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BP neural network integration model research for hydraulic metal structure health diagnosing

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Abstract

Several potential network structures are chosen to do a large number of experimental analysis, historical data is divided into training sample and testing sample, and the corresponding neural network model is established with BP learning algorithm. After checking the testing sample, a superior network integration model which can be applied for hydraulic metal structure health grade diagnosing is determined. By plenty of experimental tests and verification analysis, it is concluded that the two-hidden-layer neural network model suits hydraulic metal structure health diagnosing better. As for the gate health diagnosing, based on Bagging technology, the BP neural network integration model for hydraulic metal structure health diagnosing is researched and constructed. The analysis of the sample showed that its accuracy rate (78%) is obviously better than the single neural network model(67%). The BP neural network integration model will work together with the FAHP model the author studied, that can make the diagnosis results more reasonable and reliable.

Keywords: Hydraulic metal structure, health diagnosing, BP neural network, integration model, bagging technology.

1. Introduction

As the world's energy increasingly scarce, governments take more attention to the development and utilization of renewable energy, and spent a lot of manpower and material resources to research and develop new energies such as solar energy, wind energy, hydroelectric power and biomass power generation. The safety of these generation equipments is important guarantee for ensuring the engineering operation normally. And the safe operation of the water resources and hydropower engineering metal structure, not only an important link in the safe operation of the water conservancy, but also

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an important condition to ensure the water resources and hydropower engineering playing a huge benefits.

At present, there are many hydraulic metal structure equipments have reached or exceed the depreciation year, some even reached the design working life and is still in service. According to the literature[1], there are more than 87000 reservoirs and 3700 large and medium-sized sluices in our country, most of them are put into operation in the 60s to 70s of the 20th century. In large and medium-sized water conservancy projects, the percentage of gate and hoist which have been run into the ground reached 68.5%. The metal structure equipment health status is unknown, and some even existing significant security hidden danger. Due to the reasons such as design, manufacture, installation and operation management, many metal structure equipments running in spite of illness. Because the running state is unknown, the hidden danger is not found in time, the equipments often cause accidents and bring huge harm to the state and the people's life and property. Moreover, with the passage of time, there are more and more metal structure equipments meet or exceed the depreciation life, which make the upgrading task more and more heavier. If the equipments are tested and diagnosed timely, the competent department can make reasonable upgrading plan, so as to preventing accidents and avoiding blind investment funds. Therefore, the studies of hydraulic metal structures health diagnosing have important theoretical significance and practical value.

Hydraulic metal structure health diagnosing, which combines the investigation and analysis of equipment operating situation with the safety of the site and the review of the structure safety calculation results, is actually based on the comprehensive analysis of every diagnosing index, eventually getting the final equipment health diagnosing conclusion with fuzzy comprehensive diagnosing analysis. At present, there are many health diagnosing methods in engineering field, and each method has its advantages and disadvantages, applying to different occasions respectively. Various factors ought to be taken into consideration within a hydraulic metal structure health diagnosing system, for the sake of satisfying comprehensive diagnosis of a multi-layer, multi-standard and multi-factor analysis model. According to the hydraulic metal structure equipment health diagnosing index system and health diagnosing grade standard, the author used the fuzzy hierarchy weight analytic method to calculate and analyze certain diagnosing indexes weights, and established the hydraulic metal structure equipment health diagnosing multi-layer fuzzy comprehensive evaluation index system structure[2].

The creation and research of artificial neural network theory provide a powerful tool for the study of the nonlinear system, and has been successfully used in many research fields[3-14]. It is attracting more and more attention in water conservancy and hydropower engineering safety evaluation field, and has been widely applied[15-18]. With the steady accumulation of hydraulic metal structure safety testing data, we can make full use of the value of historical data and the neural network of its parallel computing ability, self-learning and adaptive ability, self-organizing ability, fault tolerance and self-healing capability, knowledge expression ability .etc., to research and development the hydraulic metal structure health diagnosis system based on artificial neural network technology. BP (Back Propagation) neural network, namely the error Back Propagation neural network, is a kind of multilayer forward of one-way transmission network. BP neural network is a system between grey box and black box, which has a good adaptability to atypical data, and has obvious superiority in dealing with the missing value and nonlinear problem. Therefore, it has more general applicability on the prediction. To some extent, the hydraulic metal structure health diagnosing can be seen as a classification problem, so BP neural network model is chosen to processing health diagnosing for hydraulic metal structure.

However, how to apply BP neural network to the health diagnosing of hydraulic metal structure and determine a suitable network structure, is the main problems the author faced. With help of the predecessors' research, the author training the neural network model based on historical data, and applying it to the hydraulic metal structure health comprehensive diagnosing. The diagnosis model will work together with the FAHP model the author studied, that can make the diagnosis results more reasonable and reliable. This paper, based on the hydraulic metal structure health diagnosing multilayer fuzzy comprehensive evaluation index system established by the author, using neural network technology[19,20], the author researched the BP neural network integration model for hydraulic metal structure health diagnosing and made comprehensive health diagnosis of the hydraulic metal structure.

This paper is organized as follows. In Section 2, the BP neural network model and learning algorithm are introduced. The BP neural network diagnosing model is given in Section 3. And the BP neural network integration model is given in Section 4. Finally, conclusions are given in Section 5.

2. BP neural network model and learning algorithm

Neural network[19,20] is a kind of computing model, consists of numbers of nodes (or ‘neuron’, ‘element’) and those connections between them. The neuron is basic processing unit of neural network, is a non-linear element with multiple input but single output. The mathematical model for it is: $u_j = \sum_{i=1}^{n} w_{ij} x_i - \theta_j$; $y_j = f(u_j)$. Type: x_i (i=1, 2, ..., n) is the input signal coming from other neurons; w_{ij} represents the link weight from neuron j to neuron i; θ_j is the threshold; f (•) is called excitation function or effect function.

Different categories of neural network with varying topology structure can come into being by making reasonable use of artificial neurons. So far, there are dozens of different neural network models, in some way, hydraulic metal structure health diagnosing is a classification problem, so the author choose BP (Back Propagation) neural network model (as Fig.1) for health diagnosis of metal structure. If BP net is used for classification, the excitation function f (•) of node in hidden layer and output layer usually use *Sigmoidal* function, namely: $f(u) = \frac{1}{1+e^{-u}}$.

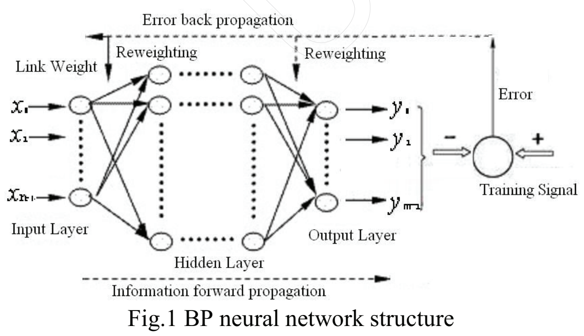

Fig.1 BP neural network structure

BP network uses the multi-layer structure, including input layer, multiple hidden and output layer, full connection between layers are achieved. Assume that the input vector of BP net is $x \in R^n$, $x=(x_0, x_1, \ldots, x_{n-1})^T$; The first hidden layer has n_1 neurons, every one of their outputs is $x' \in R^{n1}$, $x=(x'_0, x'_1, \ldots, x'_{n1-1})^T$; the second hidden layer has n_2 neurons, and every one of their outputs is $x'' \in R^{n2}$, $x=(x''_0, x''_1, \ldots, x''_{n2-1})^T$; the output layer has m neurons, the output is $y \in R^m$, $y=(y_0, y_1, \ldots, y_{m-1})^T$. Also suppose the weight from input layer to the first hidden layer is w_{ij}, and the threshold is θ_j; the weight from the first hidden layer to the second hidden layer is w'_{jk}, and the threshold is θ'_k; From second hidden layer to output layer, the weight is w''_{kl}, the threshold is θ''_l. Based on the mathematical model of neurons, neurons’ output of each layer are as follows:

$$y_l = f\left(\sum_{k=0}^{n_2-1} w''_{kl} x''_k - \theta''_l\right) \quad l = 0,1,\ldots,m-1 \tag{1}$$

$$x''_k = f\left(\sum_{j=0}^{n_1-1} w'_{jk} x'_j - \theta'_k\right) \quad k = 0,1,\ldots,n_2-1 \tag{2}$$

$$x'_j = f\left(\sum_{i=0}^{n-1} w_{ij} x_i - \theta_j\right) \quad j = 0,1,\ldots,n_1-1 \tag{3}$$

Apparently, the mapping from n dimension space vector to m dimension space will be completed.

BP algorithm is virtually about finding out the minimization of calculating error function. When a sample (assume that it’s the sample p) is input into the network, and the output is calculated, the mean square inaccuracy shall be the sum of the unit output error square:

$$E^{(p)} = \frac{1}{2}\sum_{l=0}^{m-1}\left(d_l^{(p)} - y_l^{(p)}\right)^2 \tag{4}$$

When all samples are input once, the total error is as follows:

$$E_A = \sum_{p=1}^{P} E^{(p)} = \frac{1}{2}\sum_{p=1}^{P}\sum_{l=0}^{m-1}\left(d_l^{(p)} - y_l^{(p)}\right)^2 \tag{5}$$

If the error is bigger than the given error in the system, BP network will reversibly modify weight coefficient of each layer. BP algorithm modifies weight coefficient in accordance with negative gradient direction of error function, as to output layer, set $w''_{kl}(n_0)$ for the original weight coefficient and $w''_{kl}(n_0+1)$ for the modified coefficient, then:

$$w''_{kl}(n_0+1) = w''_{kl}(n_0) + \eta\sum_{p=1}^{P}\delta_{kl}^{(p)} x_k''^{(p)} \tag{6}$$

Type: η for learning rate, or step length, the value is generally picked up between 0-1 ; $\delta_{kl}^{(p)}$ equals as follows:

$$\delta_{kl}^{(p)} = \left(d_l^{(p)} - y_l^{(p)}\right) y_l^{(p)} \left(1 - y_l^{(p)}\right) \tag{7}$$

For the middle hidden layer:

$$w'_{jk}\left(n_0+1\right) = w'_{jk}\left(n_0\right) + \eta \sum_{p=1}^{P} \delta_{jk}^{(p)} x_j^{'(p)} \tag{8}$$

Type: $$\delta_{jk}^{(p)} = \sum_{l=0}^{m-1} \delta_{kl}^{(p)} w''_{kl} x_k^{''(p)} \left(1 - x_k^{''(p)}\right) \tag{9}$$

Similarly, the modifying formula of the first hidden layer's weight is:

$$w_{ij}\left(n_0+1\right) = w_{ij}\left(n_0\right) + \eta \sum_{p=1}^{P} \delta_{ij}^{(p)} x_i^{(p)} \tag{10}$$

Type: $$\delta_{ij}^{(p)} = \sum_{k=0}^{n_2} \delta_{jk}^{(p)} w'_{jk} x_j^{'(p)} \left(1 - x_j^{'(p)}\right) \tag{11}$$

According to the above formula, when the network structure is given, ie, input layers, hidden layers, output layers, the nodes of each layer, learning rate η, target error ε and maximum number of learning times, BP learning algorithm is as follows:

(1)Initiate weight w_{sq} as a smaller nonzero random number, *sq* is *ij*, or *jk*, or *kl*.

(2)Please input *P* study samples. Set the current input as the sample *p*.

(3)According to the formula (1) to (3), calculate the output of each layer: x'_j, x''_k and y_l, here j=0, 1, …, n_1, k=0, 1, …, n_2, l=0, 1, …, m-1.

(4) According to the formula (7), (9) and (11), calculate the back propagation error of each layer.

(5) Record the number of studied samples *p*. If $p < P$, turn to step 2 continue to computing; If $p = P$, turn to step 6.

(6) According to the weight correct formula (6), (8), and (10) ,correct weight or threshold of each layer.

(7) According to the new weight, recalculate x'_j, x''_k, y_l and E_A, if $\left|d_l^{(p)} - y_l^{(p)}\right| \le \varepsilon$ （or $E_A \le \varepsilon$ ）applies to each *p* and *l* , or has achieved the maximum of learning times, then end learning. Otherwise, turn to step 2 and continue learning for another round.

3. BP neural network diagnosing model

According to the historical information, a BP neural network model for hydraulic metal structure health diagnosing is established, and applied to health grade diagnosing.

3.1. *The determination of training sample and testing sample*

The author has collected quite detailed information about gate safety test and evaluation of some projects, including the gate testing records of 118 unit projects. And all testing indexes have been classified for hierarchy with the corresponding method. These samples are randomly generated to be training samples which are used to establish network model, and testing samples serving for testing the effectiveness of models created by training, and they belong to a subset of historical data with no repeated record between each other. In other words, the training network model is a completely newcomer for testing data, thus checking the neural network's ability of predicting and diagnosing a hydraulic metal structure's health status. The number of training samples and that of testing samples are quite close, and there are 65 records of training sample of BP model and 53 records of BP model testing sample.

On account of the big difference between dimension and number value of index testing results, the original testing data of every index need to be standardized and normalized. Now set them as four grades, namely A, B, C, D. According to the assured testing index, the testing record consists of 27 indexes, and if an index is inappropriate for the corresponding gate, it will be ignored.

The node which is input into a nerve must be in the numbering form, and the number needs to fall in [0, 1]. Given this, the article has taken a way in which testing data are described by numbers, using formula:

$$Newvalue = \frac{Originalvalue - Minimumvalue}{Maximumvalue - Minimumvalue} \tag{12}$$

Making the value of index testing result fall in [0, 1].

As the form of a gate differs, some testing indexes don't exist. For example: for a radial gate, the deflection of a plane gate's main girder doesn't make sense, therefore, the value 0 is attached to the index within this article. And the index A, B, C, D corresponds to the value 1, 2, 3, 4 respectively, and then map them to[0, 1] with formula (12).

3.2. *The selection of health diagnosing network model structure*

Input layer: 27 indexes need to be tested a steel gate diagnosing, which will be regarded as the input of the neural network, meanwhile, each testing index matches a certain input node.

Output layer: Generally speaking, a single node or several nodes both work well in the output layer of a neural network. Gate diagnosing is divided into three grades, Ⅰ, Ⅱ and Ⅲ. A more natural way is to set the output of diagnosing network as three nodes, that is to say, the output of the diagnosing network is a vector. Having carried out a huge amount of experiments, the author diagnosed that, if the output layer is set as a node, the predicting effect is not so satisfying. So this paper only considers the of three-node output and makes the following regulation: if the output vector is (1,0,0), the corresponding gate health grade is Ⅰ; if the output vector is (0,1,0), the corresponding gate health grade is Ⅱ; if the output vector is (0, 0, 1), the corresponding gate health is Ⅲ.

Hidden layer: The scale of a network depends on the amount of hidden layers and hidden nodes in it, and it plays a fairly significant role in its function. The greater the scale is, the more free parameters in the network will be; On the contrary, the less free parameters in the network will be. If a neural network is used to approach a given target function (classification can be thought of as a special condition of function approximation), when the scale of a network is extremely limited, the neural network's approximating ability lacks, an inadequate fitting will be easily led to; when the scale of a network is overlarge, the neural network's approximating ability is surplus, it often fits over and over again. Too many network nodes will increase the time of training network, what's more, it can also abate generalizing ability and predicting ability of a network. But a tiny number of network nodes cannot reflect the relationship between subsequent value and precursor value, resulting in an in adequate model. Presently, there is no theoretical instruction in all BP networks about how to select the amount of hidden nodes and hidden layers, although there are some formulas can be referred to, e.g. $m=\sqrt{p+q}+a$. type: m for the amount of hidden nodes, p for the amount of input layer nodes, q for the amount of output layer nodes, a is a constant from 1 to 10, whereas , experience and numbers of experiments are required to determine a better network scale.

Initialized weight: The training result differs with varying initialized weight of BP network. Because the net is often randomly initialized, and the inaccuracy does not prove to be identical at the end of the training, nor do the weight and the threshold, leading to the difference of training result. In order to keep the error as small as possible, initial weight and bias should be reasonably set, being overlarge can easily get stuck in saturated zone, leading to a pause. In general, random number between (1, 1) is a common choice.

Learning rate η: Generally, a small learning rate is chosen with the intention of keeping the system stable, usually judging from the observing error drop curve. A sweep declining trend represents an appropriate learning rate, if there is an obvious oscillation, it means the learning rate is too large. At the same time, considering difference of network scale, the selection of learning rate should be adjusted in accordance with it. Practical examples show that it can be selected in the range of 10^{-3}~10. Choosing a suitable learning rate matters a lot, being too big may lead to instability, being too small may contribute to a long training cycle and slow convergence, and cannot reach out to the required error.

Target error: Network computing ought not to be blindly focused on the minimum of training error which may cause "over fitting" phenomenon, the optimal amount of training can be determined by the real-time test on the changes of error rate.

Often times, the expecting output value of the sample is d_l =0 or dl =1, but yl value is 0 or 1 only on condition that u=±∞, this can make some network weights tend to be an infinity. To avoid this saturation phenomenon, the range of an expecting output may be broaden appropriately, e.g. yl>0.9 for 1, yl<0.1 for 0, i.e. defining the expectation error of each sample as $(0.1)^2$=0.01.

3.3. *The realization of a case of BP neural network model training*

This paper managed an example of BP neural network model training (as Fig.2). According to relevant research experience, the author set a hidden layer in this model which consists of 11 nodes, setting learning rate and target error for 0.1 and 0.01 respectively, the initial weight of different network layer is generated randomly in the range of [-1, 1], on condition that learning times surpass 20000 but error does not reach the target value, learning stops automatically. Besides, the input layers of model can also including other different testing indexes.

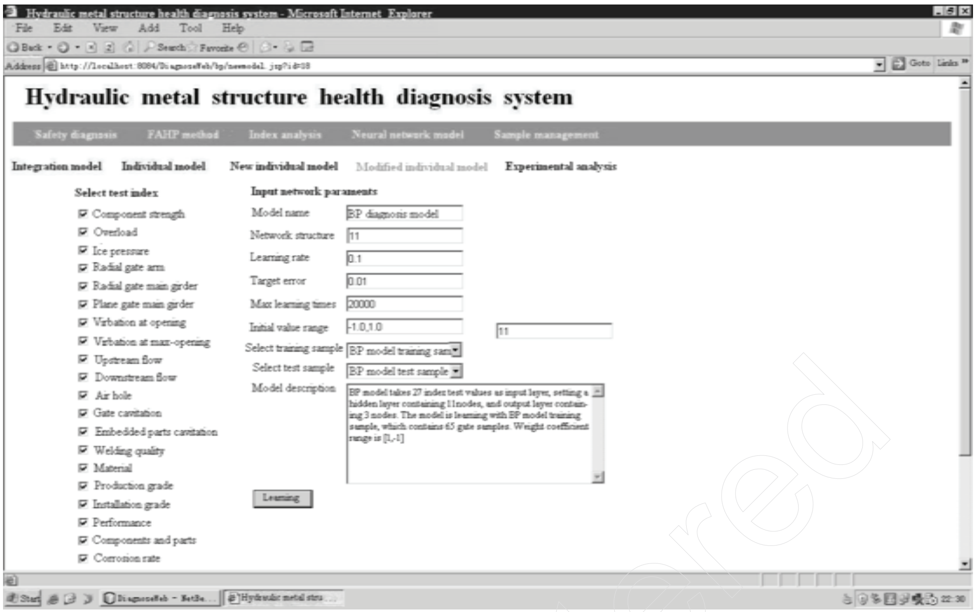

Fig.2 BP neural network model training sample

First, transform testing values into the corresponding values in [0, 1], then input it into the neural network. In the learning process, the system creates an initial value randomly for the weight between nodes of each layer in a certain range. Afterwards, calculate output value according to the forward propagation of neural network learning. If the error between expecting value and the result remains greater than the given goal, then reverse propagation, adjusting the weight between adjacent nodes and performing forward propagation. Until the neural network's sum of training error square is smaller than the target error or the maximum of learning times is reached, then stop training. Table 1 is for the hidden layer weight of model.

Table 1 BP network hidden layer weighs

	W_1	W_2	W_3	W_4	…	W_{11}
X_1	-13.317	-0.681	-9.959	-0.764	…	10.501
X_2	7.023	-0.907	5.398	-0.744	…	-7.740
X_3	-2.182	1.755	0.731	-0.989	…	0.433
X_4	1.026	1.715	-0.288	-1.015	…	-1.286
…	…	…	…	…	…	…
X_{27}	0.762	0.233	-0.606	-0.548	…	2.162

Fig.3 gives BP diagnosing model's learning curve with the abscissa for learning times and the vertical coordinate for training error. The results indicate that: for the first 700 times in the learning process, the training error decreases fast, and the training model meets the requirements of target error after 4877 times. Plus, since the initial weight between each node is generated randomly, given the same network structure, network parameters and the same training samples, the result of the training (including the weight of each layer of the model, learning curve, etc) is not necessarily identical.

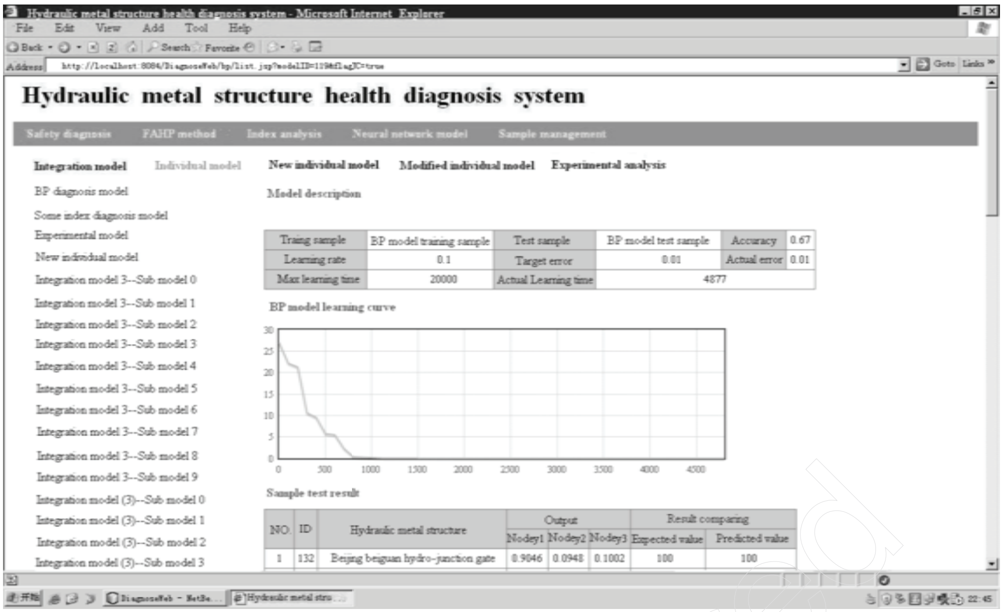

Fig.3 BP diagnostic model learning curve example

After getting the diagnosing model, please input each recorded testing index value of the testing samples into the model and calculate output values(as Fig.4). Some records of the gate are different from the real results, such as the testing result of Beijing Luopoling reservoir spillway gate is 001, i.e., the grade is Ⅲ, but actually the grade is Ⅱ. As for the testing sample, the correct rate of BP diagnosing model above is 67% (as Fig.3). Compared with FAHP diagnosing model, the correct rate of BP diagnosing model is far from being desired. Therefore the author researched in an experimental analyzing method to determine a neural network model with an appropriate structure and parameters. Through this function the author trained neural network models with different structures and parameters, although the correct rates differ, they are seldom beyond 70%.

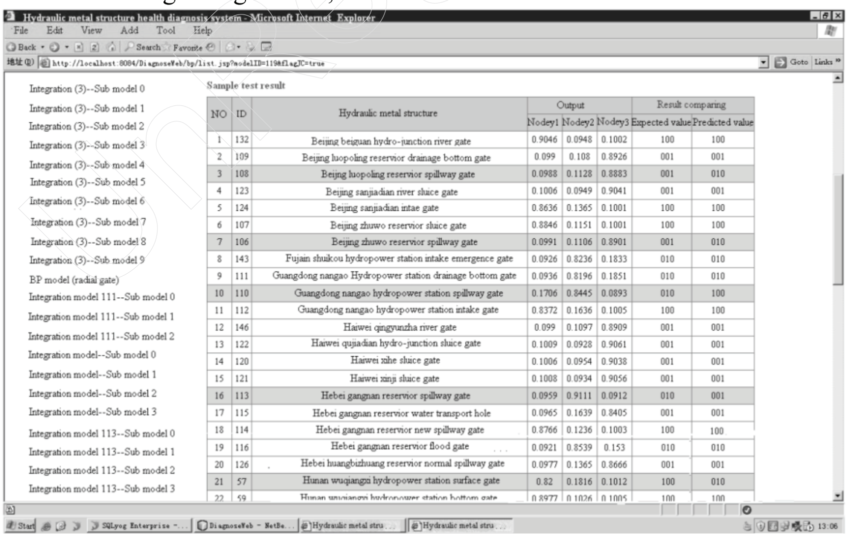

Fig.4 BP diagnostic model test result

4. BP neural network integration model

4.1. *The establishment of BP integrated model*

There is no proper selecting standard of neural network structure when using the neural network for classification or forecast, so the accuracy of parameters like weight and learning rate cannot get effective guarantee. Therefore, the author tried to improve the testing correct rate by researching on the integration of neural network. Neural network integration learning is about integrating several single classifiers when classifying new examples, making the final classification by combining classifying results of all classifiers for better characteristics. If a single classifier is considered as a single decision maker, then the integrating learning equals many people making decisions together. Fig.5 expresses the basic idea of BP integrating model, including N BP nerve network models, as to the same input, the mentioned N BP neural networks give unique output respectively, and the output results of integration model through integration is determined as the final results.

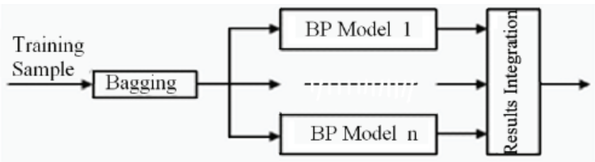

Fig.5 BP integration model

Speaking of general learning tasks, the assuming searching hypothesis space often stretches, but the centralized training examples which can be used for training classifiers are not enough to reaching exactly target assumptions, so the learning results may be a series of assumptions meeting the training integrity, and the learning algorithm can choose these assumptions as the classifier for output, because of over fitting of the machine, the hypothesis which can satisfy the training classification may not have the same good performance in practical application, so the learning algorithm is actually at risk when selecting assumptions for output, the magnitude of such a risk can be reduced by integrating multiple hypothesis. Never ignore the difference among neural network models for integrating learning, but the final decision the integrating classifier makes will be quite similar to that of single ones if those basic classifiers' sorting results are not that different , thus hardly ensuring a better performance than a single classifier. Neural network integration theory research suggests that, the generalization error of the neural network integration could be effectively decreased by enhancing the difference of networks if all the network generalization errors which make up neural network keep unchanged. Generally, there are two ways of increasing the difference between individual networks:
(1) Differing the structure of individual network.
(2)Using Boosting and Bagging technology, forming different training samples for each neural network.

Bagging refers to randomly choosing training samples from a training set on condition of putting them back, building an independent and unique training set with the same scale for each basic classifier, and training out different basic classifiers. The chief difference between Bagging algorithm and Boosting algorithm is: the Bagging training set is picked up randomly, and each round of training set is independent, while instead of being independent, the selection of each round of Boosting training set tightly relates to learning results above. Being different from Bagging's to outstanding tolerance of noise, Boosting proves to be faded on that. The more sensitive the basic classifier learning algorithm is to training data, the better effect of Bagging is, so Bagging is quite effective when speaking of a learning algorithm as artificial neural network. Assume that N basic models (BP network model) are included in a integration model, with a set of given training samples (p samples), the following example is worked out by using the integrating learning algorithm: For i=1 to N; initializing BP model Mi; generating p samples randomly with Bagging method (with the put-back form); using BP learning algorithm to establish a BP model Mi and store its parameters.

4.2. *The realization of a case of BP neural network integrated model training*

Then how will the final decision be made according to so many classifying results? This paper provides the voting method, simple but effective, classifying and forecasting the basic classifiers, choosing some principles of vote (a ticket for denying, consistent voting, the minority is subordinate to the majority, threshold voting) to a vote according to the results. The author designed and realized a software of hydraulic metal structure health diagnosing and model analyzing, which can dig out an integration model with a high diagnosing correct rate, using training samples and testing samples to train and test the integration diagnosing model, shown in Fig.6 and Fig.7.

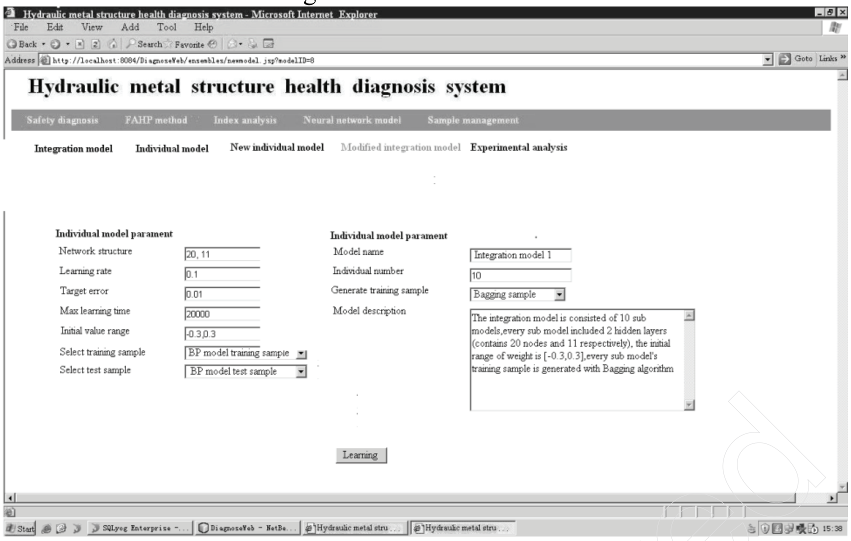

Fig.6 Neural network integration model training sample

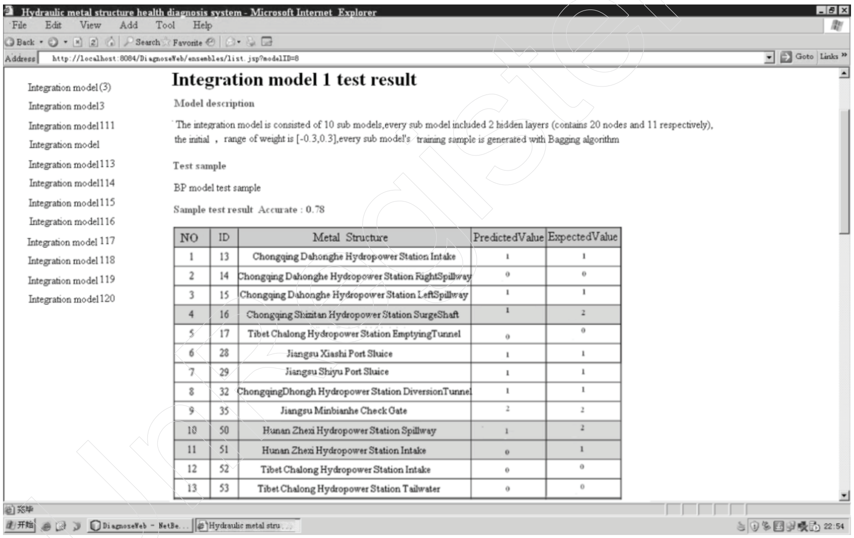

Fig.7 Integrated diagnostic model test results example

In this instance, the integration model consists of 10 basic neural network model with the same structure and parameters, and each basic model has two hidden layers, with 20 nodes attached to one layer and 11 nodes for the other one, besides, the range of initial weight is [-0.3, 0.3]. Using the same example above, 10 different training samples are generated with Bagging method and are used to train the 10 basic network models respectively, thus getting 10 different basic models. In the integration model, this paper applied the voting method of minority being subordinate to the majority. As for the testing sample mentioned above, the testing result of integration model (Fig.7) shows that its correct rate rises to 78%, being apparently better than that of a single one and more stable, either changing the training sample or training times will keep the testing correct rate in a stable level.

By testing the Random SAT problems, we can see from Fig.1 and Fig.2, that our algorithm PPSER has an obvious advantage on efficiency, which is 6-15 times higher than the relatively fast algorithm NER. Moreover, when the number of clauses increased to 130 above, the computing time of our algorithm PPSER is increased gently.

5. Conclusions

Based on neural network technology, the paper researched on the BP neural network integration model of hydraulic metal structure health diagnosing; for testing sample, the correct rate of BP diagnosing model is 67%; through a large number of experimental tests and verification analysis, concluding that the two-hidden-layer neural network model suits hydraulic metal structure health diagnosing better.

With gate health diagnosing taken for example, according to historical data, a BP neural network integration model for hydraulic metal structure health diagnosing is researched and built by using Bagging technology; the example analysis showed that the accuracy (78%) was obviously better than single neural network model, and has good stability. Other metal structure including headstock gear can use a similar method.

With the steady accumulation of hydraulic metal structure safety testing data, we can make full use of the value of historical data and the neural network of its parallel computing ability, self-learning and adaptive ability, self-organizing ability, fault tolerance and self-healing capability, knowledge expression ability.etc., to further study and development the hydraulic metal structure health diagnosis system based on artificial neural network technology. The BP neural network integration model will work together with the FAHP model the author studied ,that can make the diagnosis results more reasonable and reliable.

Neural network model is established on the basis of learning historical data , now the engineering sample data is limited which used for neural network training and testing, and all using index testing value need standardized, normalized handle for original testing data, these influence the learning function and its effectiveness of neural network model. It is a new topic to research that applying original testing data directly in neural network training and testing.

Through performing diagnosis synchronously with different methods, verifying index parameters and analyzing the diagnostic conclusions as well as the system-provided analyzing function for the indexes and the model, the BP neural network integration model making the diagnosis procedure more scientific and normative, so the interference of human factors is eliminated in all links, which results in a more objective, reasonable and reliablethe diagnosis conclusion. Meanwhile, the study provides the researcher an effective way to explore for an optimized integrated diagnostic model and multifarious potential factors' influence on the accuracy rate of a certain model, and promotes to deepen the researchers' cognition of the features of a given diagnosis model.

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