# A Hybrid Intelligent Learning Algorithm to Identify the ECNS Based on FBP Optimized by GA

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Abstract—Along with the development of computer network, the electronic commerce has become the new pattern to carry on the commercial activity gradually, but the security problem is also getting more and more prominent. How to identify the E-commerce network security (ECNS) rating and establish a security convenient application environment for the electronic commerce has already become a major concern topic that needs to be settled urgently. To identify the ECNS rating scientifically and accurately, this paper proposes a hybrid intelligent learning algorithm which uses the genetic algorithm (GA) to optimize the fuzzy backpropagation (FBP) neural network. The algorithm not only can exert the unique advantages of BP neural network (BPNN), but also overcome the shortcoming to produce the local minimum points in the network modeling process and enhance the accuracy of network security identification greatly. The ECNS identification results for 14 E-commerce systems show that the method is reliable and efficiency.

*Index Terms*—hybrid intelligent algorithm, FBP, GA, ECNS, security rating identification

# I. INTRODUCTION

With the implementation and popularization of the Ecommerce, it changed the work and the life style enormously, and has brought the infinite opportunity. However, the Internet platform that is depended by the electronic commerce actually fills the complex security risk. It is very difficult for the electronic commerce to develop smoothly for the Hacker's attack, the intended or unmeant destruction to the sensitive data, the system visit disturbance and so on; In addition, electronic commerce's development also faces the internal risk, the electronic commerce enterprise is quite blind to the security problem, the safety consciousness is light, the leadership lacks the system comprehensive understanding to electronic commerce's operation as well as the limitation of knowledge and technical. With the implementation and further popularization, the security problem of Ecommerce system is in reliefs day by day, and which

already became the biggest barrier to the E-commerce development. Identify and solve the system security problem has already become the most important work to develop the E-commerce. Therefore, it is essential to identify and evaluate the network security problem and do some qualitative and quantitative analytical research to the electronic commerce security. It is helpful for the electronic commerce enterprises to make the security policy and security management, and carry on the electronic commerce security investment.

The electronic commerce network security (ECNS) identification is a systematic evaluation process, and a scientific and quantitative argumentation. There are many methods about the ECNS identification have been widely applied, such as: analytic hierarchy process, gray systematic evaluation, fuzzy comprehensive evaluation method, etc. However, these methods are subject to stochastic factors in the evaluation, and the evaluation results are influenced by subjective experience and knowledge limitations easily, which often with personal bias and one-sidedness. In recent years, the rapid development of neural network by its unique advantage—self-learning, self-organizing, self-adapting ability, which overcame the subjective factor problem, therefore, more and more people use it in the evaluating aspect.

Generally, the neural network uses the backpropagation neural network (BPNN) algorithm, when uses the BPNN algorithm to carry on the network training, has the following 3 shortcomings: First, the convergence rate of learning process is slow; Second, the algorithm is incomplete, easy to fall into the partial minimum point, but when set the high study efficiency, it is possible to generate shake; Third, the robustness is not good, the network performance is quite sensitive to the initial network establishment. If the fuzzy neural network (FNN) trains using the BP algorithm, the speed is slow; it is possible to fall into the partial minimum point. This paper proposed the fuzzy back-propagation (FBP)-genetic algorithm (GA) algorithm, which use the characteristic of GA to search the global optimal solution in entire variable space as well as the fast and precise convergence characteristic of BP algorithm. We carry on the off-line global optimization to the FBP parameters using the GA algorithm, then carry on the real-time training according to the BP algorithm to obtain the suboptimal or optimalizing fuzzy neural network. [1][2]

# II. THE FBP NEURAL NETWORK MODEL CONSTRUCTION

In 1943, McCulloch and Pitts proposed the neuronal formalization model, the neuron can be stated by the simple zha value function, and complete the logical function. In the 1970s, when Paul Werbos researched the social sciences question, he discovered the BP algorithm mathematics principle. In 1982, J. Hopfield proposed the Hopfiel neural network, started a neural network research upsurge. In the mid-1980s, Rumelhert and his colleagues have published the famous monograph of parallel distributed processing, established the BP algorithm and the forward neural network. In the 1990s, the artificial neural network and the evolution neural network are proposed based on the knowledge.

## A.. The Basic BPNN Model

BP neural network is consisting of neurons and the connection between neurons, it can be divided into input layer, hidden layer and output layer, and it belongs to the learning algorithm with mentor. BP neural network is composed of positive propagation and the back propagation. In the positive propagation phase, the state of every layer neurons will only affect the neurons state in the next layer; if the expected output cannot be gotten in the output layer, the network enters into the error's back propagation phase. According to the error signal of back propagation, the network changes the networkconnecting of all layers, to find out the best weight set and realize the correct network output. The output of the input layer neuron is equivalent to the input values. For the p(p=1,2,...,P) sample, if the output of k(k=1,2,...,K)node (the node is on the output layer of BP neural network) is O<sub>kp</sub>, the connection weight values between hidden layer and output layer, input layer and hidden layer are  $w_{ki}$  and  $v_{ii}$ , and the hidden layer and output layer neurons use the bipolar compression function as the output function, then the error function E on output layer can be defined as a square function, namely

$$E = \frac{1}{2} \sum_{p=1}^{P} \sum_{k=1}^{K} \left( d_{k} - O_{kp} \right)^{2}$$
(1)

In the formula,  $d_k$  denotes corresponding desired output value.

BP algorithm is the guided learning, and the essential of learning is to revise the weight value constantly so as to the error function to zero, therefore, in accordance with the principle of error gradient decline and the adjustment of  $w_{kj}$  and  $v_{ji}$  can be expressed as:

$$\begin{cases} \Delta w_{kj} = -\eta \frac{\partial E}{\partial w_{kj}} \\ \Delta v_{ji} = -\eta' \frac{\partial E}{\partial v_{ji}} \end{cases}$$
(2)

 $\eta$  and  $\eta'$  denote learning rate.

The amending process of weight value is an iterative process, namely:

$$\begin{cases} w_{kj}(n+1) = w_{kj}(n) + \eta \sum_{P=1}^{P} \delta_{kp} O_{jp} \\ v_{ji}(n+1) = v_{ji}(n) + \eta' \sum_{P=1}^{P} \delta_{jp} O_{jp} \end{cases}$$
(3)

In the formula:

$$\begin{cases} \delta_{kp} = \left(\mathbf{d}_{k} - \mathbf{O}_{kp}\right) \mathbf{O}_{kp} \left(1 - \mathbf{O}_{kp}\right) \\ \delta_{jp} = \left(\sum_{K=1}^{K} \delta_{kp} \mathbf{w}_{kj}\right) \mathbf{O}_{jp} \left(1 - \mathbf{O}_{jp}\right) \end{cases}$$
(4)

BP algorithm steps are as follows:

① Initialize weight value, and give the random number between 0-1 to all the weight value.

(2) Input the samples, and specify the output layer neuron's expectations.

③ Calculate the actual output of every layer neurons in sequence.

④ Amend the weight value, starting from the output layer until hidden layer gradually.

(5) Return to step 2, the network study concluded in less than a given error. [3]-[8]

## B. FBP Model Construction

We identify the ECNS using the BP neural network, which can overcome the request to have the strict distribution supposition for the input samples and can adapt the ECNS characteristic of high misalignment and massive complex information. But the BP neural network also has the deficiency. First, the BP neural network's training has certain blindness, suits to the quantitative index analysis and neglects to the qualitative index analysis in the influencing factors; it is unreasonable, one-sided obviously. Furthermore, identify the ECNS with the neural network; it is very difficult to explain the practical application meaning of network parameter and the value after neural network training, which causes the model to convince the persuasion. Finally, because the BP neural network is the gradient descent essentially, the minimized objective function is also quite complex; therefore the convergence rate of learning process is slow and easy to fall into the partial minimum point.

Aim at the insufficiency of the BP neural network, we construct the model unified the fuzzy system and the neural network. The fuzzy neural network is one kind of fuzzy inference system based on the neural network frame. Suppose the system to have n input  $x_i$  (i=1,2,..., n), the output is y, for the fuzzy rule  $R_j$  (j=1,2,..., l), the system's input-output fuzzy model is:

If  $x_1$  is  $A_{j1}$ ,  $x_2$  is  $A_{j2}$ ...,  $x_n$  is  $A_{jn}$ Then

$$y_1 = \omega_{j0} + \omega_{j1} \times x_1 + \omega_{j2} \times x_2 + \dots + \omega_{jn} \times x_n$$

The global output may be expressed as:

$$y = \frac{\sum_{j=1}^{l} \lambda_j y_j}{\sum_{i=1}^{l} \lambda_j}$$
(5)

In the formula,  $x_i$  is the input variable.  $\lambda_i = \mu_{A_{i1}}(x_1) \Lambda \mu_{A_{i2}}(x_2) \Lambda, \dots, \Lambda \mu_{A_{in}}(x_n)$ 

 $\wedge$  expresses to carry on the fuzzy logic and the operation, namely minimum operation.  $u_{Ajn}(x_i)$  expresses the membership function of  $x_i$  to fuzzy subset  $A_{ji}$ .  $A_{ji}$  can be expressed by Gaussian membership function as:

$$A_{ji} = \exp\left[-\left(\frac{x_i - c_{ji}}{b_i}\right)^2\right]$$
(6)

In the formula,  $c_{ij}$  is the central value of degree of membership function; b is the width of membership function.

Now, we construct the four layer FBP neural network mode, including the input layer, two hidden layers and the output layer. The first layer is the input layer, the second to fourth layer has the explicit fuzzy logic significance, corresponds to the fuzzy, rule inference, and deblurring of fuzzy logic control. The two inputs are erroneous e and erroneous change rate ec respectively, an output is u.

1) Input layer

This layer has 2 nodes altogether, which will pass the input to the next layer.

2) Fuzzy layer

This layer has 14 nodes; its output is the membership degree of fuzzy subset. Divides e and the ec to 7 fuzzy subsets, namely {negative big, negative, negative small, zero, positive small, positive medium, positive big}= {NB, NM, NS, ZO, PS, PM, PB}, their membership function can be expressed by gaussian function:

$$\mu_{j}^{i} = \exp\left[-\left(\frac{x_{i} - m_{ij}}{\sigma_{ij}}\right)^{2}\right]$$
(7)

In the formula (1), i=1, 2; j=1, 2,..., 7;  $x_i$ ,  $m_{ij}$  and  $\delta_{ij}$  is the input variable, the membership function center, the membership function width respectively. Adjusts the weight and the threshold value in this level, also means to adjust the center and the width of gaussian function, and thus obtains the membership function of different position and shape.

3) Regular layer

This layer has 49 nodes, its output represents the adaptability of fuzzy rule, and the expression is:

$$\alpha_k = \mu_i^1 \cdot \mu_j^2 \tag{8}$$

In the formula (2), i, j=1, 2,..., 7; k=1, 2,..., 49. The controller has 49 fuzzy rules according to the inputoutput space fuzzy subset's division. The fuzzy regular form is:

 $R_k$ : If (e is  $A_i^{1}$ ) and (ec is  $A_j^{2}$ ) then u is  $U_k$ . i, j=1, 2,..., 7; k=1, 2, ..., 49  $R_k$  is the k<sup>th</sup> fuzzy rule,  $A_i^1$ ,  $A_j^2$ ,  $U_k$  is the fuzzy subset of e i<sup>th</sup>, ec j<sup>th</sup>, the u k<sup>th</sup>, and total fuzzy relationship:  $R = \bigcup R_k$ 

 $\sum_{k}^{k} \sum_{k}^{k}$ 

4) Deblurring layer

This level only has 1 node. The solution uses the weighted average method, fuzzy system's output is:

$$u = \sum_{k=1}^{49} \omega_k \overline{\alpha_k}$$
(9)  
In the formula (9):  
$$\overline{\alpha_k} = \frac{\alpha_k}{\sum_{k=1}^{49} \alpha_k}$$

 $\sum_{m=1}^{n} \alpha_m$ 

 $\alpha_k$  is the adaptability of k<sup>th</sup> regular.  $\omega_k$  is weight value in this level.

In this fuzzy neural network, the adjustable parameter has the weight value  $\omega_k$  in 4<sup>th</sup> layer, it represents the regular parameter; the 2nd weight value  $m_{ij}$  and threshold value  $\delta_{ij}$ , namely the parameter of Gaussian membership function.

The structural model of FBP neural network can summarize the fuzzy rule, adjust the membership degree function, process the fuzzy information and complete the fuzzy inference while inherits the neural network learning capability. Moreover, the node and parameter of FBP neural network have the obvious practical application meaning, causes the network model to have the explicable ability. Therefore, the FBP performance surpasses the sole fuzzy or the neural network structure. [9]-[15]

# III. OPTIMIZE THE FBP USING THE GA

## A. The GA Model Construction

Genetic Algorithm introduces the computer simulation research to the biology systems. Professor Holland in Michigan University inspired by the biology simulation technology, created a self-adaptation probability optimization technology which fit for the complex system optimization based on the biology genetic and evolutionary mechanism, that is the genetic algorithm.

Compared with the genetic algorithm, the most classical optimization algorithm is the gradient or higher time statistics based on a single measuring function to produce a determinate experimentation solution sequence; Genetic algorithm is not dependent on gradient information, but search for the optimal solution through simulated natural evolutionary process. It uses the coding technology to act on the number bunch called chromosome, simulates the evolutionary process that composed of these number bunches. Genetic algorithm regroups the good adaptability bunches, and generates the new bunch groups through the organized and random information exchange.

## 1) The GA model

a) The indexes standardization

To the customer loyalty problems, we suppose the evaluating set  $A = \{A_1, A_2, ..., A_n\}$ , the index set  $G = \{G_l, M_l, M_l, M_l, M_l\}$ 

 $G_2, ..., G_m$ , the index value of problem  $A_i$  to index  $G_j$  is  $x_{ij}$  (i= 1, 2, ..., n; j=1, 2, ..., m). The comprehensive evaluating indexes of customer loyalty problems include customer expectations, customer trust, customer satisfaction, customer awareness value and transfer cost. Suppose the vector  $Q_1 = \{G_1, G_2, \dots, G_k\}$  denotes k customer expectations index, the vector  $Q_2 = \{G_{k+1}, \dots, Q_{k+1}\}$  $G_{k+2}, \ldots, G_p$ }denotes p-k customer trust and satisfaction index, the vector  $Q_3 = \{G_{p+1}, G_{p+2}, \dots, G_q\}$  denotes q-p customer awareness value index, the vector  $Q_4 = \{G_{q+l},$  $G_{q+2}, \ldots, G_m$  denotes m-q transfer cost index.

This paper carries through dimensionless disposal to the problems used fuzzy subjection function, the result is as follows:

 $X = \{x_{ii} = |1, 2, ..., n; k = 1, 2, ..., m\}$ 

For customer expectations index, its subjection function is:

$$y_{ij} = \begin{cases} 1 & x_{ij} \le a \\ \frac{b - x_{ij}}{b - a} & a < x_{ij} < b \\ 0 & xi_j \ge b \end{cases}$$
(10)

 $(i=1, 2, ..., n); j \in Q_1$ 

 $\boldsymbol{x}_{ij}$  denotes the index value,  $\boldsymbol{y}_{ij}$  denotes the value after dimensionless disposal, a and b denote the maximum and the minimum of the indexes.

For customer trust and satisfaction index, its subjection function is:

$$y_{ij} = \begin{cases} 1 & x_{ij} \ge b \\ \frac{x_{ij} - a}{b - a} & a < x_{ij} < b \\ 0 & xi_j \le a \end{cases}$$
(11)

 $(i=1,2,...,n); j \in Q_2$ 

For customer awareness value index, its subjection function is:

$$y_{ij} = \begin{cases} 1 - \frac{q_1 - x_{ij}}{\max\{q_1, x_j^{\min}, x_j^{\max} - q_2\}} & x_{ij} < q_1 \\ 1 & q_1 \le x_{ij} \le q_2 \\ 1 - \frac{x_{ij} - q_2}{\max\{q_1, x_j^{\min}, x_j^{\max}(k) - q_2\}} & x_{ij} > q_2 \end{cases}$$
(12)

 $(i=1,2,...,n); j \in Q_3$ 

For transfer cost index, its subjection function is:

$$y_{ij} = \begin{cases} 1 & x_{ij} = x_j^{m} \\ 1 - \frac{|x_{ij} - x_j^{m}|}{\max_{i} |x_{ij} - x_j^{m}|} & x_{ij} \neq x_j^{m} \end{cases}$$
(13)

(i=1,2,...,n);  $j \in Q_4$ In the formula,  $x_j^{max}$  and  $x_j^{min}$  denote the maximum and minimum value of transfer cost index respectively.

#### b) Determination of the objective function

Suppose the benchmark project Ao={ $x_{0i}$  j=1, 2, ..., m), the method to select the benchmark project is as follows:

To the customer expectations index, order:

$$x_{oj} = \min_{1 \le i \le n} \{ x_{ij} \} \qquad j \in Q_1$$

$$(14)$$

To the customer trust and satisfaction index, order:

$$x_{oj} = \max_{1 \le i \le n} \left\{ x_{ij} \right\} \qquad j \in Q_2 \tag{15}$$

To the customer awareness value index, suppose the  $[q_1, q_2]$  is the optimal customer awareness value of the index value, order:

$$x_{oj} = x_j (x_j \in [q_1, q_2]) \quad j \in Q_3$$
(16)

To the transfer cost index, suppose the  $x_i^m$  is the optimal index fixed value, order:

$$x_{oj} = x_j^{m} \quad j \in Q_4 \tag{17}$$

Suppose the W=  $\{w_1, w_2, ..., w_i\}$  is the index weight value, thereinto (j=1,2,...,m), and W meets the constraint condition:

$$\sum_{j=1}^{m} w_j^2 = 1$$
(18)

The index value of the benchmark project A<sub>0</sub> After the standardization is  $y_0 = \{y_{0i} | i = 1, 2, ..., m\}, w_i y_{0i}$  denotes the weighted comprehensive performance value of the benchmark project index, and the w<sub>i</sub>y<sub>ij</sub> denotes the weighted comprehensive performance value of the project i. The change of the weighted comprehensive performance values between the project index and the benchmark project index should be stable relatively, namely, the smaller the deviation is, and the better the project is. Suppose Z<sub>i</sub> is the weighted comprehensive performance value deviation between project i and the benchmark project, the objective function can be given under the constraint condition (18):

$$\min Z_{i}(W) = \sum_{j=1}^{m} (w_{j} y_{0j} - w_{j} y_{ij})^{2} \quad (j = 1, 2, ..., n)$$

$$\sum_{j=1}^{m} w_{j}^{2} = 1 \quad (0 < \varepsilon_{j} < 1; j = 1, 2, ..., m)$$

$$w_{j} \ge \varepsilon_{j}$$
(19)

In the formula (19),  $\varepsilon_i$  is the stated minimum value of the index weighted vector, in order to solve the above problem, we can assembles the objective function as the objective function U(W) through the tantamount weight disposal:

$$U(W) = \sum_{i=1}^{n} \frac{1}{n} Z_i(W) = \sum_{i=1}^{n} \frac{1}{n} \sum_{j=1}^{m} w_j^{2} (y_{0j} - y_{ij})^{2}$$
(20)

The formula (11) divided by n on both sides of the equation, suppose F(W) = U(W)/n, we can gain:

$$F(W) = \sum_{j=1}^{m} w_j^2 \frac{1}{n^2} (y_{0j} - y_{ij})^2 = \sum_{j=1}^{m} w_j^2 (y_{0j} - \overline{y_j})^2$$
$$\overline{y_j} = \sum_{i=1}^{n} \frac{1}{n} y_{ij}$$
(21)

(j=1,2,...,m)

Then formula (19) can transfer into formula (22), namely, the objective function is:

$$\min F(W) = \sum_{j=1}^{m} w_j^2 (y_{0j} - \overline{y_j})^2$$
  
s.t. 
$$\begin{cases} \sum_{j=1}^{m} w_j^2 = 1 \\ w_j \ge \varepsilon_j \end{cases}$$
 (22)



Figure 1. The algorithm flowchart of GA

# B. Optimize the FBP Using the GA

1) Optimize the weight value of FBP using the GA

The neural network study includes the topology study and the weight study. This paper will discuss the weight value of BPNN algorithm optimized by GA mainly, and the content of GA is as follows:

(1) Code: Neural network's weight study is a complex continual parameter optimization question, if uses the binary code, will cause the code string to be too long, and need the decoding to gain the real number again, will cause the weight change to step-by-step, affects the network study precision. Therefore, we use the real number to code, each weight is linked to be a long string according to certain rule, and each string position is corresponding with a network weight.

② Evaluation function f: Distribute the weighted in the chromosome to the given network architecture, the network take training sample collection as the input and output, after the movement, take the reciprocal of squares sum of returning error as the chromosome evaluation function.

(3) Genetic operator: Regarding the different application question, we may determine the different genetic operator, and adopt the weight overlapping and the weight variation operator.

④ Weight overlapping operator: The overlapping includes the simple point overlapping, two point overlapping and the multi-spots overlapping. We select the three spots overlapping. For each weight input position in the filial generation chromosome, the (5) Weight variation operator: For each weight input position in the filial generation chromosome, the variation operator selects a value stochastically in the initial probability distribution by probability  $P_m$ , and then adds it with the weight in the input position.

6 Selector mode: The choice operator chooses the partial individuals as the father generation from the community through some kind of rule, with the aim of carrying on the genetic operations of overlapping and variation. The choice operator of traditional GA uses the adaptive proportion method generally, namely, chooses them as the father generation individual according to each individual sufficiency.

2) Optimize the training algorithm of FBP using the GA

Genetic algorithm goes on the search and optimization using the method of successive iteration, therefore GA has the global searching ability, so we can find out the global optimum solution using GA to optimize the FBP neural network and enhance the accuracy of the network appraisal.

To adjust the parameter value  $(c_{ij}, b_i)$  of the membership function of the FBP network with GA, we express the various parameters with the binary string firstly. Suppose the parameter component is in the predetermined scope  $[\theta_{min}, \theta_{max}]$ , then the relation between the parameter string value and actual parameter is:

$$\theta i_{ij} = \theta_{\min ij} + \frac{binrep}{2^1 - 1} \left( Q_{\max ij} - \theta_{\min ij} \right)$$
(23)

In the formula, binrep expresses the binary integer by 1 character string.

In GA, the crossover rate  $P_c$  and the mutation rate  $P_m$  has the very tremendous influence to the GA performance. In general, the select scope of  $P_c$  is 0.5-1.0,  $P_m$  is 0.005-0.1. In view of the different optimized problem, it needs the repeated experiments. We use one kind of autoadapted  $P_c$  and  $P_m$  method, and use the fitness function to weight the convergence condition, its expression is as follows:

$$P_c = \frac{k_1}{f_{\text{max}} - f} \tag{24}$$

$$P_m = \frac{k_2}{f_{\text{max}} - \overline{f}} \tag{25}$$

In the formula,  $f_{\text{max}}$  and  $\overline{f}$  is the biggest fitness and the average fitness in the colony respectively.  $f_{\text{max}} - \overline{f}$  expresses the convergence degree, K<sub>1</sub> and K<sub>2</sub> is constants smaller than 1.0.

If we already obtained the sample data ( $e_i$ ,  $\Delta e_i$ ,  $y_j^*$ ),  $1 \le i \le m$  from the operating data, then the problem becomes for the above fuzzy neural network model:

When inputs  $e=e_i$ ,  $\Delta e=\Delta e_i$ , then outputs  $yi_j^* = y_i$ , seeks for the optimalizing parameter  $\theta_i = [c_{ij}, b_j]$  of fuzzy membership function:

$$\min\{E\} = \frac{1}{2} \sum_{i=1}^{m} \left( y_i - y_i^* \right)^2$$
(26)

In the formula,  $y_i$  is the expected output value,  $y_i^*$  is the FBP output value.

The trained FBP by the GA algorithm can adjust the network weight using the BP fast gradient algorithm by the online learning method. Now we define:

$$J = \frac{1}{2} \sum_{i=1}^{m} \left( y_i - y_i^* \right)^2$$
(27)

$$W(t+1) = W(t) - \eta \frac{\partial J}{\partial W(t)} + \alpha \Delta W(t)$$
<sup>(28)</sup>

In the formula,  $\eta$  is the study factor,  $\alpha$  is the momentum factor.

# C. The Algorithm Step of FBP-GA

(1) Produce M binary element string stochastically, each character string expresses a group of network parameters;

2 Calculate the sufficiency each group of parameters;

③ Carry on the choice, overlapping and variation operation to produce the new colony;

4 Return to step 2 until meet to the convergence condition;

<sup>(5)</sup> Take the character string with the best sufficiency in the colony, obtain the optimized parameter of the neural network;

<sup>(6)</sup> Sample the r(t) and y(t), count the error e and error change rate ec;

 $\bigcirc$  Calculate the output u(t) of the fuzzy neural network controller using the formula (7), (8), (9);

(8) Real-time learning network parameter using the BP algorithm, online adjustment  $\omega_k$ ,  $m_{ij}$  and  $\delta_{ij}$ ;

(9) set t=t+1, and return to the step (6). [16]-[26]

# **IV. SIMULATION EXPERIMENT**

In this paper, we take the security measurement of 14 E-commerce systems as an example to carry on the network security evaluation. The specific analysis steps are as follows:

## A. The Indices System Construction

Looking from system's viewpoint, the evaluating indices system is the organic whole which is composed of certain single evaluating indices, it should reflect the goal and request of the evaluation, therefore, according to the above analysis about the electronic commerce security factor, simultaneously in line with the science standard, optimization, the system clear and concise. comprehensive practical and the feasibility principle, this paper carried on the positive exploration and essential screening to the electronic commerce security indices, the concrete indices system is as follows:

1) Network security indices

The network security is refers to guarantee the secrecy, the integrity and the exploitability of the data information in the network environment using the network management control method and the technical measure. Network security's essential goal is to guarantee the network transmission's information not to be increased, changed, lost or illegal read before arriving at the destination. The network security involves many levels, must adopt many kinds of technologies and the product to solve each kind of security problem. (1) System safety: Operating system security (U<sub>1</sub>), Special software security of electronic commerce (U<sub>2</sub>). (2) Network operation security: Data backup (U<sub>3</sub>), Data restoration (U<sub>4</sub>), Firewall security (U<sub>5</sub>). (3) Web security: Web server security (U<sub>6</sub>), Web database security (U<sub>7</sub>).

2) Transaction security indices

The electronic commerce transaction system usually is refers to any network service that includes the currency and the commodity or the service exchange. Includes specifically: (1) Logistics security: Logistics base security (U<sub>8</sub>), Logistics allocation security (U<sub>9</sub>). (2) Electronic payment security: Digital currency security (U<sub>10</sub>), Payment service security (U<sub>11</sub>), Electronic payment system security (U<sub>12</sub>).

3) Information security indices

The majority activities of electronic commerce carry on on-line, but the Internet network is famous by its openness, therefore, the data message will appear various security problems in the process of production, the transmission, the preservation, the confirmation and the identification. Includes specifically: (1) Intelligence transmission security: Data transmission encryption mechanism (U<sub>13</sub>), Data integrity distinction mechanism (U<sub>14</sub>). (2) Information storage security: Database security (U<sub>15</sub>), Terminal security (U<sub>16</sub>). (3) Information audit: Information content audit (U<sub>17</sub>), Information body confirmation (U<sub>18</sub>).

4) Physics security indices

Physics security mainly includes: (1) equipment room environment security: Management system security ( $U_{19}$ ), Construction security ( $U_{20}$ ), Equipment security ( $U_{21}$ ). (2) Hardware protection: The equipment message protection installation ( $U_{22}$ ), Input/output channel regulatory measures ( $U_{23}$ ).

## B. Analysis of Simulation Experiment

In this paper, we take the ECNS identification based on the FBP and GA of 14 E-commerce systems as an example, which are shown in table I.

TABLE I. The Expert Evaluating Data

Number	$U_1$	$U_2$	U <sub>3</sub>	$U_4$	U <sub>5</sub>	U <sub>6</sub>	U <sub>7</sub>	$U_8$
1	0.5	0.5	0.3	0.5	0.7	0.5	0.3	0.3
2	0.5	0.5	0.7	0.5	0.7	0.5	0.7	0.7
3	1.0	1.0	0.7	1.0	1.0	1.0	1.0	1.0
4	0.7	1.0	1.0	0.5	0.7	1.0	0.7	0.7
5	0.7	0.5	0.7	1.0	0.7	0.5	0.7	0.7
6	0.5	0.5	0.7	0.5	0.7	0.5	0.3	0.3

7	0.5	0.3	0.3	0.1	0.3	0.3	0.3	0.3
8	0.5	1.0	0.7	1.0	0.7	1.0	1.0	1.0
9	0.7	0.7	1.0	0.5	0.7	0.5	0.7	0.7
10	0.7	1.0	1.0	1.0	0.7	1.0	0.7	0.7
11	0.7	0.7	0.7	0.5	0.7	0.5	0.7	0.7
12	0.7	1.0	0.7	1.0	0.7	1.0	1.0	1.0
13	0.7	0.5	0.3	0.5	0.3	0.5	0.3	0.3
14	0.7	1.0	0.7	0.5	0.7	1.0	1.0	1.0

# CONTINUED TABLE

Number	U9	U <sub>10</sub>	U <sub>11</sub>	U <sub>12</sub>	U <sub>13</sub>	U <sub>14</sub>	U15	U <sub>16</sub>
1	0.5	0.5	0.1	0.5	0.3	0.5	0.7	0.7
2	0.5	0.7	0.5	0.7	0.5	0.7	0.7	0.7
3	0.7	0.7	1.0	1.0	1.0	0.7	1.0	0.7
4	0.7	1.0	1.0	1.0	1.0	0.7	0.7	0.7
5	0.7	0.5	0.5	0.7	0.7	0.7	0.7	0.5
6	0.7	0.5	0.5	0.7	0.5	0.5	0.7	0.7
7	0.5	0.5	1.0	0.5	0.3	0.5	0.3	0.3
8	0.7	0.5	0.5	0.7	1.0	0.7	0.7	0.7
9	0.7	0.7	0.5	0.7	0.7	0.5	0.7	0.7
10	0.7	1.0	1.0	0.7	0.7	0.7	0.7	0.7
11	0.7	0.7	1.0	0.7	0.7	0.5	0.5	0.7
12	0.7	0.7	1.0	0.4	1.0	0.7	0.7	0.7
13	0.5	0.7	0.3	0.5	0.3	0.5	0.7	0.5
14	0.7	0.7	0.5	1.0	1.0	0.7	0.7	0.7

## CONTINUED TABLE

Number	U <sub>17</sub>	U <sub>18</sub>	U <sub>19</sub>	U <sub>20</sub>	U <sub>21</sub>	U <sub>22</sub>	U <sub>23</sub>
1	0.7	0.7	0.7	0.7	0.7	0.7	0.5
2	0.7	0.7	0.7	0.7	0.7	0.7	0.5
3	1.0	0.7	1.0	1.0	1.0	0.7	1.0
4	0.7	0.7	0.7	0.7	1.0	0.7	1.0
5	0.7	0.7	0.7	0.7	0.7	0.7	0.5
6	0.7	0.3	0.7	0.7	0.7	0.7	0.5
7	0.3	0.3	0.5	0.5	0.5	0.3	0.3
8	1.0	0.7	0.7	0.7	0.7	0.7	1.0
9	0.7	0.7	0.7	0.7	0.7	0.5	0.5
10	1.0	1.0	0.7	0.7	1.0	0.7	1.0
11	0.7	0.7	0.7	0.7	0.7	0.7	0.5
12	1.0	0.7	0.7	0.7	0.7	0.7	1.0
13	0.7	0.3	0.3	0.3	0.5	0.7	0.5
14	0.7	1.0	0.7	0.7	1.0	0.7	1.0

We use the MatLab6.5 to realize the software program, establish the four-layer FBP and GA model. We take 1-10 group evaluating data in table I as the training set, train the network, and carry through the simulation evaluation using the evaluation indices data of the four residual groups. The given study accuracy  $\varepsilon = 0.0001$ , and we select 7 and 5 as the hidden network neurons. When computation, we obtain the overall situation most

superior network weight using the GA through 500 optimizations, then train 8623 times using FBP. In table II, the network training results and the actual comprehensive evaluation results are shown. The simulation results about the 4 test sets and the actual evaluation results, as shown in table III. The results in the table II and table III show that not only all the training samples is very close to the actual evaluation value, but the results of the four simulation test sets is also very close to the actual evaluation results and the simulation. The figure 2 can reflect that the coupling degree between the evaluation results and the simulation results is quite high.

TABLE II. The Actual Evaluation Results Compared with the Network Training Results

Number	1	2	3	4	5
Actual evaluating results	0.688	0.604	0.931	0.827	0.647
Network training results	0.681	0.611	0.931	0.809	0.661

CONTINUED TABLE

Number	6	7	8	9	10
Actual evaluating results	0.571	0.340	0.713	0.641	0.861
Network training results	0.571	0.352	0.711	0.641	0.860

TABLE III. THE ACTUAL EVALUATION RESULTS COMPARED WITH THE SIMULATION RESULTS

Number	1	2	3	4
Actual evaluation results	0.683	0.627	0.460	0.766
Simulation results	0.681	0.661	0.459	0.766



Figure 2. The actual evaluation results compared with the simulation results

# V. CONCLUSION

The ECNS identification is associated with many factors, it needs large numbers of statistical calculation, and the factitious factors can be mixed into easily, which make the identification work is difficult. This paper constructs a novel ECNS identification model through integrating the BP neural network, the fuzzy logic algorithm and the genetic algorithm, which can bring into play the superiority of the three algorithms fully. We carry on the analog simulation to the sample data using Matlab, the results indicated that the identification error of the model is small, and the ECNS identification is more accuracy and rapidity compared to one or two algorithms.

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