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Evaluation Model of Landslide Lake Risk Disposal Based on CFNN

Qiang Li, Shaoyu Wang and Xing Huang
School of Economics and Management, Harbin Institute of Technology, 150001 Heilongjiang, China

Abstract: The future performance evaluation of landslide lake risk disposal could provide a scientific basis to improve risk disposal of landslide lake. The intelligent evaluation system based on the improved Compensation Fuzzy Neural Network (CFNN) was introduced to the future performance evaluation of landslide lake risk disposal, to solve fuzzy and non-linear evaluation problem of stability, time, cost and ecological index. Through the simulation experiments, the future performance evaluation on improved CFNN which had high convergence speed, fault tolerance and adaptive ability, was an effective evaluation method of landslide lake risk disposal.

Key words: Landslide lake, risk disposal, compensation fuzzy neural network, future performance evaluation

INTRODUCTION

Landslide lake was a natural dam of horizontal obstruction to valley causing the upstream segment backwater. And the natural dam was formed by volcanic eruption, landslide, debris flow, glacier debris and so on. Typically, due to rapid accumulation, the dam was relatively loose. It is prone to dam failure in the current rush which made the downstream people's lives and property suffered heavy losses. The key to landslide lake disposal was security, rapidity, to reduce disposal costs as much as possible and protect ecological environment.

The research on landslide lake disposal was mainly the effect of draining danger, rescue and construction effects and emergency response. For the landslide damming body and damming size of landslide lake disposal, Giuseppe Mandrone *et al*. (2007) studied drainage danger and rescue effects. Liu (2008) thought that the landslide lake disposal should be based on a comparison of the costs and benefits principle and the lowest cost and shortest process, the benefits of security risk management program should be chosen. By analyzing the breach parameter selection dam break flood characteristics, including the sensitivity between flood propagation time, Chauhan *et al*. (2004) studied the key factor of dam stability in the landslide lake disposal. Zhang (2009) focused on the economic and environmental benefits assessment of landslide lake risk management and disposal. The previous research in risk disposal of landslide lake made significant progress but the future performance evaluation for risk disposal of landslide lake research had not yet been seen, resulting scientific evaluation of landslide lake risk dispose effect was difficult to carry out. In view of this, from the characteristics and the implementation phase of landslide lake risk disposal, the future performance evaluation model of that was proposed. The landslide lake risk disposal effectiveness was measured in four dimensions with stability, time, costs and ecological environment. The paper modified and supplemented the intelligent evaluation model of Compensation Fuzzy Neural Network CFNN characterized by fuzzy inference and ease of learning, introducing that to the future performance evaluation of landslide lake risk disposal. Consequently, good evaluation of the effect had been shown in the empirical studies.

EVALUATION THEORY

For building the future performance evaluation model of landslide lake risk disposal, the composition and operational characteristics of the disposal of the landslide lake risk should be understood, in order to capture the overall impact of changes in the parameters or the key indicators of the adaptability degree of risk disposal and look for suitable input/output variables for CFNN intelligent decision. Characteristic of rapidity, efficiency and stability should be underlined through effective evaluation system, in order to test the landslide lake risk disposal whether they can adapt the risk management requirements of public emergencies, at the same time contribute to find measures to deal with the shortage to adjust and improve the disposal measures.

The landslide lake risk disposal included engineering measures and non-engineering measures. Dispose effect was well received by stability, time, costs, environmental protection index, but also by the specific scope, environmental uncertainty factors and so on. The

Corresponding Author: Qiang Li, School of Economics and Management, Harbin Institute of Technology, 150001 Heilongjiang, China Tel: 0086-451-86400206

fundamental purpose is safe, fast, economical disposal of the landslide lake risk. Therefore, the impact factors of future performance evaluation of the landslide lake risk disposal were mainly the dam stability, disposition time, the costs of disposal and environmental protection (Clague and Evans, 2000; Ajami *et al*., 2004).

Dimension of dam stability: Difference and inequality in physical and mechanical properties of dams were determined by formation mechanism of dam, the complex and changeable morphology of the landslide, difference of landslide dams internal substance, granulometric composition, structural characteristics. The dimension of dam stability included two aspects of the overall stability of landslide along the sliding surface and stability of upstream and downstream slope, relates to normal operation and the security of landslide dam in the future. This dimension was basic protection dimension of time and cost indicators.

Dimension of time: The timely disposal of landslide lake risk was an important safeguard to reduce disaster losses and prevent secondary disasters. index was mainly extracted from the preparation For the time dimension of the future performance evaluation for landslide lake risk disposal which was the core indicator of adaptability of landslide lake risk dispose of the strength, evaluation phase and implementation phase, reflected in the total disposal time and the progress of key disposal nodes.

Dimension of cost: To meet the safety, scientific, timely disposal requirements of the premise, costs of landslide lake risk disposal should also be possibly reduced. Therefore, on the basis of the geographical environment or range adaptation, measures of less investment should be selected in landslide lake disposal, in order to minimize the total loss and improve the disaster emergency performance.

Dimension of environmental protection: Landslide lake destroyed or flooded terrestrial vegetation and causing further soil erosion. The changes of landslide lake and downstream river aquatic environment, spillway and other factors cause loss of fish resources and impact the species composition and quantity of aquatic organisms. On the basis of the aforementioned three evaluation dimensions, future performance evaluation of landslide lake risk dispose could be more comprehensive to consider the protection of ecological environment.

EVALUATION MODEL

Structure: The CFNN is a hybrid system with the advantages of fuzzy logic and neural network which is composed of control/decision-oriented fuzzy neurons. These fuzzy neurons are designed for fuzzification algorithm, fuzzy reasoning, compensation fuzzy operation and anti-fuzzy operation which are able to adjust fuzzy subjection function for input/output adaptively and to use compensation logical algorithm for adaptively dynamic optimization of fuzzy reasoning (Rumelhart *et al*., 1986; Zhang *et al*., 1998). CFNN fuzzy operation uses dynamical global optimization algorithm which can dynamically optimize compensation fuzzy neurons during training the neural network by initial fuzzy rules with either correct or incorrect definitions, to fill up the deficiency of static nature and partial optimization in the operation of traditional fuzzy neural system. This is a process featured by high fault tolerance and high robustness (Wang, 1998; Yin *et al*., 2007). A CFNN usually consists of 5 layers (Fig. 1): input layer (Layer 1), fuzzification layer (Layer 2), fuzzy reasoning layer (Layer 3), compensation algorithm layer (Layer 4) and anti-fuzzy layer (Layer 5).

Inference: Defines $x_{11}, x_{12},\cdots,x_{1D}$ as the fuzzy variables of time for the future performance evaluation of landslide lake disposal, with input linguistic terms {Very Short, Short, Average, Long} = $\{He_{1i}, Le_{1i}, Ne_{1i}, Se_{1i}\}$ and fuzzy subset; A^k_{1j}; $x_{21}, x_{22},\cdots,x_{2E}$ as the fuzzy variables of costs, with input linguistic terms {Very Low, Low, Average, High} = $\{Hh_{2i}, Lh_{2i}, Nh_{2i}, Sh_{2i}\}$ and fuzzy subset A^k_{2j}; $x_{31}, x_{32},\cdots,x_{3S}$ as the fuzzy variables of dam stability, with input linguistic terms {Very Stable, Stable, Average, Instable} = $\{Hc_{3i}, Lc_{3i}, Nc_{3i}, Sc_{2i}\}$ and fuzzy subset A^k_{3j}.

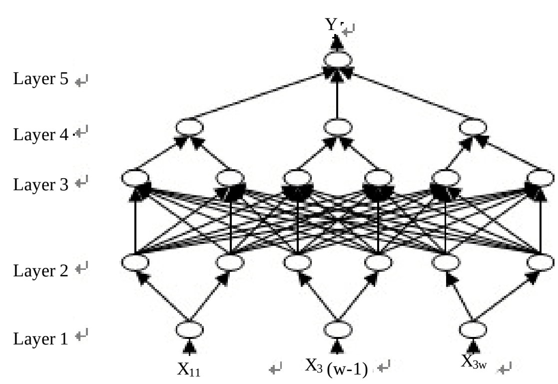

Fig. 1: CFNN structure

The single output Y is taken as the future performance evaluation of landslide lake disposal, with output linguistic terms {Very High, High, Average, Low} = {Hh, Lh, Nh, Sh} and fuzzy subset of adaptability B_k. Then, the IF-THEN rule for CFNN logical system of multi inputs and single output would be:

$FR^{(k)©}$: IF x_{11} is A^k_{11} and… and x_{3W} is $A_{3W}{}^k$ then Y is B_k (1)

where, $k = 1, 2,\cdots,Q$, $Q = 2^D 3^{D+E+S}$

Take the Gaussian fuzzy subjection functions of A^k_{3w} and B_k, then:

$$\mu_{A^k_{ij}}(x_{ij}) = \exp\left[-\left(\frac{x_{ij}-a^k_{ij}}{\sigma^k_{ij}}\right)^2\right] \quad (2)$$

$$\mu_{B^k}(y) = \exp\left[-\left(\frac{y-b^k}{\partial^k}\right)^2\right] \quad (3)$$

where, a^k_{ij} and σ^k_{ij} are the center and the width of input subjection function, respectively; b^k and ∂ are the center and the width of output subjection function respectively.

Assuming input $X = (x_{11}, x_{12},\cdots,x_{3(W-1)}, x_{3W})$ and universe $U = U_{11}\times U_{12}\times\cdots\times U_{3\text{-}(w\text{-}1}\times U_{3W}$. For any fuzzy subset A^k in universe U, an output fuzzy subset B^k could be generated in output universe V according to kth fuzzy rule. When maximum algebra product compositional operation is used for fuzzy reasoning, the fuzzy set B^k of Vderived by fuzzy reasoning rule is:

$$\mu_{B^k}(y) = \sup_{X\in U}\left[\mu_{A^k_{11}\times\ldots\times A^E_{3(w-1)}\times A^k_{3W}\to B^k}(x,y)\cdot\mu_{A^k_{11}\times\ldots\times A^k_{3W}}(x)\right] \quad (4)$$

Compensation formulas:

$$\mu_{A^k_{1j}\times\ldots\times A^k_{3W}}(x) = (\mu^k)^{1-r}(v^k)^r \quad (5)$$

where, compensation degree $r\in[0,1]$.

Negative operation:

$$\mu^k = \prod_{j=1}^{D}\mu A^k_{1j}(x_{1j})\prod_{j=1}^{E}\mu A^k_{2j}(x_{2j})\prod_{j=1}^{S}\mu A^k_{3j}(x_{3j}) \quad (6)$$

Positive operation:

$$v^k = \left[\prod_{j=1}^{D}\mu_{A^k_{1j}}(x_{1j})\prod_{j=1}^{E}\mu_{A^k_{2j}}(x_{2j})\prod_{j=1}^{S}\mu_{A^k_{3j}}(x_{3j})\right]^{1/4} \quad (7)$$

Making Eq. 6 and 7 generations into 5 and getting Compensation fuzzy operation of Layer 4:

$$\mu_{A^k_{1j}\times\ldots\times A^k_{3W}}(x) = (\mu^k)^{\frac{1}{4}(4-3r)} \quad (8)$$

Now adopts integrated operation and product operation for Fuzzy implication:

$$\mu_{A-B}(x, y) = \mu_A(x)\mu_B(y) \quad (9)$$

$$\mu(x)\bullet\mu_B(y) = \mu_A(x)\mu_B(y) \quad (10)$$

Contrary fuzzy function is:

$$f(x) = \frac{\sum_{k=1}^{Q} b^k\partial^k\mu_{B^k}(b^k)}{\sum_{k=1}^{Q}\partial^k\mu_{B^k}(b^k)} \quad (11)$$

Where:

$$\mu_{B^k}(b^k) = \left[\prod_{j=1}^{D}\mu_{A^k_{1j}}(x_{1j})\prod_{j=1}^{E}\mu_{A^k_{2j}}(x_{2j})\prod_{j=1}^{S}\mu_{A^k_{3j}}(x_{3j})\right]^{(1-\frac{3}{4}r)}$$

generations into (11) gets compensation fuzzy logic system:

$$f(x) = \frac{\sum_{k=1}^{Q} b^k\partial^k\left[\prod_{j=1}^{D}\mu_{A^k_{1j}}(x_{1j})\prod_{j=1}^{E}\mu_{A^k_{2j}}(x_{2j})\prod_{j=1}^{S}\mu_{A^k_{3j}}(x_{3j})\right]^{(1-\frac{3}{4}r)}}{\sum_{k=1}^{Q}\partial^k\left[\prod_{j=1}^{D}\mu_{A^k_{1j}}(x_{1j})\prod_{j=1}^{E}\mu_{A^k_{2j}}(x_{2j})\prod_{j=1}^{S}\mu_{A^k_{3j}}(x_{3j})\right]^{(1-\frac{3}{4}r)}} \quad (12)$$

Improved leaning algorithm: Hypothesis:

$$z^k = \left(\prod_{j=1}^{D}\mu_{A^k_{1j}}(x_{1j})\prod_{j=1}^{E}\mu_{A^k_{2j}}(x_{2j})\prod_{j=1}^{S}\mu_{A^k_{3j}}(x_{3j})\right)^{(1-\frac{3}{4}r)}$$

By (12) type getting:

$$f(x^p) = \frac{\sum_{k=1}^{Q} b^k\partial^k z^k}{\sum_{k=1}^{Q}\partial^k z^k} \quad (13)$$

It is supposed that actual output of the pth input training sample of future performance evaluation for landslide lake disposal is y_p, so sum function of error target of the pth is:

$$E^p = \frac{1}{2}\left[f(x^p) - y^p\right]^2 \quad (14)$$

The global error target functions of sample P:

$$E = \sum_{p=1}^{P} E^p$$

A gradient descent method is used to train the input/output of system and then output the center b and width ∂ of subjection function. Input the center α, width σ and compensation degree γ of subjection function, so its corresponding iterative type is:

- The center of training output subjection functions is:

$$b^k(t+1) = b^k(t) - \eta \frac{\partial E^p}{\partial b^k}\Big|_t \tag{15}$$

Where:

$$\frac{\partial E^k}{\partial b^k} = \frac{\left[f(x^p) - y^p\right]\partial^k z^k}{\sum_{k=1}^{Q} \partial^k z^k}$$

- The width of training output subjection functions is:

$$\partial^k(t+1) = \partial^k(t) - \eta \frac{\partial E^p}{\partial \partial^k}\Big|_t \tag{16}$$

Where:

$$\frac{\partial E^p}{\partial \partial^k} = -\frac{(f(x^p) - y^p)(b^k - f(x^p))\partial^k z^k}{\sum_{k=1}^{Q} \partial^k z^k}$$

- The center of training input subjection functions is:

$$\frac{\partial E^p}{\partial \alpha_{ij}^k} = \frac{2\left[f(x^p) - y^p\right]\left[b^k - f(x^p)\right]\left[x_{ij}^p - \alpha_{ij}^p\right](1 - \frac{3}{4}r)\partial^k z^k}{\sigma_{ij}^{k2} \sum_{k=1}^{Q} \partial^k z^k}\Big|_t \tag{17}$$

Existing:

$$\alpha_{ij}^k(t+1) = \alpha_{ij}^k(t) - \eta \frac{\partial E^p}{\partial \alpha_{ij}^k}\Big|_t \tag{18}$$

- The width of training input subjection functions is:

$$\frac{\partial E^p}{\partial \sigma_{ij}} = \frac{(f(x^p) - y^p)(b^k - f(x^p))(x_{ij}^p - \alpha_{ij}^k)(1 - \frac{3}{2}r)\partial^k z^k}{\sigma_{ij}^{k3} \sum_{k=1}^{Q} \partial^k z^k}\Big|_t \tag{19}$$

And then:

$$\sigma_{ij}^k(t+1) = \sigma_{ij}^t - \eta \frac{\partial E^p}{\partial \alpha_{ij}^k}\Big|_t \tag{20}$$

- Training compensation degree

Removing constraint conditions $r \in [0,1]$ and redefining compensation degree:

$$r = \frac{c^2}{c^2 + d^2} \tag{21}$$

where, c, d are any parameters:

$$\frac{\partial E^p}{\partial r} = -\frac{3(f(x^p) - y^p)(b^k - f(x^p))\partial^k z^k \ln\left(\prod_{j=1}^{D} \mu_{A_{1j}^k}(x_{1j}) \prod_{j=1}^{E} \mu_{A_{2j}^k}(x_{2j}) \prod_{j=1}^{S} \mu_{A_{3j}^k}(x_{3j})\right)}{4\sum_{k=1}^{Q} \partial^k z^k} \tag{22}$$

Then there is:

$$c(t+1) = c(t) - \eta\left(\frac{2c(t)d^2(t)}{(c^2(t) + d^2(t))^2}\right)\frac{\partial E^p}{\partial r}\Big|_t \tag{23}$$

$$d(t+1) = d(t) + \eta\left(\frac{2c^2(t)d(t)}{(c^2(t) + d^2(t))^2}\right)\frac{\partial E^p}{\partial r}\Big|_t \tag{24}$$

$$r(t+1) = \frac{c^2(t+1)}{c^2(t+1) + d^2(t+1)} \tag{25}$$

where, η is for learning rate. T = 0, 1, 2,···.

In general, η values are static constant in all of the above formulas, so it is disadvantage of improving the iterative speed of CFNN. A kind of dynamic step length is adopted which would be changed along with the changes of error gradient. Now we use the gradient descent method to fix parameters (α, b, w, σ, c, d), algorithm as follows:

$$\begin{aligned}\eta = (\eta_\alpha, \eta_\sigma, \eta_b, \eta_w, \eta_c, \eta_d) = \alpha(E(t)^{1/r} \times \{&\exp(-|\partial E/\partial \alpha_{ij}^k|), \exp(-|\partial E/\partial \sigma_{ij}^k|),\\ &\exp(-|\partial E/\partial b_{ij}^k|), \exp(-|\partial E/\partial w_{ij}^k|), \exp(-|\partial E/\partial d_{ij}^k|)\}\end{aligned} \tag{26}$$

EVALUATION

Sample set: The adaptability of the landslide lake risk disposal depended on the synergistic running effect of engineering measures and non-engineering measures. The dam stability was the basis and premise of landslide lake risk disposal. Therefore, good stability, short time, low cost, environmental protection, strong adaptability and other characteristics in a similar significant risk events must been had in emergency treatment. According to the aforementioned theory of future performance evaluation for landslide lake risk disposal, future performance evaluation index was mainly composed of dam stability, response time, the cost of disposal and environmental protection in four dimensions, each dimension of the measure based primarily on the landslide lake risk disposal program evaluation of the reference system.

Table 1: Indexes of evaluation

Dimension	Engineering measures	Non-engineering measures
Dam stability	penetration and deformation of sliding surface, Level of dam settlement, degree of sand liquefaction	Reduce the possibility of population emergency refuge, mitigate possible degree of economic losses
Time	Design of drainage trough and discharge channel, dam reinforcement and dismantle, landslide analysis and processing,	Transfer of personnel and assets, necessary communication security equipment, material supply, transport security measures and decision
Cost	Earthwork volume of dam body, submerged zone of landslide and collapse body, buildings within the downstream river	Personnel transfer and hedging services, communication system, transport security and decision cost
Environmental protection	flooded vegetation submerged, degree of soil erosion damage degree of ecological species	Pollution extent of water quality, upstream inundated areas and lake water discharged

Considering the engineering measures and non-engineering measures of landslide lake risk disposal, the comprehensive and objective evaluation of natural disposition effect and social disposition effect of the landslide lake risk disposal must be a combination method of quantitative evaluation and qualitative evaluation. According to four fuzzy sets of input parameters, the fuzzy domain should be divided into several intervals so that experts evaluate and obtain the original data of training. It is supposed that the corresponding ranking ranges are $X_{1D}\in\{[85, 95], [75, 84], [60, 74], [45, 59]\}$, $X_{2E}\in\{[80, 90], [70, 79], [60, 69], [45, 59]\}$, $X_{3S}\in\{[0.85, 0.95], [0.75, 0.84], [0.65, 0.74], [0.60, 0.64]\}$. Experts gain the original data after assessment to accord to the evaluation interval of parameters (to ensure that the original data is reliable, also can choose other methods, for example, investigation, statistics, etc.). This study intends to select 180 simulation data and divided into 3 groups to constitute the Sample set, one group is used to CFNN study training and the other two groups are used to test sample to inspect the accuracy of network. To eliminate the different impacts of input/output on account of the different dimension, the original data should be normalized and make its input/output data are quantitative to interval [0, 1] range. Quantitative formula is:

$$x_i^* = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (27)$$

where, x_i^* is the quantitative data, x_i is original data, x_{max}, x_{min} are the maximum value and minimum value of the original data, The fuzzy number of specific division is shown by Table 2.

Selecting initial value of input parameters for CFNN subjection function: According to the fuzzy variables above, there are 16 fuzzy rules in CFNN model for future performance evaluation of landslide lake disposal. The inputs for the three nodes in Layer 1 are time x_{1D}, cost x_{2E} and stability x_{3S}. There are 12 nodes in Layer 2, for all the fuzzy subsets of the three inputs. There are 16 nodes in Layer 3, as the 16 fuzzy rules. Layer 4 is CFNN compensation operation layer. Layer 5 is fuzzy solution layer, where fuzzy scalars are transformed into accurate output vectors, to determine the level values Y of future performance evaluation for disposal of landslide lake. During network training, iteration times required for the network to reach desired accuracy vary for different initial values of the network parameters that initial values closer to the actual condition allow for less iteration times relatively. As each CFNN parameter has definite physical significance, heuristic assigning is allowed for these parameters, to speed up network learning. Table 3 assigns the initial values for CFNN according to fuzzy rules.

Table 2: Input/output parameters of fuzzy set

	Parameters fuzzy division				
	H	L	N	S	Width
X_{1D}	[0.8,1.0]	(0.7,0.8)	(0.5,0.7]	[0.5,0]	0.5
X_{2E}	[0.7,1.0]	(0.6,0.7)	(0.4,0.6]	[0.4,0]	0.4
X_{3S}	[0.9,1.0]	(0.8,0.9)	(0.6,0.8]	[0.6,0]	0.6
Y	[0.8,1.0]	(0.6,0.8)	(0.4,0.6]	[0.4,0]	0.4

Table 3: Initial parameters of CFNN

	X_{1D}		X_{2E}		X_{1D}		Y	
	α	σ	α	σ	α	σ	α	σ
1	1.231	2.887	2.221	1.443	2.000	1.883	-0.632	2.000
2	2.231	2.667	1.333	2.100	1.888	2.231	-0.9210	2.000
…	…	…	…	…	…	…	…	…
16	6.002	0.833	5.990	3.665	4.663	3.472	0.9213	2.000

Table 4: Parameters after training of nestwork

	X_{1D}		X_{2E}		X_{1D}		Y	
	α	σ	α	σ	α	σ	α	σ
1	1.240	2.879	2.212	1.427	2.003	1.890	-0.628	2.002
2	2.228	2.672	1.323	2.099	1.879	2.219	-0.9106	1.953
…	…	…	…	…	…	…	…	…
16	6.009	0.841	5.989	3.658	4.659	3.484	0.9356	1.897

CFNN simulation: One group of data is fetched from the sample set for network training, with a desired training error of 0.0001 and initial global error of 0.9390. With dynamic learning step, network parameters after training, training outputs and simulation outputs are summarized into Table 4-6.

It can been seen from Fig. 6 that all training values of learning sample are very close to the desired value, with relative errors less than 0.01 and absolute errors $0.15\text{-}8.2\times10^{-3}$ which means the initial input parameters are reasonable. See Fig. 2 for the error curve of network training.

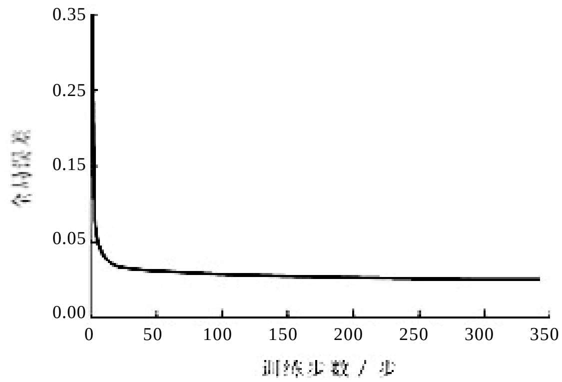

Fig. 2: Error curve of training

Table 5: Training output datum of CFNN

Sample	Expected value	Training value	Error value	Judgment result
1	0.6	0.600 3	0.000 3	Lh
2	0.2	0.199 8	-0.000 2	Sh
...	...	...	...	...
59	0.7	0.699 8	-0.000 2	Lh
60	0.5	0.500 4	0.000 4	Nh

Table 6: Simulation verification output datum

Sample number	X_{1D}	X_{2E}	X_{3S}	Network output result	Judgment result
1	77	67	0.66	0.588 3	Nh
2	66	55	0.61	0.377 5	Sh
...	...	...	...	...	...
119	72	48	0.68	0.533 9	Nh
120	77	68	0.81	0.710 1	Lh

It can been seen from Fig. 8 that the error sum of squares for the first 50 steps of training decreases rapidly and the required network accuracy is met after 348 steps of iteration training. Meanwhile, BP neural network is employed to train an identical sample and it is found that 4980 steps are needed to reach the same global error level as CFNN training. The steps needed by CFNN that is far less than that by BP neural network.

CONCLUSION

The future performance evaluation for disposal of landslide lake was a complicated and huge system with high robustness required for smooth emergency relief works. The future performance evaluation method could provide a scientific basis to improve risk disposal of landslide lake.

According to the theory of risk management, future performance evaluation model framework of landslide lake risk disposal was presented and from the four aspects of dam stability, response time, the cost of disposal and environmental protection, the future performance evaluation index of landslide lake risk disposal was proposed. To ensure the safety of the dam and the protection of ecological environment, the key to risk disposal of landslide lake is to implement engineering and non-engineering measures as soon as possible and at the same time to reduce the cost of disposal as far as possible. For the angle of risk disposal, the future performance evaluation of similar risk events can also be safety, timeliness, economy and environmental protection.

From the process of modeling and simulation, the improved CFNN can effectively combine neural network with fuzzy logic. Single value fuzzy membership function, Gauss, multiplicative reasoning, positive/negative compensation operation and the dynamic learning step length of gradient magnitude were used to effectively solve the fuzzy and nonlinear problem of stability of dam, landslide lake disposal time, disposal costs and environmental protection indexes. The improved CFNN had strong robustness and fault tolerance which was advantageous to computer implementation. In the future, evaluation of landslide lake risk disposal can use the improved CFNN.

By the MATLAB7.0 programming of sample data for training and testing simulation results proved that, compared to the BP neural network, the improved CFNN was superior to BP neural network in the number of training, the training time and the accuracy and it had a strong convergence advantage in the intelligent decision. In addition, the model of improved CFNN had strong adaptive ability. When external conditions or sample number changed, model would train the network in the new conditions and the relative error could be very good controlled in less than 10%. This method could be provided for future performance evaluation for risk disposal of landslide lake in the future.

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