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Research Article

Performance Simulation of Identification System Based on Improved Neural Network Algorithm

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After decades of development, neural network theory has made considerable progress in many research fields such as pattern recognition, automatic control, signal processing, decision support, and artificial intelligence. This article discusses the application of neural networks in pattern recognition and system recognition and proposes several new methods for recognizing system models and recognizing model parameters. In order to achieve high-precision control of smart structure actuators, a robust model must first be created. For various modeling tasks, many scientists have done a good job and proposed different modeling methods. There are three main ways to create a system model: one is a physical model based on the mechanism of the material itself, the other is an operator model based on experimental phenomena, and the third is an intelligent model based on computer intelligence. The problem of the recognition system stems from the fact that with the development of science and technology, the research methods of various disciplines have been further quantified. In industrial practice and scientific experiments, the purpose of observing and calculating the quantitative identification of complex objects that need to be studied is usual. According to its inherent laws, it is necessary to establish a mathematical model of the research object in order to make decisions such as analysis, design, prediction, and control. This article uses the neural network model to study the best improvement method of the dynamic process. The research results of this article represent the theoretical basis of future scientific research to a certain extent and have important research value.

1. Introduction

Neural network is a kind of abstraction, simplification, and modeling of the human brain. It reflects several basic characteristics of human brain function. Information processing in the network is carried out through the interaction between processors, which has the characteristics of parallel processing [1]. The knowledge and storage of information is manifested as a distributed physical connection between processing units. The training and recognition of the network is determined by the dynamic evolution process of the connection authority of the processing unit, which has the characteristics of associative memory [2]. The information processing function of the artificial neural network is realized by the powerful computing power of the computer, but it is different from the general computer system in that it

has no predefined sequential arithmetic operations and serial operations. It is composed of many interconnected simple processing blocks [3]. After the learning is balanced, the distribution state of the entire network composed of the weights of each neuron is the desired result. This paper creates a random system whose input and output are disturbed by noise as the goal [4]. The system recognition problem is transformed into a pattern recognition problem by dividing the system error space [5]. This paper proposes a method to describe the system model and creates a corresponding neural network to identify the model. This model makes full use of known interference probability information, can quickly simulate the probability distribution information output by the system, and make the recognition results more intuitive and practical [6]. At the same time, the establishment of the rapid identification model also provides

a practical solution for the online identification of stochastic systems. This paper uses D-FNN and ANFIS in the fuzzy neural network, RBF, BP in the feedforward neural network and five advanced algorithms to simulate three sets of measured traffic flow data and the chaotic time series of McKee Glass [7]. This article first introduces the D-FNN and ANFIS. D-FNN method is applied to the principle of prediction. Second, it introduces the data sample, pre-processing method, prediction performance scoring index used in this paper, as well as the definition of D-FNN network structure and membership function [8]. Finally, when pre-processing the data, the input and output of the neural network are determined by using the above related theoretical methods. Based on the chaotic time series of Mackey-Glass, two sets of short-term traffic flow data and a set of video network flow data, this paper adopts appropriate methods to establish various prediction models and conduct comparative studies [9, 10]. A variety of methods are used to predict and test the chaotic McKee-Glass time series and traffic time series, and the experimental results of different methods are compared and analyzed to test the effectiveness of this method in traffic forecasting [11].

2. Related Work

The literature mentions that well-known scientists in the field of artificial intelligence wrote a very influential book "Perceptron," which had a negative impact on the research and development of perceptrons at that time [12]. Some scientists have turned their research interests to artificial intelligence or theories related to digital computers. This application has stimulated the development of artificial intelligence and made it dominate. The United States never funded neural network research in the next 15 years, which slowed down the development of neural network research. The literature shows that backpropagation neural network can be used for function approximation, pattern classification, statistical analysis, and data compression [13]. Then, this paper proposes a cellular neural network model, which is a large-scale nonlinear computer simulation system with dynamic characteristics of cellular automata. The literature points out that the perceptron is the simplest feedforward network in the traditional neural network. It is mainly used to classify images [14]. The RBF network is a radial basis function neural network with good local approximation ability and is often used for system identification. BP network is used for emergency processing, evaluation function, image recognition, model recognition, system management, and so on, due to its good approximation to nonlinear mapping [15]. Hopfield network is the main feedback network, mainly used for associative storage and calculation optimization. CMAC network is a typical local approximation network. It has the advantage of fast learning speed [16]. It is suitable for robot control, pattern recognition, signal processing, and adaptive control. It is especially suitable for adaptive modeling and control. Fuzzy neural network is similar to human this way of thinking, as well as the self-learning and adaptability of neural networks. In addition, there are many neural networks with special structures, such as adaptive resonance neural networks, stochastic neural networks, and HMM neural networks. It is mentioned in the literature that some researchers have established RBF neural network-based electrocutaneous actuator models to eliminate the multivalue display of hysteresis characteristics and write hysteresis coefficients based on the PI model. The Hammerstein model is constructed by combining the ARX function model to characterize the speed-dependent nonlinear hysteresis characteristics of the system. In this paper, the FIR filter algorithm is used to optimize the input data of the simulation, which improves the accuracy of the model and reduces the difficulty of calculation. Experimental results show that the constructed model can effectively adjust the hysteresis characteristics of piezoelectric actuators and adapt to changes in signal frequency. Based on the MPI model, this paper establishes the piezoelectric actuator model and the BP neural network model to establish the piezoelectric actuator model, compares the effects of the H model modeling, and analyzes the results. The literature introduces the working principle of the *d* SPACE hardware simulation platform and explains the entire experimental development process. Combined with the closed-loop PID compound control strategy, the forward compensation control based on the inverse model of RBF neural network is designed, and the control experiment of tracking signals of different frequencies is designed. At the same time, comparing the compound control strategy based on the MPI inverse model and the compensation control strategy based on the RBF inverse neural network model, the advantages and disadvantages of the three control strategies are analyzed.

3. Improved Experiment of Dynamic Process Neural Network

3.1. Mackey-Glass Chaotic Time Series Prediction Simulation. In order to create a chaotic McKee-Glass time series, this paper uses the BP algorithm and its five improved algorithms in the feedforward neural network method, RBF method, to optimize the differential evolution algorithm of the BP neural network. They are the network method and ANFIS used for prediction and benchmarking. Five improved BP algorithms include improved extra pulse algorithm, improved adaptive parameter tuning algorithm, elastic BP algorithm, improved conjugate gradient algorithm, and improved LM algorithm. BP algorithm has the advantages of nonlinear mapping, strong generalization, and so on, and is widely used in the field of prediction. BP algorithm and its five improved algorithms are RBF method, DE optimized BP neural network, ANFIS method, and D-FNN method. The error results are shown in Table 1.

It can be seen from Table 1 that the prediction accuracy of the BP neural network optimized for DE is higher than that of the feedforward neural network method. The prediction effect of ANFIS and D-FNN is better, but the performance of generalized D-FNN is better, slightly worse than ANFIS, but it does not affect the overall prediction effect of D-FNN.

TABLE 1: Comparison of six-step prediction of Mackey-Glass chaotic time series by different methods.

Method of prediction	Root mean square error
Standard BP network algorithm	0.0978
Improved algorithm for additional momentum	0.0972
Improved algorithm for adaptive adjustment of parameters	0.0970
Elastic BP algorithm	0.0956
Improved algorithm of conjugate gradient	0.0953
LM improved algorithm	0.0486
RBF network algorithm	0.0194
DE optimized BP neural network	0.0265
ANFIS	0.0032
D-FNN	0.0078

3.2. Example Prediction of Short-Term Traffic Flow at a Certain Inspection Station

3.2.1. Comparison Experiment of Short-Term Traffic Flow Prediction Based on Different Methods. Table 2 shows the prediction errors of all methods in the short-term traffic flow at a specific detection station in Beijing.

3.2.2. Prediction Performance Analysis of Different Embedding Dimensions and Time Delays. It can be seen from Table 2 that the LM algorithm of the feedforward neural network has a better prediction effect, but the prediction ability of the fuzzy neural network method is better than that of the feedforward neural network method.

The difference in network structure also leads to different prediction results. The embedding size and delay determine the input and output of the network structure. Various embedding sizes and delays are selected for further prediction experiments.

When $m = 3$ and $\tau = 1$, the data are normalized first, and the normalized data are divided into two groups. In order to reflect the forecasting effect of each forecasting model, the forecasting results of all forecasting models are summarized in Table 3.

If $m = 4\tau = 2$, divide these data into two groups and create a prediction model based on multiple neural network methods and a fuzzy neural network for experiments. The prediction results of all prediction models are shown in Table 4.

Table 4 shows that for $m = 4\tau = 2$, the prediction effect of each method is better, and the prediction effect of the D-FNN method is better than that of BP and RBF.

Table 5 shows that the usual root mean square error is used as a metric to evaluate the prediction results.

From Table 5, this paper can conclude that Table 5 reflects the prediction results of different methods of predicting models under different embedding sizes and time delays. The D-FNN method and the ANFIS method show higher prediction effects regardless of the time delay of the optimal embedding measurement or the time delay of the suboptimal embedding measurement. Therefore, the D-FNN technology is effective for predicting the time series of the transmission stream.

4. Identification Method of Neural Network Model

4.1. Dynamic Recognition of Neural Network Patterns. In the real world, most real-world patterns are created by objects with time-varying characteristics. The characteristic of this pattern is that its amplitude fluctuates repeatedly. The closed-loop neural network mentioned earlier in this article can be used to identify this type of system. Here is another model of the identification network: a time-delay neural network.

4.1.1. Deterministic Time Delay Neural Network. Deterministic neural networks with delay are usually divided into sequential and parallel structures as shown in Figure 1:

The serial delay neural network classifier has a network layer structure. The output layer and hidden layer of the network are exactly the same as the double-layer perceptron, except that the input port is composed of a tapped delay block formed by a serial delay line, and the input block is sent for processing. The number of delay units in the delay line is determined by the characteristics of the time-varying mode, and the parallel structure only provides interlayer delay operations. Depending on the circumstances, this may be a structure with multiple hidden layers. The transfer function of the hidden layer neuron can be a sigmoid function or a radial basis function, and the network algorithm can be a general BP algorithm. The working principle of the delay deterministic neural network is still similar to the approximation of the model display scale, and its application has mature theories. The random delay neural network mainly refers to the network model based on the Markov model.

Random time model mainly refers to Markov model or hidden Markov model. MM is a single random process with unknown state, and HMM is a double random process with unknown state and acting in the state.

The basic definition of Markov chain is given by:

$$P(X_0 = q_0, X_1 = q_1, \ldots, X_n = q_n) > 0. \tag{1}$$

And there is formula (2):

$$P\left(X_{n+1} = \frac{q_{n+1}}{X_0}, X_1 = q_1, \ldots, X_n = q_n\right) = P\left(\frac{X_{n+1} = q_{n+1}}{X_0 = q_0}\right). \tag{2}$$

TABLE 2: Forecast errors based on different methods.

Method of prediction	Regularized root mean square error	Equalization coefficient
Standard BP network algorithm	0.2790	0.9413
Improved algorithm for additional momentum	0.2706	0.9415
Improved algorithm for adaptive adjustment of parameters	0.2694	0.9436
Elastic BP algorithm	0.2685	0.9365
Improved algorithm of conjugate gradient	0.2720	0.9350
LM improved algorithm	0.2609	0.9253
RBF network algorithm	0.2678	0.9250
ANFIS	0.2667	0.9275
D-FNN	0.2683	0.9456

TABLE 3: $m = 3\tau = 1$ prediction performance comparison.

Method of prediction	Regularized root mean square error	Equalization coefficient
Standard BP network algorithm	0.4013	0.9013
Improved algorithm for additional momentum	0.3496	0.9154
Improved algorithm for adaptive adjustment of parameters	0.3765	0.9389
Elastic BP algorithm	0.3763	0.9345
Improved algorithm of conjugate gradient	0.3798	0.9311
LM improved algorithm	0.3391	0.9238
RBF network algorithm	0.3215	0.9261
ANFIS	0.2898	0.9276
D-FNN	0.2885	0.9336

TABLE 4: $m = 4\tau = 2$ prediction performance comparison.

Method of prediction	Regularized root mean square error	Equalization coefficient
Standard BP network algorithm	0.3510	0.9104
Improved algorithm for additional momentum	0.3346	0.9159
Improved algorithm for adaptive adjustment of parameters	0.2856	0.9165
Elastic BP algorithm	0.2895	0.9337
Improved algorithm of conjugate gradient	0.2783	0.9284
LM improved algorithm	0.2750	0.9219
RBF network algorithm	0.2890	0.9211
ANFIS	0.2763	0.9427
D-FNN	0.2798	0.9184

TABLE 5: Prediction errors under different embedding dimensions and time delays.

Method of prediction	$m = 3\tau = 1$	$m = 4\tau = 2$	$m = 4\tau = 1$
Steepest gradient descent	0.4012	0.3513	0.2890
Improved algorithm for additional momentum	0.3846	0.3046	0.2806
Improved algorithm for adaptive adjustment of parameters	0.3561	0.2348	0.2781
Elastic BP algorithm	0.3745	0.2798	0.2790
Improved algorithm of conjugate gradient	0.3764	0.2648	0.2716
LM improved algorithm	0.3135	0.2684	0.2749
RBF network algorithm	0.3546	0.2489	0.2887
ANFIS	0.2458	0.2478	0.2659
D-FNN	0.2168	0.2757	0.2680

This is called a discrete Markov chain. HMM is a double random process in which the state is implicit and the observed characteristics are related to probability. That is, the corresponding final Markov state is implicit. In addition, this article usually studies the first-order HMM, which implies two assumptions. The first is the Markov condition. The probability of a state at time $t + 1$ is only related to the state at time t and has nothing to do with the previous state. The second is the assumption of independence of conclusions. The probability of the conclusions of d and a is only observed in specific observations. At time t refers to the current state and has nothing in common with the past state.

From the perspective of training a multilayer perceptron network, HMM is seen as a repetitive neural network.
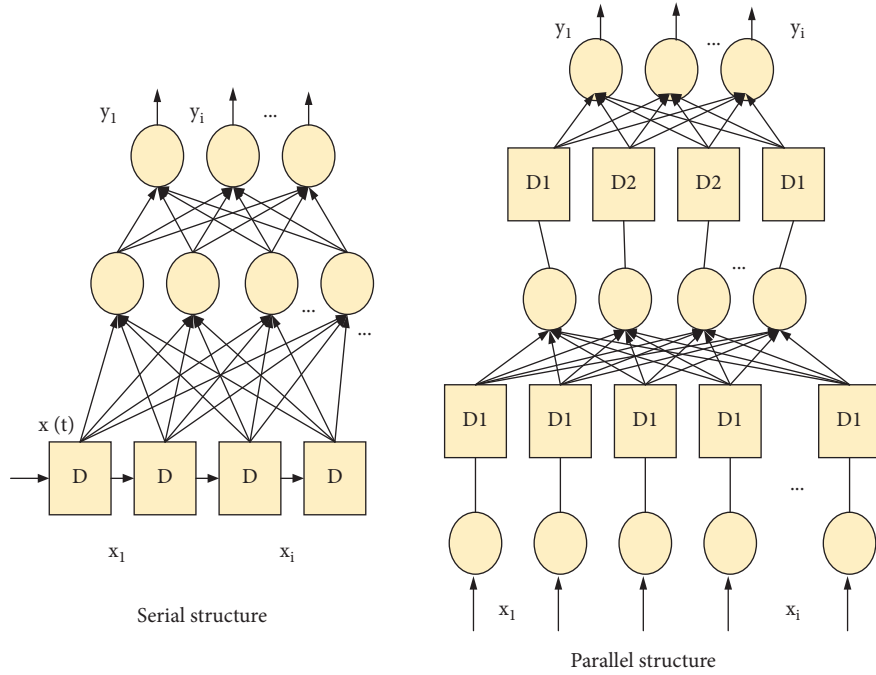
FIGURE 1: Two structures of time-delayed neural network.

Suppose that the N states of the HMM are counted as N neurons, and these N neurons expand over time to form a feedforward network. In fact, this network structure corresponds to the process of constantly updating the states of N neurons. It is actually a recursive network. The following objective function can be defined at the exit of the network as shown in the following formula:

$$E = \sum_{k=1}^{K} \Pr\left(\frac{O^k}{\Lambda}\right). \tag{3}$$

Baum-Welch iterative algorithm

① Given observation sequence C, as formula (4):

$$
\begin{cases}
a_{ij}^o = \dfrac{1}{N}, & j = 1, 2, \ldots, N, \\[2mm]
b_{ij}^o = \dfrac{1}{M}, & j = 1, 2, \ldots, M, \forall i, j = 1, 2, \ldots, N, \\[2mm]
\pi_j^o = \dfrac{1}{N}, & j = 1, 2, \ldots, N.
\end{cases} \tag{4}
$$

② Calculate the parameters from $t = 1$ to $t = T$ and from $k = 1$ to $k = N$, such as formulas (5)–(8):

$$a_i^{k(m)}(t+1) = b_i\left(O^k(t+1)\right)\sum_{j=1}^{N} a_{ij}a_j^{k(m)}(t), \tag{5}$$

$$\beta_i^{k(m)}(t) = \sum_{j=1}^{N} \beta_j^{k(m)}(t+1)b_j^m\left(O^k(t+1)\right)a_j^{k(m)}(t), \tag{6}$$

$$\xi_{ij}^{k(m)}(t) = a_{ij}\beta_i^{k(m)}(t+1)b_i^{(m)}\left(O^k(t+1)\right)a_i^{k(m)}(t), \tag{7}$$

$$\gamma_j^{k(m)}(t) = a_j^{k(m)}(t)\beta_j^{k(m)}(t). \tag{8}$$

③ Calculate according to the following formulas:

$$a_{ij}^{(m+1)} = \frac{\sum_{k=1}^{k}\sum_{r=1}^{r-1}\xi_{ij}^{k(m)}(t)}{\sum_{k=1}^{k}\sum_{r=1}^{r-1}\gamma_{ij}^{k(m)}(t)}, \tag{9}$$

$$b_i^{(m+1)} = \frac{\displaystyle\sum_{k=1}^{k}\sum_{\substack{r=1 \\ \Omega^{(k)}(t)=v_1}}^{r-1}\gamma_{ij}^{k(m)}(t)}{\displaystyle\sum_{k=1}^{k}\sum_{r=1}^{r-1}\gamma_{ij}^{k(m)}(t)}, \tag{10}$$

$$
\begin{aligned}
\pi_i^{(m+1)} &= \sum_{k=1}^{k} \frac{\gamma_j^{k(m)}(t)}{\Pr\{O^k/\Lambda\}}, \\
\Pr\left\{\frac{O^k}{\Lambda}\right\} &= \sum_{j=1}^{N} a_j^{k(m)}(T).
\end{aligned} \tag{11}
$$

④ The iteration ends.

Network test: Calculate any observation sequence, as in formula (12):

$$\Pr\left\{\frac{O}{\Lambda_c}\right\} = \sum_{j=1}^{N} a_j^k(T). \tag{12}$$

Use the following formula to select the category attribute of the specified sequence:

$$c_j = \arg\max\left\{\Pr\left(\frac{O}{\Lambda_c}\right)\right\}, \quad c = 1, 2, \ldots, C. \quad (13)$$

Then, ci is the category of the corresponding observation sequence.

The test is over, continue to test.

4.1.2. Model Checking.
The detection model essentially calculates the probability that the output will be in different failure modes at the next moment based on current and historical inputs, as shown in Figure 2. The ideal signal and the actual output signal are combined into one, partially amplified. Figure 2 is a schematic diagram of the recognition results of $k = 377$ points; the local small coordinate system shows the failure mode probability value, and the system output of $k = 378$ points.

Figure 2 shows that if the two end points of the error subinterval correspond to the most probable system failure mode output, the system output has the highest probability of belonging to the third failure mode at the next moment.

4.1.3. Establishment of Recognition Neural Network for HMM System.
Before configuring the HMM network, the system must convert the error output state and then construct a corresponding HMM network model for each mode. Similar to the RBPNN configuration process mentioned above, preprocessing and postprocessing modules need to be added as needed. The errors mentioned below, unless otherwise specified, refer to the difference between the observed value of the system and the ideal value.

Assuming that it is divided into N subslots, N failure modes are as shown in the following formula:

$$E = \{e_1, e_2, \ldots\}. \quad (14)$$

At the same time, assume that this set of failure modes can be applied at any time, that is, E is not a function of time and assume that the system input error mode set is given by:

$$E_I = \{e_{11}, e_{12}, \ldots, e_{IN}\}. \quad (15)$$

Assuming that the setting error mode output by the system isgiven by:

$$E_O = \{e_{O1}, e_{O2}, \ldots, e_{ON}\}. \quad (16)$$

When the system is running, the real-time system output error keeps jumping between different error modes. If the system outputs a failure mode at time k, as shown in the following formula:

$$e_{Oi}, i = 1, 2, \ldots, M. \quad (17)$$

Defined as formula (18):

$$U^k = \{u(k), u(k-1), \ldots, u(k-n_b)\}. \quad (18)$$

This is the effective input of time k and can also be used as a generalized effective input.

If the system is still in a specific operating state, record its fault sequence and establish the corresponding HMM
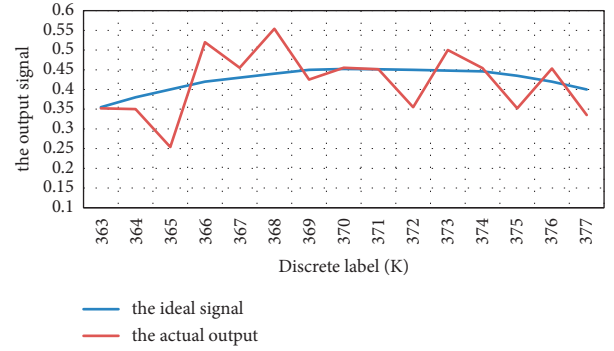

FIGURE 2: Schematic diagram of Markov neural network identification process.

network model. A similar method can be used to compare a group of HMM models to determine the location of the system.

4.2. Parameter Identification of Neural Network Mode.
In fact, many systems not only require this article to evaluate its type but also require this article to understand some important parameters of the system. However, due to the constraints of objective or man-made conditions, this article cannot obtain accurate and complete system information, such as the chemical properties of unknown materials, and a certain evaluation of its physical parameters used to evaluate the type and extent of failure of a complex system and used to evaluate the type and characteristics of remote targets.

4.2.1. Problem Description and Related Concepts.
The identification of the target system usually requires two aspects of information: the evaluation of the type or operation mode of the system, which is called quality evaluation. Obtaining the corresponding parameters or parameters of the current state of the system is called quantitative evaluation here.

For the sake of simplicity, now take the target recognition of a long-range ship as an example. First, we must selectively collect and process the target (current information such as radar image characteristics, trajectory, magnetic field emission, or hull vibration information), hereinafter referred to as all requirements. The collection of target information collected and processed is a measurement space. This article concludes that the target is the head aircraft carrier, not the small fishing boat. This is often based on the distribution of each piece of information in the target measurement space and the relationship between different types of information. This relationship is consistent with the information distribution and relationship in the aircraft carrier measurement room known in this article under the same conditions or closer, which is qualitative.

In practice, the system types are nested layers, qualitative and quantitative processes can be transformed into each other, and smaller types of assessments can be carried out. For larger category judgments, this is also a quantitative

process, and the values of target-related parameters are restricted to a smaller range.

This article makes the following assumptions or definitions: the motion state of the system can be described by a set of coupled differential equations, and the parameters in the equations are the key quantities that affect the spatial distribution of information during measurement.

If any $n-1$ dimensional state parameter in the extended state space takes a certain value, the remaining one-dimensional state parameters exist and only a finite number of values satisfy the corresponding equation, then the center of the state space is called the complete state point, hereinafter referred to as the state point. The subset obtained by dividing the state space of the equation in a certain way is called the sampling range corresponding to the equation. In practice, this article can only get a limited number of points in the sample area, that is, the sample set. Assuming that the known and measurable state parameters of a state point form known data, it is expressed as follows:

$$X_k = \{x_{k1}, x_{k2}, \ldots, x_{ki}\}. \tag{19}$$

Other unknown parameters are expressed as follows:

$$X_u = \{x_{u1}, x_{u2}, \ldots, x_{uj}\}. \tag{20}$$

Therefore, the combination of known and unknown parameters forms the state point of the equation, as shown in the following equation:

$$X = \{X_k, X_n\} = \{x_1, x_2, \ldots, x_n\}. \tag{21}$$

4.2.2. Neural Network Integration of Parameter Identification.
An ideal set of samples should reflect the distribution characteristics of the parameters in the sample area. All neural networks involved in the following are trained from a set of samples.

(1) Selection of state parameters: assuming that the accuracy of the comparison of each parameter is guaranteed by the corresponding equation (function), secondary factors should be ignored as much as possible to reduce the size of the state point and save uptime. Second, the selection of state parameters should be as close as possible to the characteristic information of the system that this article is most interested in. The response characteristic parameters must effectively distinguish different types of systems, but they can still remain stable when the operating conditions of the same type of system change.

The mapping realized by the closed network group is $Y = F(X)$. Due to the certainty of the mapping, each individual network can have better approximation accuracy. According to the neural network approximation theory, it can be known that if the ideal state point X is inserted into a network group, it should be $Y = X$. There is a one-to-one correspondence between such a set of networks and the differential equations in a specific sample ranges. The process of calculating the closed network combination is given by:

$$\begin{cases} X^o = \{X_k, X_u^o\}, \\ X^i = \{X_k^i, X_u^i\} = F(X^i), \\ X^{i+1} = \{X_k, X_u^i\}, \end{cases} \tag{22}$$

where $i = 1, 2, \ldots$. That is to say, in each iteration, only X_a is updated.

Definition 1. The iteration error is as shown in the following formula:

$$E_x = \text{dist}(X^i, X^{(i+1)\gamma}). \tag{23}$$

The recognition error is given by:

$$E_R = \text{dist}(X^i, X^i). \tag{24}$$

The initial recognition error is given by:

$$E_o = \text{dist}(X_u^o, X_u). \tag{25}$$

In the above formula, X_u^* is the true value of the target, and dist($\bullet$) is the ranging function. When the balance index and ER are close to zero, the model is considered to be asymptotically to the equilibrium point. If the starting point of the iteration meets certain conditions, the network integration model approaches the equilibrium point asymptotically, and the recognition accuracy of the equilibrium point is approximately equal to the approximate accuracy of a single subnet.

Since each parameter of the state point is independent only in a mathematical sense, and there may be objective constraints between each other in practice, the sample area is neither a continuous multidimensional area in real space nor a possible subset of columns. Its spatial shape depends on the constraints between the parameters.

4.2.3. Stability Analysis of the Integrated Network Model.
In addition, if it only comes from the sample area, rather than the corresponding point from the initial state of the sample set, it will cause the model to approach the equilibrium point asymptotically, and the corresponding memory will increase the capacity of the network. From the perspective of the entire integrated macrostructure model, it is similar to a Hop field neural network, except that each neuron of the Hop field neural network is replaced with an independent neural network as shown in Figure 3.

Figure 4 shows the error convergence curve of 100 times network training, and the minimum value of its Y coordinate is 10–1 and 10–8. Therefore, the state of the model represents information about the target category in probability, and it is necessary to try to replace models that match other domain examples. If a balance point is found in multiple recognition models at the same time, it can be interpreted as follows: if the target belongs to a certain sample area, the recognition result is the corresponding balance point.

The size of the initial detection network is [5 10 3], and all six individual networks are [5 10 1]. After 1000 times of training, the approximate error percentages of the sample set are [10–1,10–1] and [10–12,10-9, and], which means that the
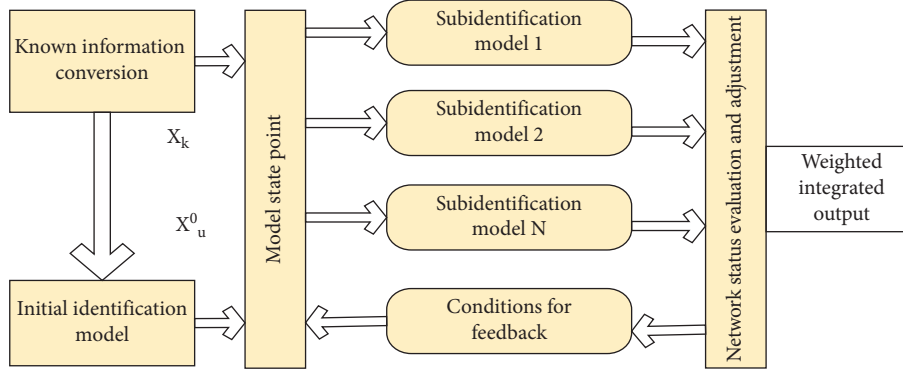
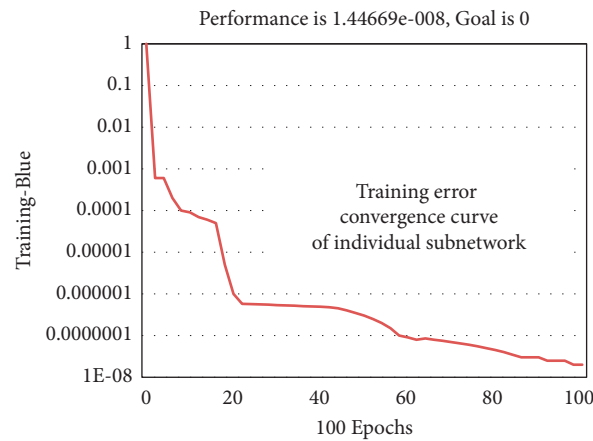FIGURE 3: Network integration model of parameter identification.

FIGURE 4: Individual network training error convergence curve.

accuracy output of an approximate five input and one subnet is at least three The initial detection network with one input and three outputs is several orders of magnitude higher. From the perspective of network training, this difference in accuracy is necessary and easy to implement. Aiming at the problem of right distribution in the current financial management of modern enterprises, this article believes that improvements and optimizations should be made from two aspects, based on the above-mentioned basic ideas and principles: first, modern enterprise financial management maximizes the value of stakeholders. As a guide, a power distribution model based on a static configuration structure should be established to allow all stakeholders to share the company's financial management authority, while balancing the configuration parameters of corporate financial management authority, and enhancing the interactive configuration of financial management authority between objects to make a certain Financial management achieves a balanced state of mutual restraint and mutual restraint among all configuration levels and objects. The second is to improve the distribution of modern financial management power by improving the company's internal management structure and stabilizing the company's external market mechanism. All parties can have equal opportunities to participate in the

distribution of corporate financial management power to own their property rights.

This digital simulation experiment is based on the MATLAB/SIMULINK platform and neural network toolkit. In any case, the time is 5 seconds. Figure 5 shows the convergence process of a sample point in the corresponding recognition model, and the ordinate of the convergence trajectory graph is a logarithmic coordinate.

If the test sample points are inserted into a suitable integration model, the model can still converge to a (pseudo) equilibrium point, which reflects the generalizability of neural network integration. At this point, these diagrams are similar to Figure 6, except that if the final state is not close to zero and the initial state points from different scan sets are inserted into the recognition model, the state will diverge, and the program will automatically terminate with similar results.

It can be seen from the above simulation experiments that the model as a whole is close to the convergence state in the third iteration, that is, the overall recognition accuracy has reached the approximation accuracy of a single network. However, the process of model creation requires the identity modeler to have certain experience and relevant knowledge.
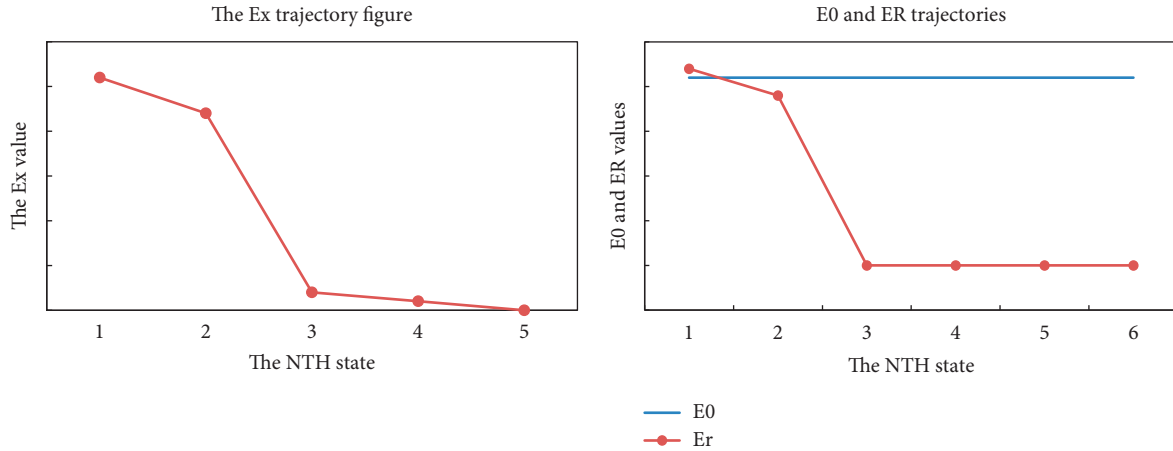
FIGURE 5: Convergence process of parameter identification accuracy E_x, E_r.
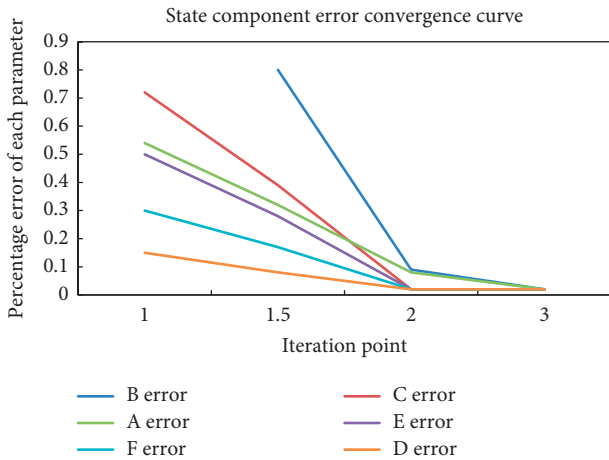

FIGURE 6: Convergence process of each component of the state point.

5. Conclusion

In terms of identifying system parameters, this paper proposes a new method of neural network integration based on the concept of complete state points. The method combines system type recognition and parameter recognition to ensure the accuracy and versatility of neural network integrated recognition, thereby reducing the requirement of the recognition system for test information knowledge. Neural network is an effective tool to identify the system. It does not need the internal mechanism of the system but only needs the input and output data of the system to simulate the NN model, which characterizes the input and output characteristics of the system and surpasses the traditional identification methods. Therefore, the system recognition based on neural network has a wide range of technical foundation, theoretical significance, and academic value. After systematically studying the wide application of neural networks in system identification and remaining problems, this paper proposes a separate method to build neural network models for various types of more complex systems. Before creating a predictive model, we must first define the input and output of the network structure. This article introduces chaos theory and uses chaotic phase space reconstruction technology to determine the input and output of the predictive model. This method solves the problem of determining the input and output definitions of the network structure based on intuitive experience. First, by calculating the maximum Lyapunov exponent, determine whether the three traffic flow data sets used in this paper are chaotic time series and then use the chaotic time series processing method to deal with these three time series are processed, and methods and methods of mutual information are used. This paper determines the embedding size and delay, based on the BP algorithm in the neural network method and its five improved algorithms, the ANFIS method in the RBF method, the fuzzy neural network method and the D-FNN method to construct nine prediction models, and combine these nine, the prediction model is applied to three sets of measurement data to test the prediction performance of D-FNN in the transmission basin. Choose different embedding sizes and time delays to create different prediction models for prediction experiments. Experiments show that the prediction model effect of the three sets of measurement data is the best in the optimal embedding measurement and time delay, indicating that the combination of chaos theory and D-FNN is useful for improving the prediction performance. At the same time, in terms of identifying system parameters, this paper proposes a new neural network integration method, which combines the identification of system types and parameters. On the basis of maintaining the accuracy and generalization of recognition, the neural network reduces the requirements for the recognition system, that is, it can deal with fuzzy, incomplete, or even uncertain system test information.

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.

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