

Forecast of financial industry development trend based on particle swarm optimization BP neural network

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Abstract: Finance is the core of the economy. Under the current complex economic structure, how the financial industry develops has become a hot issue that urgently needs to be resolved. Therefore, this article characterizes the development speed and quality of the financial industry through the change rate of total bank assets and the rate of non-performing loans of commercial banks. Therefore, this article uses the change rate of total bank assets and the rate of non-performing loans of commercial banks to characterize the development speed and quality of the financial industry, and the forecast of the development trend of the financial industry is studied. Based on this, this paper uses particle swarm algorithm and BP neural network to predict the development trend of the financial industry, and optimizes the weights and thresholds of BP neural network through particle swarm algorithm, and the prediction model of BP neural network optimized by particle swarm optimization is established. The simulation results show that the prediction accuracy of the prediction model optimized by the particle swarm algorithm has been greatly improved to meet the requirements of prediction accuracy. This method has very important reference value for my country's financial industry.

1. Introduction

With the rapid development of my country's economy, the financial industry has also grown rapidly. In today's era of rapid development of artificial intelligence industry and big data technology, the traditional financial industry is gradually transforming to financial technology, so it is particularly important to study the prediction method of the financial industry development trend.

Literature [1] compares and analyzes the results of the least squares regression prediction, and then applies the ARMA model for time series analysis, and more accurately predicts the deposits of financial institutions in November 2016. Literature [2] uses neural networks to directly predict future asset price changes as buying points and selling points, and uses case-based dynamic windows to further optimize the forecast results, which has achieved good returns in practical applications. Literature [3] combines historical price data and sentiment indicators as predictor variables, and trains support vector machines to predict stock price changes, which proves that the introduction of sentiment variables can further improve the prediction accuracy of machine learning models.

Based on this, this paper establishes a prediction model of particle swarm optimization optimized BP neural network, and predicts the development trend of the financial industry.

2. Particle swarm optimization optimizes BP neural network

2.1 Basic principles of BP neural network

The essence of BP neural network is a multi-layer feedforward network, and its learning algorithm is divided into: signal upward transmission and error downward transmission. When passing upward, the input samples are processed layer by layer from the input layer through hidden layer units and then passed to the output layer. The output layer compares the actual output with the expected output. If the error value is greater than the set value, the error will propagate downward, and the network weights and thresholds will be continuously adjusted according to the prediction error to improve the learning ability of the neural network, so that the predicted output of the BP neural network is constantly close to the expected output. BP neural network mainly includes input layer, output layer and hidden layer. The diagram of BP neural network is shown in Figure 1.

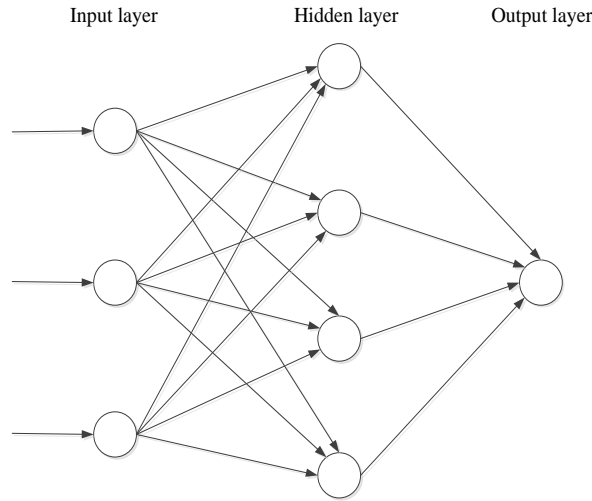


Fig. 1 BP neural network structure

2.2 Basic principles of particle swarm algorithm

Particle swarm algorithm is a kind of swarm intelligence optimization algorithm. Because of its concise concept, fast convergence and easy implementation, it is widely used in scheduling optimization, data mining, and neural network training. The basic idea is to find the optimal value through information sharing inspired by the hunting behavior of animal and bird groups. In the particle swarm algorithm, each particle is a potential solution. The particles search in the solution space and find the optimal solution through continuous iteration. In each iteration, the particles will update themselves by tracking the local optimal solution and the global optimal solution.

It is generally assumed that there is a particle in the group, and the particle has an m -dimensional vector. Suppose the position of the i -th particle is represented as $X_i = (x_{i1}, x_{i2}, \dots, x_{im})$, the local optimal solution is $P_i = (p_{i1}, p_{i2}, \dots, p_{im})$, and the current global optimal solution is $G_i = (g_1, g_2, \dots, g_n)$, and the particle change rate is $V_i = (v_{i1}, v_{i2}, \dots, v_{im})$. According to the principle of finding the global optimal solution, the particle update speed and position are based on the current local optimal solution and the current global optimal solution. The specific update formula is as follows:

$$v_{ij}(t+1) = \omega \cdot v_{ij}(t) + c_1 \cdot \mu_1 \cdot (p_{ij}(t) - x_{ij}(t)) + c_2 \cdot \mu_2 \cdot (p_{gj}(t) - x_{ij}(t)) \quad (1)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (2)$$

$$v_{ij} \begin{cases} v_{\max} & v_{ij} > v_{\max} \\ v_{ij} & | -v_{ij} | < v_{\max} \\ -v_{\max} & v_{ij} < -v_{\max} \end{cases} \quad (3)$$

Where: w is the weight of inertia; t is the number of iterations; $i=1, 2, 3, \dots, n$; $j=1, 2, 3, \dots, l$; c_1, c_2 are acceleration factors, respectively represent the step size of the particle to find the current local optimal solution and the global optimal solution; μ_1 and μ_2 are random numbers from 0 to 1. Formula 3 is to reduce the possibility of particles leaving the solution space in the iterative process, so that the particle change rate is limited to the range of $[-v_{\max}, v_{\max}]$.

2.3 Particle swarm optimization optimizes BP neural network prediction model

Because the BP neural network has the shortcomings of low prediction accuracy, easy to fall into local minimum and slow convergence speed, in order to overcome this shortcoming and improve the training speed and prediction accuracy of the network. This paper optimizes the weights and thresholds of the BP neural network through the particle swarm algorithm, and then continuously updates the particle position and velocity until the optimal fitness value is found, and then the optimal parameters are assigned to the BP neural network, finally, it is predicted through the BP neural network. The model process of particle swarm optimization optimization BP neural network is shown below.

1) Establish a BP neural network and set parameters. Since there is no definite calculation formula for the number of hidden layer nodes, it is generally determined by the empirical formula of Equation 4.

$$h_i \leq \sqrt{h_i \cdot (h_i + 3)} \quad (4)$$

2) Initialize the weights and thresholds of the BP neural network, as well as the particle position and velocity of the particle swarm.

$$V_{ij} = V_{ij} + \mu X_j (1 - X) p(i) \sum_{k=1}^m V_{jk} e_k \quad (5)$$

$$V_{jk} = V_{jk} + \mu X_j e_k \quad (6)$$

Among them, $i=1, 2, 3, \dots, n$; $j=1, 2, 3, \dots, l$; $k=1, 2, 3, \dots, m$; V_{ij}, V_{jk} is the connection weight of the BP neural network; P_i, X_j are the input layer input and hidden layer output respectively; μ is the learning rate; e_k is the error.

$$b_k = b_k + e_k \quad (7)$$

$$a_j = a_j + \mu X_j (1 - X) p(i) \sum_{k=1}^m V_{jk} e_k \quad (8)$$

Among them, $j=1, 2, 3, \dots, l$; $k=1, 2, 3, \dots, m$; a_j, b_k are the thresholds of the hidden layer and the output layer.

3) Calculate the fitness value F of the particle as shown in Equation 9.

$$F = \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^C (\omega_{j,i}^1 - \omega_{j,i}^2)^2 \quad (9)$$

Among them, N is the number of training samples; C is the number of output network neurons; $\omega_{j,i}^1$ is the ideal output value of the wind power of the j th network output node of the i sample; $\omega_{j,i}^2$ is the actual output value of wind power at the j th network output node of the i sample.

4) Search the individual extreme value G_{best} of the particle and the group extreme value Z_{best} .

If the current fitness value is better than Gbest, update the particle's Gbest, if not, update the particle's speed and position. If the current fitness value of all particles is better than Zbest, Zbest is updated.

5) Update the particle's velocity V and position X according to the following formula 10 and formula 11, respectively.

$$V_i^{k+1} = \omega \cdot V_i^k \cdot \mu_1 (p_i^k - x_i^k) + c_2 (p_g^k - x_i^k) \quad (10)$$

$$V_i^{k+1} = X_i^k + \rho V_i^k \quad (11)$$

Among them, c_1 is the particle's own acceleration coefficient; c_2 is the global acceleration coefficient; μ_1 and μ_2 are random numbers distributed in the interval $[0, 1]$; ρ is the constraint factor.

6) Update the weights according to formula 12.

$$\omega = \omega_{\max} \frac{(\omega_{\max} - \omega_{\min}) \cdot t}{T_{\max}} \quad (12)$$

Among them, T_{\max} is the number of iterations, ω_{\max} and ω_{\min} are the maximum and minimum weights respectively, and t is the current iteration value.

7) Check whether the termination conditions are met. If yes, stop the iteration and get the optimal weight and threshold of the BP network. Otherwise, return to step 3 to recalculate the fitness value of the particle.

8) Calculate the error, and then update the weight and threshold to check whether the end condition is met (whether the current position or the number of iterations reaches the predetermined error). If it stops the iteration, output the optimal weight and threshold of the neural network, otherwise recalculate the error.

3. Forecast of the development trend of the financial industry

3.1 Selection of model parameters

The development trend of the financial industry can be determined by the development speed and quality of the financial industry, and the speed of development can be characterized by the rate of change of total bank assets, and the quality of development can be characterized by the rate of non-performing loans of commercial banks; The development speed and quality of development are mainly affected by six factors including the balance of RMB loans of financial institutions, GDP growth rate, money supply growth rate, tertiary industry contribution rate, financial industry contribution rate, and interbank lending rate. Therefore, this paper selects the change rate of total bank assets and the rate of non-performing loans of commercial banks as the output of the prediction model, and selects the above 6 variables as the input of the model.

The simulation parameters of the prediction model in this article are set as follows: For the BP neural network, the number of training times is 1000, the target error is 0.0001, and the learning rate is 0.01; The parameters of the particle swarm optimization algorithm are as follows: the number of iterations is 1000, the maximum speed is 0.5, the acceleration factor $c_1=c_2=2$, $\omega_{\max}=0.9$, $\omega_{\min}=0.3$, the minimum error is set to 0.0001, and the number of particles is 50, the individual dimension of the particle swarm is 31.

3.2 Model prediction results

This paper selects 20 sets of data from 1997 to 2016 as the simulation data for this article [4], among which 12 sets of data from 1997 to 2012 are selected to train the prediction model of this article. a total of 4 sets of data from 2013 to 2016 are used to predict the development trend of the financial industry using the trained model. BP neural network and particle swarm algorithm optimization BP neural network predicts the rate of change of total bank assets as shown in Table 1, and predicts the rate of non-performing loans of commercial banks as shown in Table 2. The

specific prediction curves are shown in Figure 3 and Figure 4 respectively.

Tab. 1 The predicted value of the bank's total asset change rate

years	Actual value /100 million yuan	PSO-BP	error/ %	BP	error/ %
2013	13.27	13.9	4.7	14.3	7.8
2014	13.862	13.4	3.3	12.6	9.1
2015	15.667	15.5	1.1	14.9	4.9
2016	16.514	17.1	3.5	17.9	8.4

Tab. 2 Predicted value of non-performing loan rate of commercial banks

years	Actual value /100 million yuan	PSO-BP	error/ %	BP	error/ %
2013	1.0	1.05	5.0	1.09	9.0
2014	1.25	1.29	3.2	1.33	6.4
2015	1.67	1.58	5.3	1.51	9.6
2016	1.75	1.77	1.1	1.86	6.3

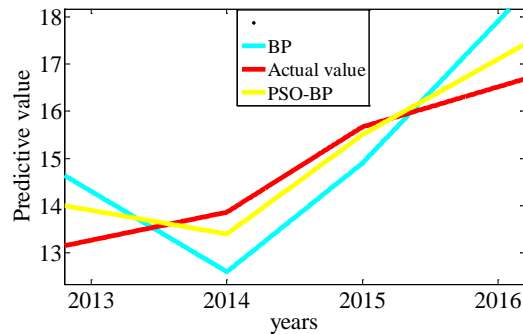


Fig 3 The forecast curve of the bank's total asset change rate

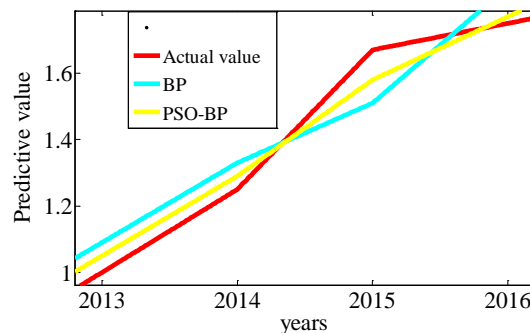


Fig 4 The prediction curve of the non-performing loan rate of commercial banks

According to the above prediction results, it is obvious from Table 1 and Table 2 that the highest prediction error of the POS-BP prediction model for the bank's total asset change rate is 4.7%, the average error is 3.15%, and the highest prediction error of the bank's total asset change rate is 5.3%, with an average error of 3.65%; the highest prediction error of the BP neural network for the bank's total asset change rate is 9.1%, and the average error is 7.55%. The highest forecast error of the bank's total asset change rate is 9.6%, and the average error is 7.83%. The prediction accuracy of the BP neural network optimized by the particle swarm algorithm is higher than that of the BP neural network.

4. Conclusion

This paper uses particle swarm optimization BP neural network to predict the development trend

of the financial industry, and its main conclusions are as follows.

1) This paper uses particle swarm algorithm to optimize the prediction model of BP neural network. The development trend of the financial industry is predicted, and the prediction accuracy is high. This method provides a new idea for the prediction of the financial industry.

2) Compared with the traditional BP neural network prediction model, the prediction model established by optimizing the BP neural network through particle swarm optimization has greatly improved its convergence speed and prediction accuracy.

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