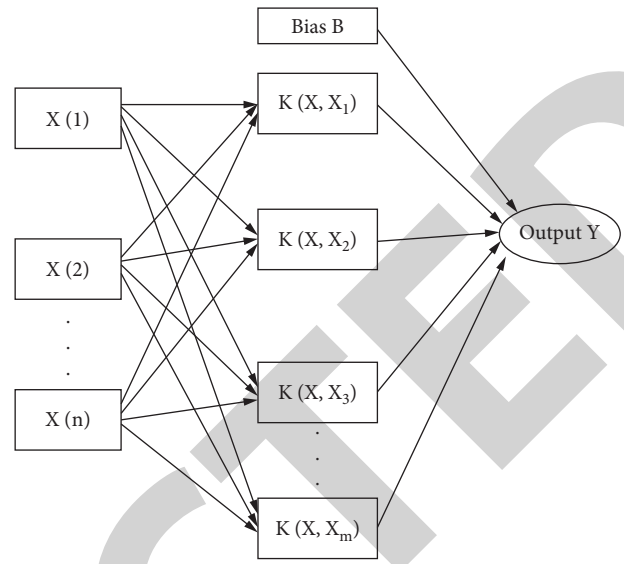

Figure 9: Structural diagram of support vector machine.

$$x_a(m) = f(y_a(m)), \quad = \frac{2}{1 + e^{-y(t)/\varepsilon}}. \tag{13}$$

Among them, the above formula is the Sigmoid excitation function (activation function), x is the neuron of the ith output, ε is the steepness parameter in this formula, and $z(t)$ represents the connection weight of the self-feedback term.

Based on the traversal search mechanism of the transient chaotic neural network, the search is realized by the exponential decreasing method of the self-feedback connection item. The simulated annealing parameter determines the length of the search time. The larger the parameter value, the shorter the annealing time, that is, the shorter the transient chaos search time, the shorter the network training time. However, the short training time of the neural network can easily make the network calculation fall into a minimum point. Similarly, when the value of the annealing parameter is smaller, the transient chaos search time is long, which can prevent the network training calculation from falling into the minimum point.

6. Analysis and Discussion

Based on the original chaotic neural network model, this study innovates a chaotic simulated annealing neural network model to gradually reduce the noise generated in the chaotic process and applies the model to the problem of economic forecasting to establish an economic forecasting model. In this study, the validity and feasibility of the model can be further verified through three examples. The following related issues are our main focus in this study (Figure 10):

(1) The mechanism of introducing chaos in the chaotic simulated annealing neural network model is

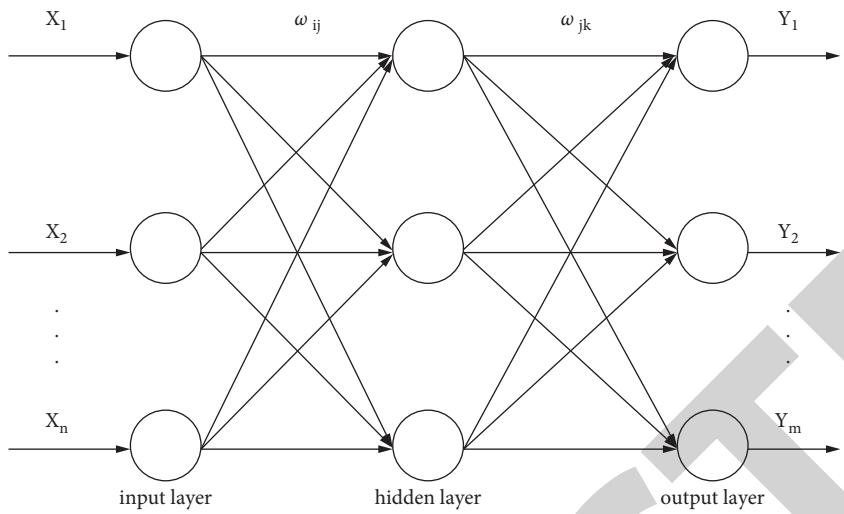

Figure 10: Chaos annealing neural network topology diagram.

different from that in the neural network model. For example, the chaotic simulation model generates chaotic motion through the self-feedback term inside the neural network. The network model generates chaos by continuously outputting the neural network time to control the decay time in the model. The main way to obtain the chaotic motion in this network model is to add the chaotic noise to the discrete neuron output by means of model operation. The chaotic simulated annealing neural network model is based on the chaotic model, and the chaotic motion introduced by the attenuation chaotic noise term is added to the internal state function of the neuron. The convergence of chaotic motion is controlled by setting the decay rate coefficient so that the chaotic model has richer and better neural dynamics characteristics. As shown in, due to the interaction between the neurons in the coupling structure of the chaotic simulated annealing neural network model, the internal structure of the nonlinear and multiconstraint optimization problems such as economic efficiency is mapped. When the neuron transfer function of this network is continuous and bounded and the weight coefficient matrix of the network is symmetric, the output result of this model is stable. Therefore, the model proposed in this study has a good global search ability [31].

(2) There are many parameters to be selected in the chaotic simulated annealing neural network model. Input a proportional coefficient for the neuron, A0 is the coefficient of the economic equilibrium constraint, and B0 is the coefficient of the objective function constraint. These coefficients need to be appropriately selected according to the definition domain of the optimization variables. is the gain of the output function ($\varepsilon > 0$), which is used to adjust the steepness of the neuron output Sigmoid function. The smaller the value of ε, the greater the steepness and the faster the optimization convergence. However, if the value of ε is too small, the chaotic state will not converge, so the value of ε should be appropriately selected according to the value of ε. γ is a proportional coefficient of chaotic noise, which is used to adjust the range of chaotic noise traversing space. a 0 and β are the decay rates ($1 \leq a\ 0 \leq 3.0$, $0 < \beta < 1.5$), which are used to adjust the speed at which the chaotic noise exits the network. Multiple simulation calculations show that, as long as other parameters are properly selected, parameters such as γ, $a0$, β, and other parameters within a certain range will not affect the final calculation results. Compared to traditional models, the improved HNN model used in this study is a convergent stable network [31]. The changes generated by this feedback and iterative calculation process are getting smaller and smaller. Once a stable equilibrium state is reached, the model will output a stable constant value.

$$z(t+1) = (1-\beta)z(t). \tag{14}$$

7. Conclusion

The model fully combines the advantages of HNN, simulated annealing algorithm, and chaotic neural network. On the basis of the annealing model, attenuated chaotic noise is introduced, and the output function is modified so that the chaotic motion can traverse the definition domain space of the entire optimization variable and it has richer and better neural dynamics characteristics. This algorithm is suitable for solving high-dimensional, discrete, nonconvex, and nonlinear constrained optimization problems. The chaotic simulated annealing neural network model is applied to solve the problem of economic forecasting under the premise of comprehensively considering economic losses, life and production effects, etc. The simulation results of several examples show that the model is feasible and effective to solve the economic

forecasting problem. Since the chaotic simulated annealing neural network model is a highly applicable optimization model, it can also be applied to the optimization problems of economic systems or other industrial systems. The neural network model proposed in this study has advantages in artificial intelligence, such as machine learning, associative memory, pattern recognition, and optimization calculation, and can be widely used in national macroeconomic forecasting.

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 or personal relationships that could have appeared to influence the work reported in this paper.

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