

## Research Article

# Combination Forecast of Economic Chaos Based on Improved Genetic Algorithm

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The deterministic economic system will also produce chaotic dynamic behaviour, so economic chaos is getting more and more attention, and the research of economic chaos forecasting methods has become an important topic at present. The traditional economic chaos forecasting models are mostly based on large samples, but in actual production activities, there are a large number of small-sample economic chaos problems, and there is still no effective solution. This paper proposes a combined forecasting model based on the traditional economic chaos forecasting method. First of all, through the decision tree classification, priority selection of features, rough prediction is achieved. Secondly, we use BP neural network to make secondary prediction. Because the initial weight is randomly selected, it is easy to fall into the defect of local minimum. This paper optimizes the BP neural network. Finally, the decision tree model and the BP neural network model optimized by the improved genetic algorithm are combined, and the combined model is optimized by the improved GA. This method can take advantage of many prediction models and combine the prediction information of multiple different prediction models to effectively improve the fitting ability of the model and improve the prediction accuracy.

## 1. Introduction

The phenomenon of chaos is very common, and the field of its penetration involves almost all aspects of the natural world. Chaos theory and its application have extensive research value [1, 2]. Its development not only provides satisfactory answers for the study of general nonlinear dynamic systems but also provides a brand new theoretical framework for the study and understanding of complex dynamic systems [3]. Research shows that a deterministic economic system will also produce chaotic dynamic behaviour. Therefore, economic chaos is getting more and more attention, and the research of economic chaos forecasting methods has also become an important topic at present. Most of the traditional economic chaos forecasting models are based on large samples. However, in actual production activities, there are a large number of small-sample economic chaos problems, and there is still no effective solution.

In terms of economic system, Huang et al. [4] revealed chaos in the Haavelmo economic growth equation, which

made people realize that economic models based on traditional economic theories also have inherent randomness. The randomness caused by the inherent nonlinear mechanism of the economic system shakes the neoclassical hypothesis that economic fluctuations stem from the impact of factors outside the economy. Jetin and Reyes Ortiz [5] studied the classical economic growth model including the net natural birth rate, productivity, and per capita wage income. They pointed out that when the population is the largest and the per capita income is lower than the income required to maintain the minimum standard of living, the change in population will appear chaotic. Liang et al. [6] studied the chaotic conditions of general dynamic economic growth equations under unilateral and bilateral restrictions. Al Gahtani et al. [7] studied the consumption propensity function and believed that the consumption behaviours of different income groups are different. The consumption behaviour of the poor is stable, while the consumption behaviour of the rich may be periodic or chaotic. Zysiak et al. [8] proved that the optimal economic growth trajectory is

also chaotic under certain conditions. This means that chaos can be a dynamic behaviour to achieve a certain optimization goal of an economic system.

The economic system is a time-varying and complex nonlinear system. Its characteristics of uncertainty and nonlinearity make it more difficult to predict economic trends in real time. In terms of short-term prediction, many researchers have made a lot of attempts and improvements. The existing forecasting models are mainly divided into three categories: time series models, neural network models, and hybrid models. Time series models mainly include exponential smoothing [9], differential autoregressive moving average model [10], spectral analysis model [11], and Kalman filter [12]. When the historical data and the predicted data differ greatly, the performance of the above model is severely degraded, and it is not suitable for such a sudden scene. Neural network models mainly include backward propagation neural network [13], radial basis function neural network [14], wavelet neural network [15], deep learning model [16], and support vector regression [17]. The powerful nonlinear fitting ability enables the neural network to map any complex nonlinear relationship. In addition, its learning rules are simple, and it can be easily implemented using a computer, so it is suitable for short-term prediction. Hybrid models mainly include Bayesian neural network combination model [18], adaptive hybrid fuzzy rule model [19], spectrum analysis combined with statistical fluctuation model [20], empirical mode decomposition combined with neural network model [21], and chaotic wavelet analysis combined with the support vector machine [22]. The above-mentioned hybrid models are combined with two or more forecasting models to realize economic chaos forecasting. The neural network adopts the "black box" learning mode, which only needs input and output samples to establish a good mapping model between input and output, so it is widely used in short-term prediction. Among them, BP neural network is the most commonly used predictive model. However, this model has some shortcomings when solving such problems, such as being easy to fall into local minimum and slow convergence speed.

Combinatorial optimization problem [23] is a kind of problem that uses mathematical methods to find the optimal arrangement, selection, and grouping of discrete events. As many optimization problems in real life become more and more complicated with the development of science and technology, traditional optimization algorithms cannot obtain the solution accuracy and solution time that meet the actual needs when solving them. Therefore, many scientific researchers are inspired by the intelligence of the natural world to propose a large number of intelligent optimization algorithms, such as ant colony algorithm [24], genetic algorithm [25], artificial bee colony algorithm [26], and invading weed optimization algorithm [27]. Genetic algorithm is a random search method, with good global search ability and inherent implicit parallelism, so it is widely used in combinatorial optimization, signal processing, and database query fields. Mohammadi and Forghani [28] proposed a dynamic similarity parameter part family coding, which greatly shortened the coding length and running time. Gou et al. [29] proposed a local competitive selection operator

based on individual differences to enhance the ability of the algorithm to jump out of the local optimum. Wang et al. [30] proposed a genetic algorithm that eliminates the crossover mechanism, which simplifies genetic operations and improves computational efficiency. Bouzary and Frank Chen [31] proposed an implicit implementation scheme of binary mutation operator and decoding algorithm, which improved the optimization speed of GA.

Based on the above analysis, this paper proposes a combined forecasting model based on the traditional economic chaos forecasting method. First of all, through the decision tree classification, priority selection of features, rough prediction is achieved. Secondly, we use BP neural network to make secondary prediction. This paper optimizes the BP neural network. Finally, decision tree and BP network optimized by improved genetic algorithm are combined.

### 1.1. Related Knowledge

*1.1.1. Forecast of Economic Chaos.* The requirements of economic forecasting are different from mathematical forecasting. Mathematical prediction requires a more accurate state of the system in the future, while economic prediction requires a qualitative or quantitative judgment or estimation of the system for the future state and does not require it to be very accurate. The economic chaos forecast includes two aspects, the qualitative forecast of economic chaos and the quantitative forecast of economic chaos. Figure 1 is a flow chart of economic chaos forecast.

Given a set of economic chaotic time series. Although a system is described by multiple components, the evolution of any component of the system is determined by other components interacting with it. That is, the time series itself contains information about all the variables participating in this economic system. Therefore, Sun and Wang [32] proposed phase space reconstruction technology. Mapping the given time series into a finite-dimensional state space, the chaotic attractor is obtained. The attractor has overall stability, attractiveness, and internal shape. From the embedding theorem, a function determines the sequence between the current state and the future state.

Suppose an economic time series  $\{A(a), a = 1, 2, \dots, L\}$  of length  $L$ ; to predict the future state of the sequence is to determine the current state  $A(L)$  and the future state  $A(L + K)$  functional relationship between

$$A(L + K) = \Phi_K(A(L)). \quad (1)$$

Among them,  $K$  is the predicted length and  $L$  is the length of source. According to the space reconstruction technology, the sequence is embedded in the  $p$ -dimensional Euclidean space, and its elements are

$$B(a) = \{A(a), A(a - \varepsilon), \dots, A(a - (p - 1)\varepsilon)\}, \quad (2)$$

$$a = L, L - 1, \dots, K + 1 - K_p.$$

Among them, the variable  $K_p \leq K - (p - 1)\varepsilon$ , where  $\varepsilon$  is the delay time, which can be determined by calculating the autocorrelation function of the original time series:

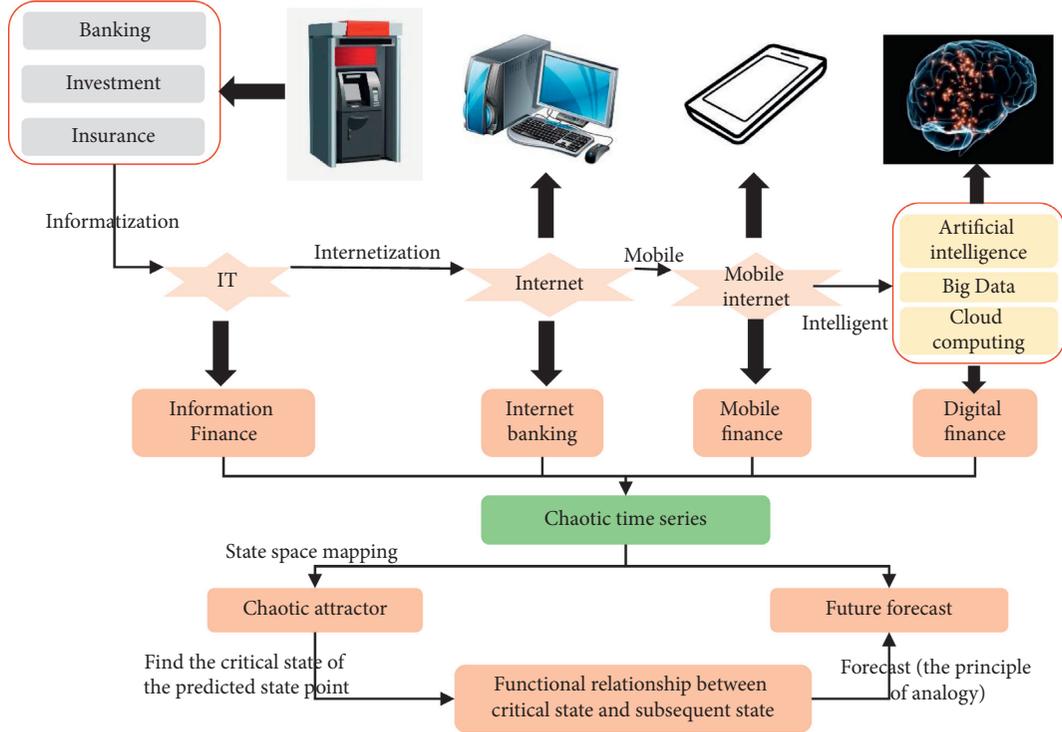


FIGURE 1: Economic chaos forecast modelling program.

$$C(K) = \sum_{i=1}^{L-K} (A(a) - A_M) * (A(a + K) - A_M). \quad (3)$$

Among them, the variable  $A_M$  is the mean value of economic time series  $\{A(a), a = 1, 2, \dots, L\}$ . The variable  $K$  takes values from small to large, so that the  $K$  that makes variable  $C(K)$  zero for the first time is the delay time. Variable  $p$  is the dimension of the phase space. In this way, we get  $p$ -dimensional vectors and find out the change rule of the economic index  $A(a)$  through the change rule of the vector sequence. Let  $A(a)$  be the predicted state point. According to the embedding theorem, there is a smooth map  $F$  in  $p$ -dimensional Euclidean space that satisfies

$$B(a + K) = F(B(a)). \quad (4)$$

From  $B(a) = (A(a), A(a - \epsilon), \dots, A(a - (p - 1)\epsilon))$ , variable  $L + 1 - K_p$  knows that  $A(a + K)$  is the first element of the vector  $B(a + K)$ , so that we can predict the economic chaos sequence.

## 2. Genetic Algorithm

**2.1. Coding Mechanism.** The coding mechanism corresponds to the coding rules of the chromosome gene string in genetics. The genetic algorithm is to code individuals into a specific string. The most commonly used encoding mechanism is binary encoding. That is to use zero and one to encode the individual into a binary string.

**2.2. Fitness Function.** The fitness function evaluates the fitness of each individual. In the optimization problem, the introduction of fitness function can compare individuals.

**2.3. Genetic Operator.** Genetic operators mainly include selection duplication operators, crossover operators, and mutation operators.

The selection duplication operator allocates breeding opportunities according to the different fitness of individuals, and individuals with high fitness have more chances to produce more offspring.

The crossover operator evolved according to the genetic process of parental gene cross-recombination during the mating process of organisms. It refers to the random exchange of certain genes between two individuals in a population based on a certain probability. Since the evolution process has a higher probability in biological evolution, the probability setting in the algorithm is generally larger.

The mutation operator corresponds to the phenomenon of gene mutation, which is a small probability event. In genetic algorithms, mutation operators provide new genes for the algorithm and expand the search range of the algorithm.

**2.4. Control Parameters.** The control parameters refer to the parameter values that need to be used in GA operation.

Traditional genetic algorithm uses idea of survival in the biological evolution to generate individuals with strong environmental adaptability through operations such as duplication, crossover, and mutation. Compared with traditional optimization algorithms such as enumeration method, genetic algorithm is based on biological evolution, with strong randomness and good global optimization ability.

### 3. Optimize the Prediction Model Based on Improved Genetic Algorithm

**3.1. Economic Chaotic Combination-Forecasting Model.** It can be seen from formula (4) that after the phase space reconstruction technology is processed, determining the prediction function becomes a key step in the chaotic economic prediction. In forecasting practice, due to different modelling mechanisms and starting points, there are usually different forecasting methods for the same problem. However, there are trend changes, seasonal changes, and periodic changes in the economic chaotic sequence. Among them, there are linear characteristics and nonlinear characteristics. That is, the prediction function is the result of the fusion of several features.

If only a certain single forecasting method is used, there are certain limitations and it is difficult to obtain satisfactory results. For example, using the least squares method to fit a linear function like  $B = ax + K$ , this method focuses on local behaviour. Each step of this method is linear, but overall economic chaos is nonlinear. Therefore, the linear function is only a linear approximation of the unknown global nonlinear function in the local range. There are  $n$  kinds of prediction methods, and their prediction functions are

$$\begin{cases} F_1(B(a)) = B_1(a + K) \\ \dots \\ F_n(B(a)) = B_n(a + K) \end{cases} \quad (5)$$

Let variable  $\gamma = (\gamma_1, \gamma_2, \dots, \gamma_n)$  be the weight vectors of  $n$  kinds of forecasting methods in the combined forecasting; then, the combined forecasting model of economic chaos is

$$\text{Model} = \sum_{i=1}^n \sum_{j=1}^K \gamma_i B_{ij} - a_i. \quad (6)$$

Among them, the variable  $a_j$  is the real value at time  $j$ . The equivalent form of model (5) is

$$\text{Model} = \max[-F(\gamma) - \gamma(1 - e^T \gamma)]. \quad (7)$$

For the economic time series  $\{A(a), a = 1, 2, \dots, L\}$ , the optimal combination-forecasting model at the time  $a + 1$  can be obtained through model (6):

$$B(a + 1)' = \sum_{j=1}^n \gamma_j B_{j,a+1}. \quad (8)$$

The variable  $B(a + 1)'$  is the optimal combination predicted value at the time  $a + 1$ . The variable  $\gamma = (\gamma_1, \gamma_2, \dots, \gamma_n)$  is the optimal weight vector satisfying formula (6). Then the optimal combination function of economic chaos is

$$B(a + K) = \sum_{j=1}^n \gamma_j B_j(a + K). \quad (9)$$

Since this article uses two models of decision tree and BP neural network for prediction, the optimal combination function of economic chaos is

$$B(a + K) = \gamma_1 B_1(a + K) + \gamma_2 B_2(a + K). \quad (10)$$

**3.2. Forecast Model Based on Decision Tree.** Since the prediction effect of a single model is not good, we use a combined model for prediction. This article first chooses a decision tree for rough prediction. By using the classification contribution of the decision tree, the feature is preferentially selected to achieve rough prediction.

Let the training data set be  $H$ . Variable  $C_q$  is a number class.

Suppose feature  $A$  has  $n$  different values  $(a_1, a_2, \dots, a_n)$ , and the different values of feature  $A$  can divide the data set  $H$  into  $n$  subsets  $(H_1, H_2, \dots, H_n)$ . Among them,  $H_i$  is the number of samples of  $H_i$ . If the set of samples belonging to class  $C_q$  in the subset  $H_i$  is  $H_{iq}$ ,  $H_{iq} = H_i \cap C_q$ . Variable  $H_{iq}$  is the number of samples of variable  $H_{iq}$ .

- (1) Calculate the empirical entropy  $S(H)$  of the data set  $H$ :

$$S(H) = -\log_2 \frac{C_q}{H} \sum_{i=1}^K \frac{C_q}{H}. \quad (11)$$

- (2) Traverse the feature set and calculate the conditional entropy  $S(H|A)$  of each feature  $A$  to the data set  $H$  in turn:

$$S(H|A) = S(H) \sum_{i=1}^K \frac{H_i}{H}. \quad (12)$$

- (3) Calculate the information gain  $Y$ :

$$Y = -\log_2 \frac{C_q}{H} \sum_{i=1}^K \frac{C_q}{H} - -\log_2 \frac{C_q}{H} \sum_{i=1}^K \frac{C_q}{H} \sum_{i=1}^K \frac{H_i}{H}. \quad (13)$$

- (4) Repeat (2) and (3) until the information gain of all features in the feature set is calculated.
- (5) Use the feature combination to make a rough prediction and get the prediction result.

**3.3. Forecast Model Based on BP.** The basic principle of BP is to modify the weights of the nodes until the network output reaches the target output value, and it has a good generalization ability.

When faced with a small amount of data processing, it is possible for each individual to discuss independently that it is possible to use a linear relationship to deal with nonlinear problem. This paper adopts specific expression of unary regression model and uses the time series forecast value to subtract the corresponding error amount obtained by the regression model to obtain the revised  $E$  value.

There is still a problem of selecting the step size. Too large  $\eta$  will cause convergence too fast and cause instability. Although  $\eta$  is too small to avoid instability, the convergence speed will be very slow. At this time, aiming at the method of increasing the optimization factor  $\alpha$ , the BP algorithm is optimized again. Use this momentum to change the value of  $\eta$  so that  $\eta$  is no longer a constant value. After introducing this optimization factor, the adjustment is changed toward the average direction of the bottom, so that no big swing will

be produced. That is, the optimization factor plays a role of buffering and smoothing.

If the system enters the flat area of the error function surface, the error will change very little. Then  $\Delta w(t+1)$  is approximated to  $\Delta w(t)$ . In addition, the average  $\Delta w$  will become

$$\Delta w = \frac{\partial \eta}{1 - \alpha}. \quad (14)$$

In order to adjust the departure from the saturation zone as soon as possible, the relationship of “optimization factor” is added to the algorithm, as shown in the following formula:

$$w_{ij}(a) = \alpha w_{ij}(a-1) + \eta \Delta w. \quad (15)$$

Combined with the above analysis results, after the second improvement, the following formula is shown:

$$w_{ij}(a+1) = \alpha w_{ij}(a) + \eta (\alpha (w_{ij}(a) - w_{ij}(a-1))). \quad (16)$$

After correcting the predicted value, the weight function can be obtained. Finally, the correction function is updated successfully through the weight and threshold adjustment again, and we can obtain the final BP neural network, as shown in Figure 2.

Use genetic algorithm to solve the optimal weight coefficient of the combined forecasting model.

The purpose of GA is to explain the natural adaptive process and design a software system that reflects the mechanism of nature. The basic idea of GA to solve the optimal weight coefficient is expressing solution of problem as “chromosomes”, thus forming a group of “chromosomes”. Through crossover and mutation, a new generation

of “chromosomes” groups that are more adaptable to the environment are produced.

Based on the above understanding of the genetic algorithm, the steps to solve the optimal weight of the combined forecasting model (10) are as follows:

- (1) Initialization: determine the feasible region  $U = \{U | 0 < U < 1\}$ , the fitness function  $F$ , the maximum capacity  $J$ , the error precision  $e$ , the crossover probability  $P_c$ , and the mutation probability  $P_m$ .
- (2) Select the initial solution: randomly select  $m$  points  $U_i$  from  $U$  in the feasible region as a chromosome. In addition, calculate the fitness value  $F(U_i)$ , respectively. Eliminate individuals with low fitness to obtain population with a capacity of  $R$  ( $R < J$ ). Moreover, select  $d$  chromosomes to form a matching set  $S$ , and divide the new population into several subpopulations.
- (3) Identify the initial conditions: calculate the fitness of each individual in each subpopulation. If an individual with error accuracy is obtained, the algorithm ends. This individual is the optimal value. Otherwise, go to step (4).
- (4) Iteration: according to the survival probability of each generation of individuals, a random selection strategy is designed. The greater the survival probability of an individual, the greater the probability of being selected. Then calculate the crossover probability  $p_c$  and mutation probability  $p_m$  of each individual in each subpopulation. Here, according to the size of the fitness, the  $p_c$  and  $p_m$  are constructed as follows:

$$P_c = \left\{ \frac{\sum_i [\max F(U) - F(U_i)]}{([\max F(U)] - F(U_i))} \right\}, P_m = \left\{ \frac{\sum_i [\min F(U) - F(U_i)]}{([\min F(U)] - F(U_i))} \right\}. \quad (17)$$

Among them,  $p_c$  is the crossover probability and  $p_m$  is the mutation probability. Then cross and mutate between each subpopulation. Moreover, exchange good individuals between subpopulations. Through selection, crossover, and mutation, gradually put individuals with large fitness values into the matching set  $S_2$  until  $S_2 = S$ , update  $S_1$ ,  $S_2$ , and go to step (3).

- (5) Output the maximum fitness value  $F(U)$  that meets the accuracy requirements and the optimal weight vector  $\gamma = (\gamma_1, \gamma_2, \dots, \gamma_n)$ , and substitute  $\gamma$  into (10) to obtain the optimal combination function of economic chaos. Figure 3 shows the final economic chaotic combination-forecasting model.

## 4. Results and Discussion

**4.1. The Influence of Different Parameter Values on the Model.** Verify availability and performance advantages of BP in terms of prediction; the basic training data set is used, and the prediction results are analysed.

Training and testing error curves of optimized BP and unoptimized BP are shown in Figure 4.

From Figure 4, after iterations are greater than 40, the rate of change of error curve is smaller, and unoptimized BP approaches convergence. After iterations are greater than 20, the optimized BP has slowly converged. The optimized algorithm has better convergence performance and prediction accuracy than the unoptimized algorithm.

Using the existing data, the second exponential smoothing method of the time series-forecasting model is used to simulate and forecast the time series. In addition, compared with the result of exponential smoothing method, the simulation result is shown in Figure 5.

After experiments, the experiments are in full agreement with predictions. One-time exponential smoothing method has a large number of lagging responses in the simulation results of 25 data sets. Regardless of  $\alpha = 0.2$ ,  $\alpha = 0.5$ , or  $\alpha = 0.8$ , the hysteresis response cannot be changed. This also reflects the higher accuracy of the quadratic exponential smoothing forecast.

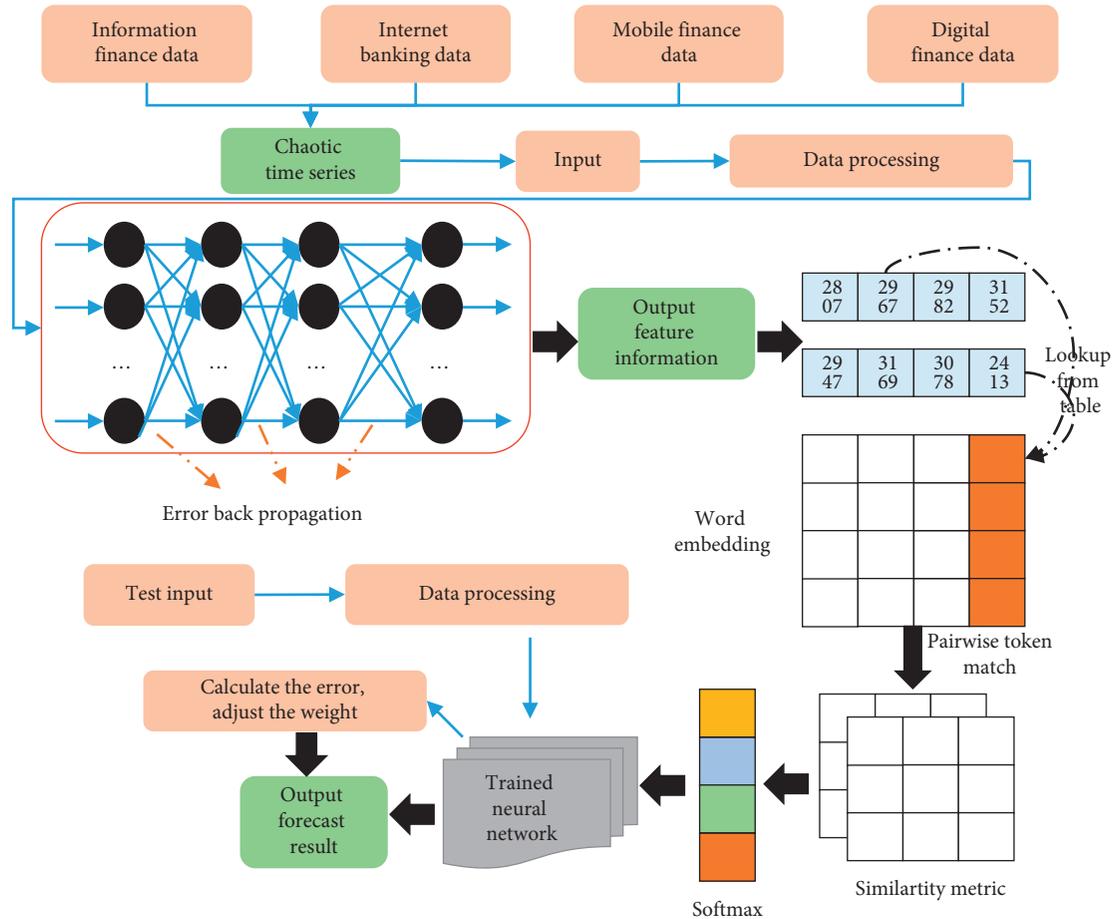


FIGURE 2: The improved BP neural network structure in this paper.

**4.2. Performance Analysis of the Combined Forecasting Model.** Verifying the optimization performance of improved GA to combined model, this paper uses multiple optimization algorithms for comparative analysis. Figure 6 shows the error results obtained by different optimization analyses.

From Figure 6, traditional GA and ant colony algorithm can also optimize the combined model well. However, through comparison, it can be found that the predicted data obtained by the optimization algorithm used in this paper are the closest to the actual data, and the fluctuation range of the error is smaller. We can see that the improved GA used is better for prediction.

This paper uses wavelet neural network, unoptimized BP neural network, decision tree, grey prediction GM (1, N) model, optimized BP neural network, multiple regression model, and combined prediction model of literature [33] and literature [34].

The prediction results of wavelet neural network, unoptimized BP neural network, decision tree, gray prediction GM (1, N) model, optimized BP neural network, multiple regression and combined prediction of this article and relative error curve of predicted value are, respectively,

as shown in Figures 7 and 8. Figure 9 shows the relative error curve of the combined prediction model of literature [33], the combined prediction model of literature [34], and the combined prediction model of this paper.

It can be seen from Figure 7 that the combined prediction model proposed in this paper has higher prediction accuracy. Especially in the time point where the difference between the prediction results of the wavelet neural network and the actual load value is large, the fatigue and root mean square error is reduced by 0.12. The analysis proves that the nonlinear searching ability of the optimized combined prediction model can effectively improve the prediction accuracy of the neural network and avoid the phenomenon of neural network overfitting.

As can be seen from Figure 8, the relative error curve of the predicted value of the combined prediction model is always between the relative error curve of the predicted value of the single prediction model. When the prediction errors of the single prediction model are all positive or negative, the prediction error of the combined prediction model is not large, but when the prediction errors of the single prediction model are different, the prediction error of the combined

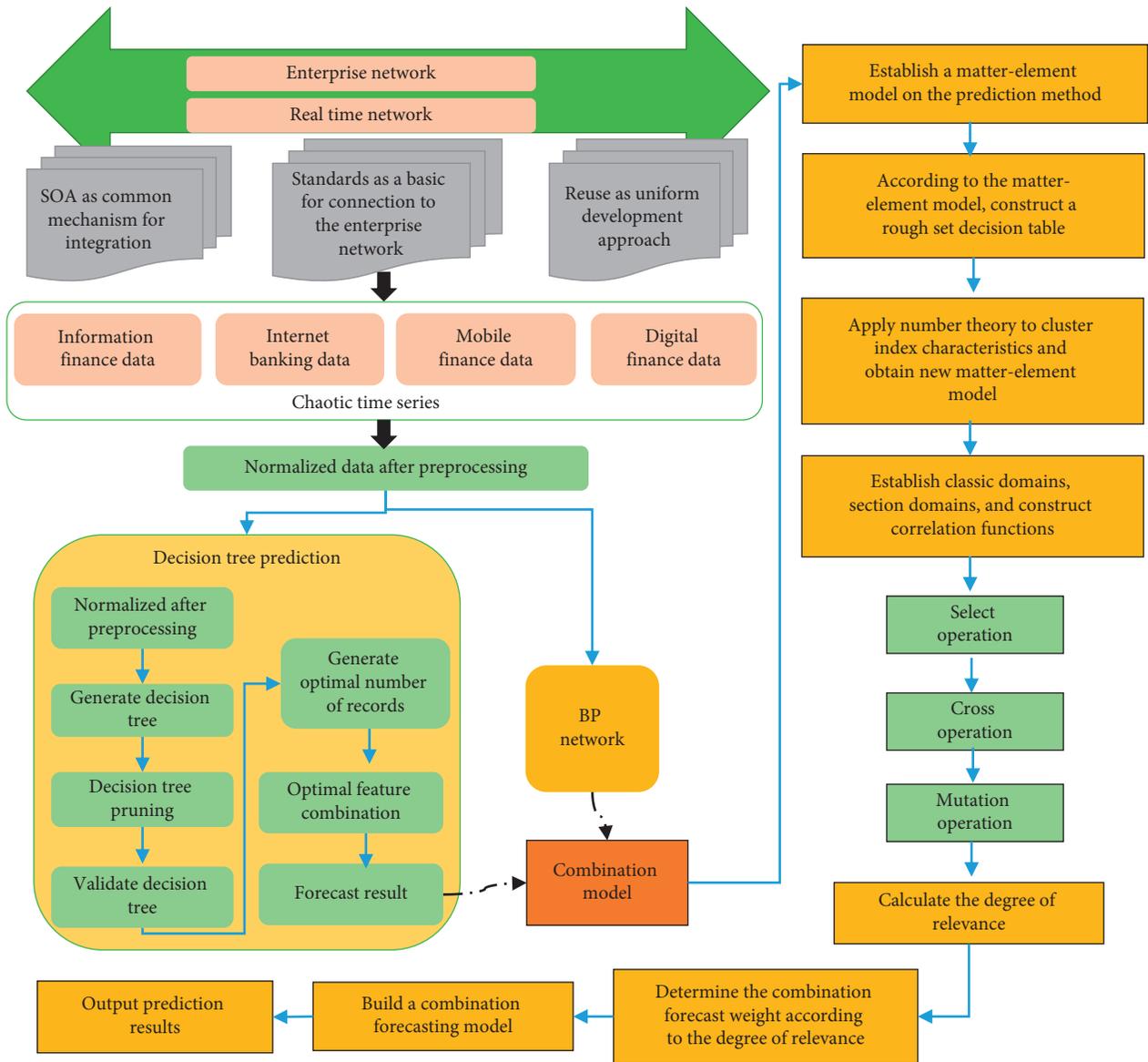


FIGURE 3: Economic chaos combination model.

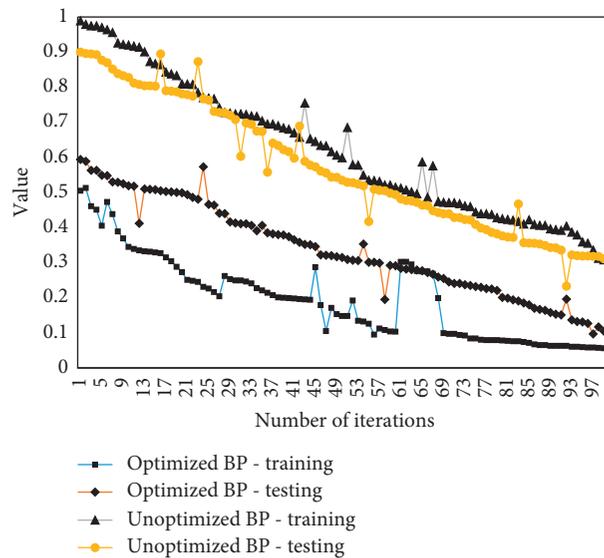


FIGURE 4: Error curve of BP neural network training and testing.

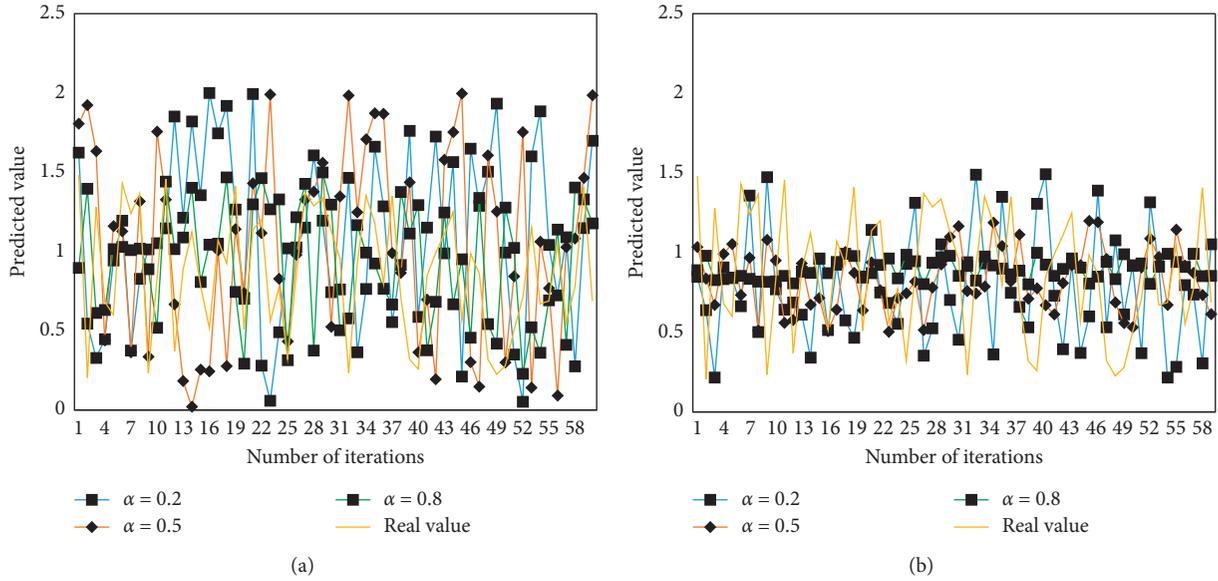


FIGURE 5: Exponential forecast chart of first smoothing and second smoothing. (a) Smooth once. (b) Smooth second.

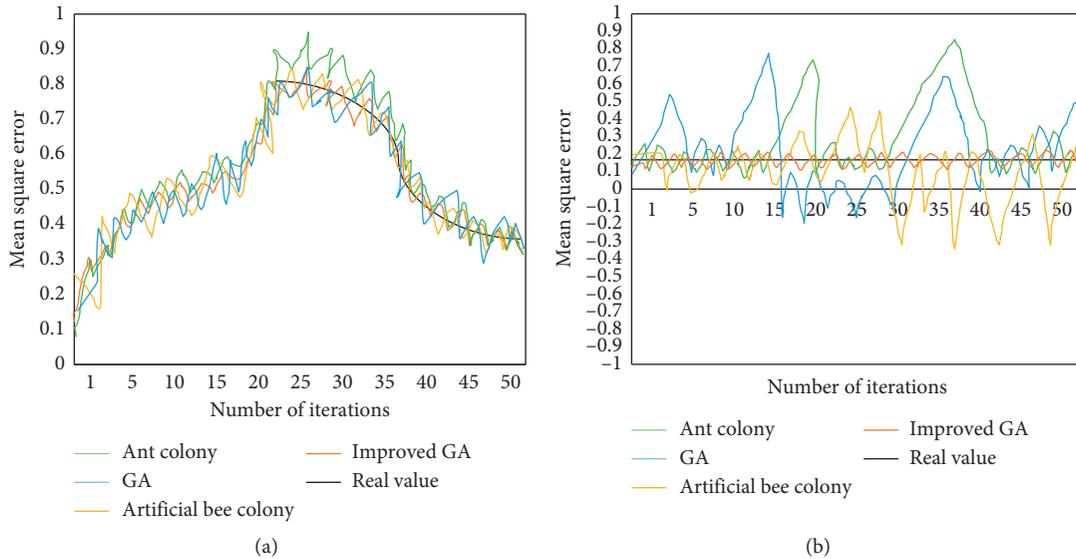


FIGURE 6: The prediction results and absolute error results of different optimization algorithms. (a) Predicted and true values. (b) Forecast absolute error and mean absolute error.

prediction model can be smaller than that of the single prediction model. Therefore, the prediction result of the combined prediction model is better than that of the single prediction model.

Figure 9 shows that the relative error curve of the combined forecasting model in the literature [32] is close to that of the combined forecasting model in this article, but it is not optimal for the objective function of this article. In [33] the relative error curve of the combined forecasting model fluctuates greatly. It shows that the combined

prediction method of the algorithm in this paper reduces the relative error and makes its value more balanced. And the relative error distribution is more uniform, and there will be no case where the relative error of the predicted value at a certain time node is particularly large. This is because the algorithm in this paper first classifies contributions through decision trees, preferentially selects features, and achieves rough prediction. Secondly, use BP neural network to make secondary prediction. The method in this paper can take advantage of many prediction models and combine the

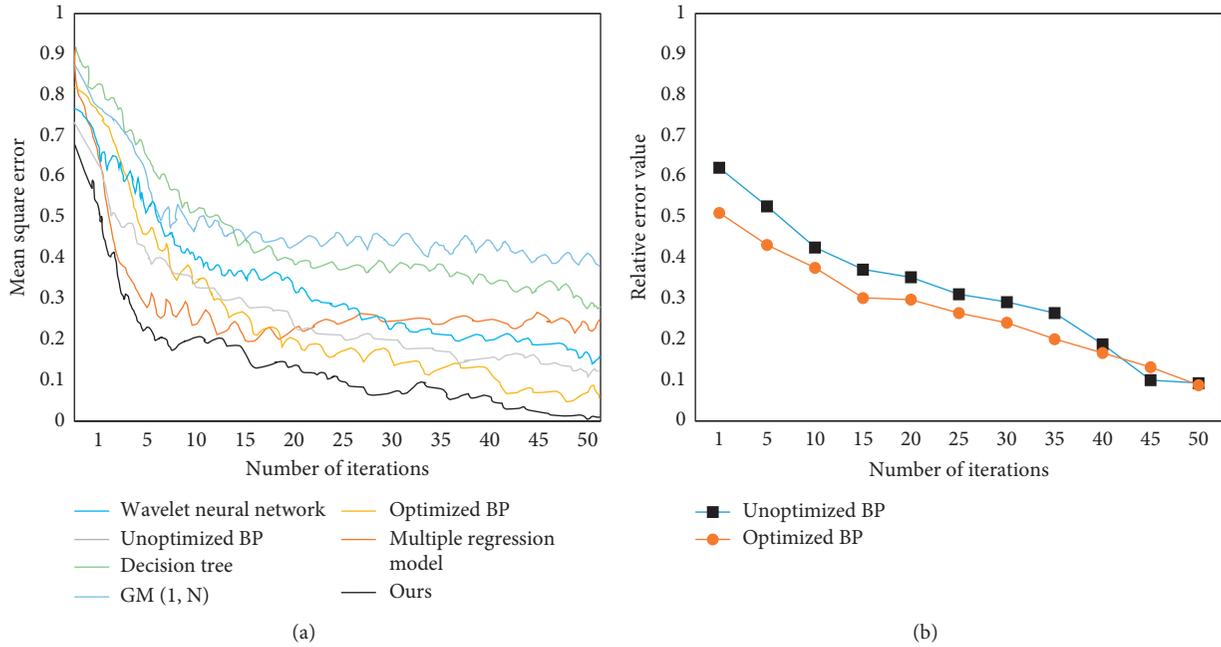


FIGURE 7: Convergence curves and prediction errors of different prediction models. (a) Convergence curves of different prediction algorithms. (b) Prediction error before and after BP network optimization.

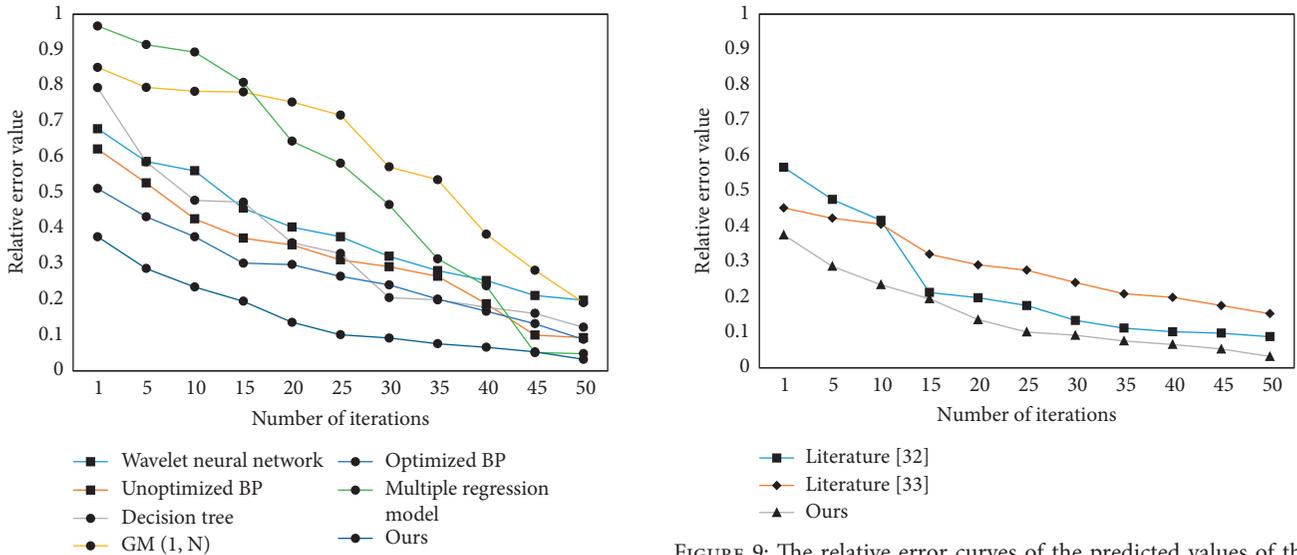


FIGURE 8: The relative error curve of the predicted value of the single prediction model and the combined model in this paper.

FIGURE 9: The relative error curves of the predicted values of the three combined forecasting models.

prediction information of multiple different prediction models in order to effectively improve the fitting ability of the model and improve the prediction accuracy. Therefore, the prediction accuracy of the combined prediction model in this paper is also higher than that of the other two combined prediction models.

The combined forecasting model used in this paper is based on the decision tree and the improved BP neural network, so the complexity of this paper is the same as that of the BP neural network, both of which are  $O(n^2)$ . The following Table 1 shows the time performance of the three algorithms. It can be clearly seen that the algorithm in this paper has higher time performance.

TABLE 1: Time performance of the three algorithms.

Methods	Test time (s)
Literature [32]	1.873
Literature [33]	1.034
Ours	0.876

## 5. Conclusions

The development of economic chaos not only provides satisfactory answers for the study of general nonlinear dynamic systems, but also provides a brand new theoretical framework for the study and understanding of complex dynamic systems. Therefore, this article has carried out work on the prediction of economic chaos. The traditional prediction models of economic chaos are all single models. However, there are certain limitations in choosing a single forecasting method. Therefore, we propose a combined forecasting model based on the traditional economic chaos forecasting method. First of all, through the decision tree classification, priority selection of features rough prediction is achieved. Secondly, we use BP neural network to make secondary prediction. Finally, decision tree model and BP optimized by the improved GA are combined, and improved GA optimizes the combined model. Experiments show that the combined model can well complete the function of ability prediction and has good stability.

Although this article has done a certain amount of work, the study of chaotic information, especially economic chaos, is a relatively complex and extensive field. This article only does a certain research on the forecasting methods of economic chaos. As for other aspects, such as the control of economic chaos, there is no discussion, and these will await our further study and research. Secondly, our method is also applicable to the prediction of other problems. Therefore, our next research plan is to improve the portability of the algorithm. The algorithm of this paper will be transplanted to other problems to solve the prediction of other problems.

## Data Availability

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

## Conflicts of Interest

The author declares that there are no conflicts of interest.

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