Research on Computer Network Security Evaluation Method Based on Levenberg-Marquard Algorithms

Dongqi Wang, Xuanyue Shuai, Xueqiong Hu, Li Zhu*
Department of Control Science and Engineering, Dalian University of Technology
Dalian, China
Vj162774@163.com

Abstract. As we all know, computer network security evaluation is an important link in the field of network security. Traditional computer network security evaluation methods use BP neural network combined with network security standards to train and simulate. However, because BP neural network is easy to fall into local minimum point in the training process, the evaluation results are often inaccurate. In this paper, the LM (Levenberg-Marquard) algorithm is used to optimize the BP neural network. The LM-BP algorithm is constructed and applied to the computer network security evaluation. The results show that compared with the traditional evaluation algorithm, the optimized neural network has the advantages of fast running speed and accurate evaluation results.

Keywords-BP neural network, Computer network security, Evaluation

I. INTRODUCTION

With the development of Internet technology, computers have been widely used in people's life and play a decisive role in the whole of production [1]. However, there are many security problems in the practical application of computer technology, such as system security vulnerabilities, computer virus invasion and dissemination. Therefore, accurate and reasonable evaluation of computer network security has an important role in network security management to the system security and performance [2].

Network security is a complex project, to create a complete network information security system is the key to ensure the security of network information. In recent years, domestic and foreign scholars have adopted a variety of methods to evaluate the network security, and have made important progress, which mainly include Fei Jun and Yu Lihua set up the hierarchical structure model of computer network security evaluation according to the characteristics of the computer network and network security related factors, the fuzzy analytic hierarchy process based on triangular fuzzy number is used to realize the comprehensive quantitative evaluation of network security [3], Feng Ling and Yu Qun built the evaluation model of BP neural network based on the AHP, it is found that the neural network can not only be applied to network security evaluation, but also the accuracy has certain improvement [4]. When constructing the judgment matrix, the analytic hierarchy process has some subjectivity, so the BP neural network technology with its in dealing with nonlinear problems is becoming a key method for evaluation of computer network security.

Aiming at the shortcomings of BP neural network in dealing with the problem of nonlinear mapping, for example, the network parameters are difficult to determine, the convergence rate is slow and easy to fall into the small value and so on. Many scholars have put forward many methods to improve it, such as the Newton method, additional momentum term, the adaptive learning rate and other methods. And have made important research progress [5-8]. In this paper, the BP neural network is improved by using the LM algorithm, combined with the network security evaluation example to test, then compares and analyses the test result with the standard BP neural network.

II. BP NEURAL NETWORK

A. Network structure

The error back propagation multilayer feed forward neural network (BP neural network) is a kind of neural network which is widely used in dealing with the problem of nonlinear mapping [5]. The network structure is composed of three parts, which are input layer, hidden layer and output layer. All the adjacent neurons are connected to each other, and the same layer neurons are not connected [6]. Processing information from the input layer through the network hidden layer nodes to calculate the actual output of each node, if the actual output and the expected line, then the network learning ends; otherwise transferred to the reverse transmission. Error back propagation, which the information from the output layer through the hidden layer nodes to the input layer by layer to return to calculate the actual output and the desired error of each node, according to the error adjustment of the node link weights. When the error correction is carried out, the BP algorithm uses the Steepest Descent Method. This method only uses the first order derivative information, although the method is simple, the network convergence speed is slow, and it is easy to fall into local minimum. In order to speed up the convergence speed of the network, some improved methods introduce the idea of the two order derivative to correct the error of the first derivative in the error correction, commonly used conjugate gradient methods, newton method and LM algorithm. The LM algorithm makes full use of the information of the two order derivative, which is a kind of local improvement of Gauss Newton method. The main idea of LM algorithm is to add a non-negative diagonal matrix in the Gauss Newton method, using the strategy of forced positive definite.
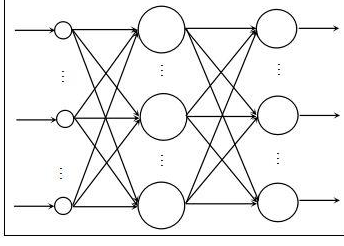
Figure 1   The structure of BP neural network

B.   LM algorithm

LM algorithm is the improvement of the Gauss Newton method, the basic optimization idea is using Gauss Newton method to produce an ideal search direction in function approximation near the optimal value, and adjust the weights of the network through the adaptive algorithm, so as to overcome the disadvantage that the negative gradient descent method is blindly searching in a single direction, and accelerate the convergence speed of the network.

Firstly, the weights and thresholds of each layer of network are set, and then they are adjusted continuously.Adjust the, is to adjust the weights and thresholds of the network, so as to achieve the purpose of training learning.

$$Y = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{IH} & \theta_j(1) & \cdots & \theta_j(H) \\ v_{11} & v_{11} & \cdots & v_{HO} & \theta_i(1) & \cdots & \theta_i(O) \end{bmatrix} \quad (1)$$

Set performance function:

$$P(Y) = \sum_{i=1}^{I} e_i(Y)^2 \quad (2)$$

indicates the square of the error in the formula, and then

$$\nabla P(Y) = J^T(Y)E(Y) \quad (3)$$

$$\nabla^2 P(Y) = J^T(Y)J(Y) + S(Y) \quad (4)$$

represents a vector consisting of , in this formula, is the Jacobian matrix, is the error function.

$$J(Y) = \begin{pmatrix} \dfrac{\partial e_1(Y)}{\partial Y_1} & \dfrac{\partial e_1(Y)}{\partial Y_2} & \cdots & \dfrac{\partial e_1(Y)}{\partial Y_i} \\ \dfrac{\partial e_2(Y)}{\partial Y_1} & \dfrac{\partial e_2(Y)}{\partial Y_2} & \cdots & \dfrac{\partial e_2(Y)}{\partial Y_i} \\ \vdots & \vdots & \vdots & \vdots \\ \dfrac{\partial e_I(Y)}{\partial Y_1} & \dfrac{\partial e_I(Y)}{\partial Y_2} & \cdots & \dfrac{\partial e_I(Y)}{\partial Y_i} \end{pmatrix} \quad (5)$$

$$S(Y) = \sum_{i=1}^{I} e_i(Y)\nabla^2 e_i(Y) \quad (6)$$

As the LM algorithm is an improved form of Gauss Newton method, and then:

$$\Delta Y = [J^T(Y)J(Y) + uI]^{-1} J^T(Y)E(Y) \quad (7)$$

is the unit matrix, and the is constant.

When,the LM algorithm is transformed into the Newton Gauss method with the similar matrix of Hessian matrix. When is larger, the LM algorithm approaches the small step length gradient method. In the training process, the modification coefficient of is set to. If the training is successful, reduce the value of,if the training fails, increase the value of. After the above process, the performance function will eventually be reduced to a certain value, to achieve the purpose of learning.

III.   THE ESTABLISHMENT OF COMPUTER

The structure of LM-BP neural network is composed of three parts, which are input layer, hidden layer and output layer. The number of input layer and output layer node is determined by the dimension of the input and output vectors. For the hidden layer node number, there is no specific standard for reference, generally by trial and error method to choose. According to the Kolmogorov theorem, the single hidden layer BP neural network can approximate any nonlinear continuous function on closed set with arbitrary precision, so the number of hidden layer is set to 1 in this paper.

A.   Selection of evaluation index

Strictly speaking, computer network is a complex network, In the actual quantitative evaluation, we need to consider almost all the key factors that affect the network security, so as to build an accurate and rigorous computer network security evaluation system. This study fully considers the management security, physical security and logical security of computer network system, and the evaluation index of network security is evaluated by expert system, Network security evaluation index system is shown in table 1.

Table 1   COMPUTER NETWORK SECURITY EVALUTION INDEX SYSTEM

Target	First-grade Index	Second-grade Index
Computer network security evaluation	Management security X_1	Safety organizational structure X_{11}, Safety management system X_{12}, Personnel safety training X_{13}, Emergency response mechanism X_{14}
	Physical security X_2	Network room security X_{21}, Safety of power supply system X_{22}, Line safety X_{23}, Fault tolerant redundancy X_{24}, Device security X_{25}
	Logical security X_3	Data backup X_{31}, Data recovery X_{32}, System audit X_{33}, Access control X_{34}, Software security X_{35}, Anti-virus measures X_{36}, Data encryption X_{37}, Intrusion Prevention X_{38}

B.   Evaluation of the realization

1) Data preprocessing

Computer network security indicators reflect the safety of computer network in different ways, but due to various safety indicators represent different dimensions, at the same time, some safety indicators are not directly with actual values for recording, such as the virus prevention measures, line security, and there is no uniform calculation method. This index is through the expert experience to determine its weight. On the basis of the quantitative data of all indexes, in

order to make every safety index to compare and calculate, and make the neural network training more accurate and sufficient, uniform dimensional treatment of all safety indicators is required. The following mathematical formula can be used for the quantitative analysis of the safety index, and the normalization value of the safety index is:

$$x_c = \frac{x_i - x_{min}}{x_{max} - x_{min}} \qquad (8)$$

In the formula is the safety indexes of raw data, andare the maximum and minimum values respectively of the I safety index.

2) Evaluation weight determination

Safety evaluation of computer network based on the weight of safety index. In practical applications, computer network security evaluation grades can be divided into four grades, which are security (Grade A), basic security (Grade B), insecurity (Grade C), very insecure (Grade D), the scores of each security level are shown in table 2.

Table 2   SAFETY ASSESSMENT LEVEL

Level	Security type	Value	Security descriptor
A	Security	1.0~0.85	Network has a strong security capabilities, network application security
B	Basic security	0.85~0.7	Network has a certain security capabilities, network applications basic security

Level	Security type	Value	Security descriptor
C	Insecurity	0.7~0.6	Network security capabilities are limited, network applications exist security risks
D	Very insecure	0.6~0.0	Network security capability is poor, and the network application security situation is grim

3) Network training and evaluation

The value of the 17 evaluation indexes of network security as the input of BP neural network, and the expected output of the network is only one, that is, the comprehensive evaluation score of security. Expert evaluation results are shown in table 3. BP neural network requires a certain number of known samples to train, then we can use the trained network to evaluate. At present, the comprehensive evaluation of network security data is still very little,In this paper, several groups of relevant data for network security evaluation are obtained through experiments, and the evaluation results are scored by three experts. The average value is taken as the final evaluation results, and 10 groups of evaluation data are screened out. We use the 10 groups of typical network security single index evaluation data, using AHP to get comprehensive evaluation results, as shown in table 4. These 10 sets of data are used as training samples to train the BP network, data in Table 3 is used as a test sample to test the effectiveness of the network security evaluation.

Table 3   EXPERT EVALUTION SAMPLES

	X_{11}	X_{12}	X_{13}	X_{14}	X_{21}	X_{22}	X_{23}	X_{24}	X_{25}	X_{31}	X_{32}	X_{33}	X_{34}	X_{35}	X_{36}	X_{37}	X_{38}	Y
E_1	0.85	0.80	0.96	0.78	0.83	0.88	0.9	0.92	0.95	0.82	0.85	0.75	0.88	0.91	0.83	0.92	0.79	0.84
E_2	0.75	0.65	0.62	0.77	0.71	0.82	0.65	0.78	0.73	0.80	0.75	0.81	0.63	0.74	0.78	0.82	0.85	0.77
E_3	0.62	0.43	0.58	0.65	0.61	0.73	0.35	0.41	0.58	0.52	0.61	0.71	0.38	0.41	0.55	0.57	0.65	0.40
E_4	0.21	0.38	0.42	0.35	0.29	0.33	0.26	0.45	0.18	0.36	0.21	0.24	0.38	0.28	0.41	0.25	0.35	0.38
E_5	1.00	0.75	0.91	0.88	0.81	0.83	0.92	0.85	0.95	0.93	0.9	0.81	0.85	0.87	0.93	0.99	0.95	0.79

Table 4   LEARNING SAMPLES

	X_{11}	X_{12}	X_{13}	X_{14}	X_{21}	X_{22}	X_{23}	X_{24}	X_{25}	X_{31}	X_{32}	X_{33}	X_{34}	X_{35}	X_{36}	X_{37}	X_{38}	Y
1	0.85	0.91	0.85	0.92	0.87	0.81	0.93	0.77	0.98	0.88	0.92	0.94	0.89	0.83	0.92	0.88	0.83	0.90
2	0.71	0.85	0.73	0.65	0.82	0.77	0.63	0.75	0.81	0.67	0.72	0.89	0.62	0.71	0.83	0.65	0.71	0.75
3	0.81	0.76	1.00	0.77	0.92	0.87	0.77	0.89	0.82	0.91	0.76	0.85	0.79	0.91	0.83	0.77	0.8	0.82
4	0.65	0.52	0.48	0.51	0.74	0.62	0.58	0.48	0.71	0.62	0.75	0.61	0.64	0.78	0.71	0.69	0.71	0.62
5	0.34	0.28	0.10	0.45	0.37	0.44	0.46	0.23	0.29	0.37	0.25	0.39	0.17	0.45	0.31	0.21	0.38	0.35
6	0.36	0.45	0.38	0.50	0.35	0.52	0.37	0.45	0.33	0.41	0.58	0.45	0.38	0.41	0.32	0.45	0.49	0.41
7	0.31	0.34	0.45	0.52	0.28	0.21	0.33	0.38	0.21	0.39	0.41	0.39	0.27	0.31	0.35	0.38	0.29	0.31
8	0.81	0.75	0.73	0.65	0.85	0.87	0.91	0.86	0.77	0.63	0.81	0.85	0.93	0.87	0.95	0.91	0.78	0.82
9	0.61	0.88	0.66	0.78	0.91	0.68	0.77	0.73	0.82	0.79	0.71	0.91	0.93	0.87	0.84	0.77	0.72	0.75
10	1.00	0.95	0.89	0.91	0.78	0.87	0.75	0.80	0.77	0.93	0.96	0.89	0.79	0.82	0.9	0.91	0.96	0.88

This algorithm is implemented by Matlab programming language. Through the actual experimental analysis, this paper set the number of hidden layer nodes in the network to 5, Weight adjustment parameter .Threshold adjustment parameter , and the learning accuracy . After 2000 times of training, the network converges to the required error, the test samples and expert evaluation sample simulation results are shown in Table 5. Wherein the change in training parameters shown in figure 2.
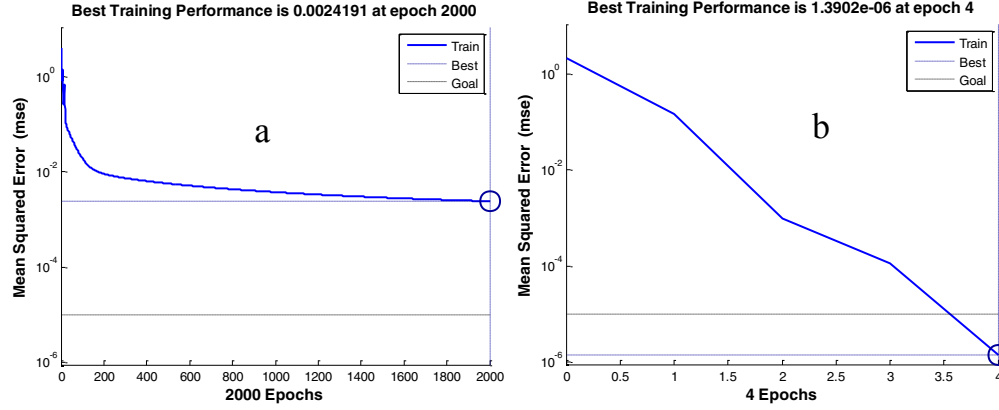
Figure 2   Training parameter variation of standard BP neural network (a), Training parameter variation of standard LM-BP neural network (b)

4) Result evaluation

The expert evaluation results as the simulation data input to the LM-BP neural network and the standard BP neural network to simulate experiment, the results are shown in table 5, According to the table, we can see that the average error of the LM-BP network model in computer network security evaluation is smaller, only 2.13%, the simulation value and the standard output value is very close, it shows that LM-BP neural network has good generalization and fit for network security evaluation. However, the average error of the standard BP network prediction results is 4.96%. Predicted value and the actual value deviates greatly, so that the standard BP network performance is not good in the network security evaluation, and the test result is not good at all. At the same time, the LM-BP neural network is only running 4 steps to converge to the minimum error, time consuming 2.7s. While the standard BP neural network convergence to the minimum error need running 2000 steps, time consuming 28.3s. Therefore, the convergence speed of LM-BP neural network is faster, and the fitting efficiency is higher.

Table 5   NEURAL NETWORK TRAINING RESULTS OF EXPERT EVALUATION

Dot	Ex-pected output	LM-BP neural network			Standard BP neural network		
		Actual output	Relative error	Corre-sponding level	Actual output	Relative error	Corresponding level
E1	0.84	0.852	1.41	B	0.873	3.78	A
E2	0.77	0.763	0.92	B	0.742	3.77	B
E3	0.40	0.392	2.04	D	0.427	6.32	D
E4	0.38	0.399	4.76	D	0.411	7.54	D
E5	0.79	0.778	1.54	B	0.764	3.40	B

IV.   CONCLUDING REMARKS

BP neural network with its characteristics of self-learning and nonlinear, avoiding the shortcomings of the traditional analytic hierarchy process to construct the judgment matrix, and providing a new solution for the computer network security evaluation. But in the standard BP neural network, the error correction is based on the steepest descent method, but the convergence rate is slow, and it is easy to cause the phenomenon of non-convergence and over fitting. LM-BP net-

work uses the Gauss Newton method to generate an ideal search direction near the optimal value of the function approximation, through the adaptive algorithm to adjust the weights of the network, to overcome the shortcomings which the negative gradient descent method in a single direction blind search. It has the advantages of fast learning speed and strong generalization ability in the field of nonlinear fitting, to provide an efficient, accurate and reliable method for computer network security evaluation.

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