A Forecast Model Based on The BP Neural Network Used in Refinery's Steel Equipment's Corrosion*

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***Abstract*—The forecasting of the corrosion of refinery's steel equipments shows great importance in preventing the accident. Considering the numerous factors affecting the corroding of refinery's steel equipments, which are uneasily predictable and with complex relationships, this paper proposed a new technology based on the BP neural network technology used in forecasting of the corrosion of refinery's steel equipments. A new model is also built and implemented in this paper. Finally, the experimental results prove the feasibility of the new model and the forecasted results by this new model fixes well with the sample data set.**

***Index Terms*—neural network ,BP algorithm, corrosion**

I. INTRODUCTION

The corrosion of refinery's steel equipments include corrosion of inner walls and outer walls. The inner corrosion stems from petroleum and natural gas including corrosive substances, such as H_2S, CO_2, HCl and so on. The outer corrosion comes from the outer environment. In both the domestic and foreign refinery's equipment failure accidents, those caused by corrosion hold a very great proportion. [1,3,8]If we analyze the related influencing factors, calculate the probability of corrosion failure, and propose the corresponding effective measures, then we can effectively reduce accidents of this kind. Because there are too many factors resulting in corrosion failure, and the relationships of these factors are very complex, it is very difficult to express the relationships among the factors with a precise mathematical formula. Therefore it is necessary to use some scientific methods to analyze the experimental data, in order to distinguish and judge each factor's influence clearly from the quite dispersive experimental data, and finally get the conclusions without subjective ingredient. The statistical analysis method is the commonly used method when we analyze all kinds of experimental data, but the neural network has became a widely used powerful tool in processing misalignment mapping in recent years, its misalignment mapping ability makes itself possible to be used in building the model which represents the relationships among the factors affecting the corrosion of refinery's steel equipments.[2,4,7] In this article, the BP neural network is used to analyze the main environmental medium factors that affect the corrosion of refinery's steel equipments, build the forecast model used to forecast the probability of corrosion under different environmental medium factors.

II. ARTIFICIAL NEURAL NETWORK

A. *Artificial Neural Networks*

The artificial neural network is also called neural network, it is a kind of computation structure which can simulation biology process based on the modern neurobiology research and reflect the human brain's certain characteristics. The artificial neuron is the basic unit of artificial neural network. It acts as a component with multi-input but single output, which is usually called the node or the processing unit. The artificial neuron is a formal description of the biological neuron, which abstracts the biological neuron's information processing process, describes that process with the mathematical language, and simulates the biological neuron's structure and function. The neural network is a complex network consisting of simple neurons which is concurrent operation.[2,8]

B. *BP Neural Network*

The BP neural network is an error back propagation network, which belongs to the multi-layer propagation network and belongs to the neural network which has teacher leads the study; it uses the error back propagation algorithm to train to the network. The BP neural network is the most widely used neural network. Being simple and compatible, the BP neural network has been applied successfully in teaching, scientific research and production, which accounts for 80%~90% of the applications of artificial neural network. [5,8,9]

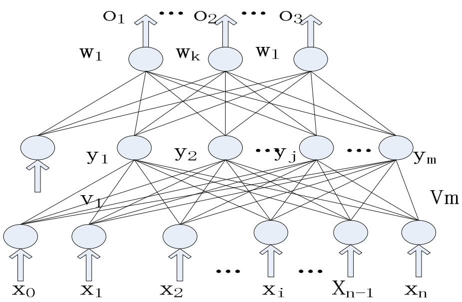

Figure 1. A Three-layer BP network's Structure

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A three-layer BP network composes of the input layer, the hidden layer and the output layer, each layer contains certain information processing unit—— neurons. These are shown in Fig. 1. Neurons among the same layer have no relations; adjacent layers are connected by weight value. Each neuron only accepts the preceding layer's input and transmits the result to the next layer, without feedback. The hidden layer is between the input layer and the output layer, which is the internal expression of input pattern. It can extract the features which belong to a kind of input pattern but different from other input patterns, and transmits them to the output layer. Therefore, the hidden layer is also called the feature extraction layer. This extraction process is actually a self-organizing process between the weight values of the input layer and the hidden layer. That is to say, the weight values of different layers finally can evolve into values which can represent the input pattern characteristics from the initial random values in the network training process.

The BP algorithm's basic idea is: The learning process composes of signal forward propagation and error back propagation. In forward propagation, the input samples propagate from the input layer, after processed by all hidden layers, pass on to the output layer. If the output layer's actual output is not correspondent with the expected output (teacher signal), then the propagation changes to error back propagation. The error back propagation is a process that propagates the output error through the hidden layers to the input layer, and allocates the errors to each layer. Thus each layer's error signal can be obtained, these error signals are used to revise each layer' weight value. The processes of signal forward propagation and error back propagation are carried on again and again. The process of adjusting weight values is the study training process of network. This process continues until the network's output errors reduce to an acceptable degree, or until it is carried out times as many as the value set in advance.[2,9]

Three BP neural network's weight adjusting formula is (1):

$$\begin{cases} \Delta\omega_{\mathrm{jk}} = \eta\delta_k^o y_j = \eta(d_k - o_k)o_k(1-o_k)y_j \\ \Delta v_{ij} = \eta\delta_j^y x_i = \eta(\sum_{k=1}^{l}\delta_k^o\omega_{jk})y_j(1-y_i)x_i \end{cases} \tag{1}$$

And $X=(x_1, x_2, \cdots\cdots, x_i\cdots\cdots, x_n)^T$ is the input vector , the hidden layer's output vector is $Y=(y_1, y_2, \cdots\cdots, y_j, \cdots\cdots, y_m)^T$,the output vector is $O=(o_1, o_2, \cdots\cdots, o_k, \cdots\cdots, o_l)^T$, the expected output vector is $d=(d_1, d_2, \cdots\cdots, d_k, \cdots\cdots, d_l)^T$, $v=(v_1, v_2, \cdots\cdots, v_j, \cdots\cdots, v_m)^T$ is used to express the weight matrix between the input layer and the hidden layer , and the vector V_j is the weight vector corresponding to the j_{th} neuron of the hidden layer . The weight matrix between the hidden layer and the output layer is represented with W, and the vector wk is the weight vector corresponding to the k_{th} neuron of the hidden layer. The constant $\eta \in (0, 1)$ represents the proportional coefficient, reflecting the study speed in the training.[9]

III. ESTABLISHMENT OF CORROSION FORECAST MODEL

The corrosion forecast model's design contains the training sample collection's preparation, the Initial weight's design, and the BP network architecture's design.

A. Preparation of The Training Sample Set

1) Selection of the input and output [1,3,4]

The input and output of a model system to be built is the input and output variable of a neural network. Therefore the corrosion probability of steel equipments is chosen as the output variable. The factors affecting the corrosion probability of steel equipments are the input variables. After studying massive historical data and the magnanimous literature, a conclusion can be drawn that the factors affecting the corrosion of refinery's steel equipments consist of the medium type and density, the stress size and the distribution, the temperature, the pH value, the fracture mode of the materials and so on. Based on previous literature and experience, the temperature, the Cl density and the O_2 density in the medium environment are selected as the input of the model proposed in this article.

2) Design of the training set

A good training sample set emphasizes both the size and the quality of the sample. Generally speaking, the more the training sample numbers are, the more correctly the training result can reflect its inherent laws. But the sample's collection and reorganization are very difficult because they are often limited by objective conditions. In addition, when the sample number rises to certain degree, the network's precision is also very difficult to enhance. The practice shows that the sample number the network training needs depends on the complexity of the input-output nonlinear mapping relationship. The more complex the mapping relations are, the bigger the noise in the sample is. Therefore, to guarantee certain mapping precision, more samples will be needed, and thus resulting in the larger scale of the network. In order to get a good training effect, one empirical rule is referred to in designing the training sets: The training sample number is 5~10 times as many as the whole network connections. Therefore, we selected 20 model training samples to train the forecast model.[7,8]

3) Pretreatment of the input-output data

Because different input data of the network has different physical meaning and different dimension, we need to pretreat the input data, making all components change in certain interval through scale transformation, in order to make all input components have the equally important status from the very beginning of the network training. The temperature value distribution of the model in this article is ideal, so the formula (2) below is used in scale transformation[9]:

$$\overline{x_i} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{2}$$

In the formula, x_i represents the input data, x_{min} represents the minimum value of the data variation range; x_{max} represents the maximum value of the data variation range. The distribution of the Cl density and the O_2 density is not very ideal in the sample; logarithm transformation is used to

TABLE I. FORECAST MODEL TRAINING SAMPLES

Temperature (℃)	$\overline{x_i} = \frac{x_i - x_{min}}{x_{max} - x_{min}}$	Lg(Cl)	Lg(O_2)	Cl consistency (ppm)	O_2 consistency (ppm)	Corrode or not in fact
260	0	-2	-3.2189	0.01	0.004	N (0)
286	0.8667	2.7782	2.3424	600	220	Y (1)
270	0.3333	-1	-0.3979	0.1	0.4	N (0)
265	0.1667	-1	2.301	0.1	200	N (0)
275	0.5	0	-1.3979	1	0.04	N (0)
270	0.3333	0	1.4771	1	30	Y (1)
280	0.6667	0	2.301	1	200	Y (1)
285	0.8333	0.6021	1.6021	4	40	Y (1)
260	0	0.7782	0.9031	6	8	Y (1)
265	0.1667	1	-0.0969	10	0.8	N (0)
276	0.5333	1	1.6232	10	42	Y (1)
260	0	1.4771	2.1987	30	158	Y (1)
290	1	1.47741	0.9031	30	8	Y (1)
285	0.8333	1.9191	1.4771	83	30	Y (1)

transform the Cl density and the O_2 density. This transformation is nonlinear; the transformation result not only reduces the data variation range, but also improves the sample distribution rule. The samples pretreated are showed in Table I.

B. *Design of Iinitial Weight* [5,8,9]

The weight initialization decides which point on the error curved surface the network training begins from; so the initialization method is very important to reduce the time needed for network training. All neuron's transfer functions are zero point symmetry, if each node's input is near zero, and then its output lies at the center point of the transfer function. This position not only is far away from the transfer function's two saturation areas, but also is the region where the variations are the most sensitive, inevitably causing a faster network study speed. In order to make sure that each node's input is near zero, the weight of the hidden layer, $v=(v_1, v_2, \cdots, v_j, \cdots, v_m)^T$, is set to be small enough, whereas for the output layer's weight $w=(w_1, w_2, \cdots, w_k, \cdots w_l)^T$,those whose initial value is +1or -1 are set to have the same weigh value. If the output layer's weight is too small, the hidden layer's weight adjustments will decrease in the begging of the training period. Therefore, the design described above is adopted.

C. *Architecture Design of BP Network*

After the problem of network training sample is solved, the node number of the input layer and the output layer of the network can be determined. The architecture design of BP network is mainly to solve the problem that how many hidden layers are needed and how many hidden nodes each hidden layer has.

1) *Hidden layer's number's design*

The theoretical analysis shows that a neural network having one hidden layer is possible to map all continuous functions; two hidden layers are needed only when studying discontinuous functions. Therefore, the BP neural network needs two hidden layers at most. While designing the BP network, one hidden layer is considered first. When the hidden node number of one hidden layer is not enough to improve the network performance, another hidden layer is added. The same principle is used in the model.[2,6,7,9]

2) *Design of hidden node number*

The hidden node's function is to withdraw and save its inherent rules from the sample, each hidden node has several weights, and each weight is a parameter to strengthen the network's mapping ability. When the hidden node number is too small, the network's ability to gain information from the sample is too weak to summarize the sample rules in the training set; When the hidden node number is too large, the network also possibly learn the non-regular content (noise and so on) in the sample, then the problem "excessive anastomosis" appears, and decrease the generalization ability. What's more, too many hidden nodes may also increase the training time.

The method used to determine the hidden node number is the commonly used trial-and-error method. Firstly, set training network with a few hidden nodes. Secondly, increase the hidden nodes number gradually. Then train them with the same sample set, and determine the hidden node number when the network error is the minimum. The following formula (3) was referred to in determining the initial value. [2, 6, 7, 9]

$$m = \sqrt{n + l} + a \tag{3}$$

In this formula, m is the hidden layer's node number; n is the node number of the input layer, in the model proposed in this article n=3; l is the node number of the output layer. In the model, a is a constant ranging from 1 to 10, in the model a=1. Therefore, m= 5.

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TABLE II. THE RESULT OF TESTING THE MODE

Temperature (℃)	Cl density (ppm)	O_2 density (ppm)	Corrosion probability（model output）	Corrode or not in reality
260	0.1	0.2	0.4	N（0）
275	0.1	0.3	0.09	N（0）
276	0.1	220	0.2	N（0）
280	600	8	0.9	Y（1）
282	10	0.01	0.1	N（0）
290	15	10	0.9	Y（1）
266	4.4	40	0.9	Y（1）
286	1000	0.01	0.3	N（0）
285	100	40	0.9	Y（1）
260	1	0.02	0.1	N（0）

IV. NETWORK TRAINING AND TESTING

The model which has been trained is tested by the real known corrosion data of the refinery's steel equipments. The result is shown in Table II. The result shows that when the corrosion does not happen actually, the probability of corrosion failure is 0.4 at most, 0.09 at least. When stress corrosion happens actually, the probability of corrosion fracture is bigger than or equal to 0.9. The test result is consistent with the reality, showing that this network model is effective in reality, and the accuracy is high.

V. CONCLUSIONS

The BP network has a good fitting effect on multi-input and multi-output nonlinear mapping. It is widely used in a number of fields, especially in experimental data processing, the complicate relationship hidden in the data may be found through the BP network. A neutral network model for forecasting the corrosion of refinery's steel equipments is established successfully using the BP neural network, which finds the complex relationships between factors influencing the corrosion of refinery's steel equipments and corrosion probability. It is proved to be reasonable, and may be used to predict the corrosion probability of tubular steel. However, due to the limitation of experimental samples and data, the effect still needs to be further enhanced. The template is designed so that author affiliations are not repeated each time for multiple authors of the same affiliation. Please keep your affiliations as succinct as possible (for example, do not differentiate among departments of the same organization). This template was designed for two affiliations.

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