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Abstract :Neutral network model has been developed for the computation of corrosion rate of carbon steel in LiBr solutions. The results indicate that the model is capable of re- producing the effects of changes in alkalinity ,temperatures ,LiBr and Na_2MoO_4 concen- trations on the rates of general corrsion and good agreement between calculated and ex- perimental corrosion rate is obtained. The model can be used to satisfactorily predict the corrosion rate of carbon steel in different concentrations of LiBr solutions containing dif- ferent inhibitors at different temperatures. It also provides a novel method for corrosion monitoring of metals used in LiBr absorption chiller.

Key words :Corrosion ,Carbon steel ,Lithium bromide ,BP neural network

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1   Introduction

Because of a growing concern to environment welfare ,Lithium bromide absorption chiller , which uses concentrated lithium bromide as the absorption fluid and water as the refrigerant ,is gradually substituted for refrigerator making use of fluorohydrocarbon as refrigerant and applied in the whole world owing to their high hydration heat ,high solubility of solid phase ,appropriate vis- cosity and good thermal stability. However ,lithium bromide solution is very corrosive toward the structural materials ,generally carbon steel ,used for the solution containment parts in the machine. In industry ,the most effective and economic method is to add different inhibitors to the system , such as $LiOH$,Li_2MoO_4 ,Li_2CrO_4 ,Na_2MoO_4 ,$LiNO_3$,PMA/ Sb ,etc. Corrosion protection proper-

ties of these inhibitors have been reported in the literature by several authors[1 5]. In our previous paper , the corrosion behavior of carbon steels and stainless steels have been studied in different LiBr solutions ,which contain different concentrations of LiOH and Na_2MoO_4 at different temperatures under static conditions through weight-loss tests and electrochemical measurements[6 8].

In these days ,neural network is a rapidly growing field of artificial intelligence and has been found many applications in the modeling of nonlinear systems because of its characteristic of approximating any nonlinear continuous arbitrarily well on a compact set. The most widely used neural network is back propagation (BP) network ,which accounts for most neural network applications ,for its simplicity and its power to extract useful information from samples[9]. BP neural network has also been applied to the study of corrosion behavior[10 12] such as forecasting corrosion forms ,corrosiveness ,service life of equipment ,etc.

A literature research shows no works describing the effect of factors such as temperature , concentrations of LiBr and inhibitors ,pH etc on corrosion rate of carbon steel in lithium bromide absorption chiller by using neural network. This paper is a continuation of the previous work. Specifically ,the study is expanded to develop the model of corrosion rate of carbon steel relating to LiBr concentrations ,inhibitor concentrations and temperatures using BP neural network based on these data we have obtained.

2   Experimental

Rectangular sheet specimen (30mm × 20mm × 2mm) was used for corrosion loss measurement and its chemical composition is shown in Tab. 1. The specimens were ground with 1000-grit SiC paper ,rinsed with deionized water ,and finally degreased with acetone. Test solutions were prepared from a reagent grade LiBr and deionized water. Two specimens and $90cm^3$ of the test solution in a polytetrafluoroethylene (PTFE) cylinder bush (50mm inner diameter ,65mm length) , which was transferred into a stainless steel autoclave ,and the solution was deoxygenated for 1 hour with nitrogen. The autoclave was then held at predetermined temperature for 200 hours in a thermostat(Kosumosu AT-S13). The corrosion rate was determined from the weight changes of the specimen after the specimen was cleaned by 3 mol/ L HC1 containing 1 % hexa-methyleneteramine at 50   for 5min. The results have been previously reported[6 8].

Tab. 1   Chemical composition of the carbon steel/ %

C	Si	Mn	P	S	Fe
0. 12	0. 01	0. 35	0. 02	0. 02	Bal

3   BP network algorithm

3. 1   Principle of BP network algorithm

BP neural network is basically a gradient decent algorithm designed to minimize the error

function in the weights space. A typical three-layer BP neural network is shown in Fig. 1. Commonly used activation function is the Sigmoid function. During training of the neural network, weights and threshold values are adjusted to decrease the total error, which is defined by the following equation, so as to make the calculated output data as close to the given output data as possible.
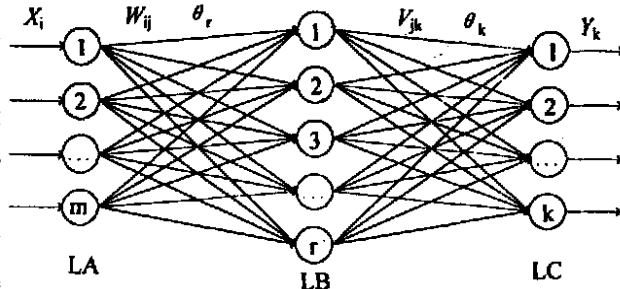

Fig. 1 Structure diagram of a three-layer BP neural network

$$E = \sum_p E_p = \frac{1}{2} \sum_p \sum_k (T_{pk} - Y_{pk})^2$$

Where P indexes the patterns in the training set, K indexes the output units, T is the actual value of output layer, Y is the calculated value of output layer.

Based on the input of the input layer, modification formulas of weights can be obtained by adopting gradient descent methods.

$$\Delta V_{jk} = -\eta (\partial E/ \partial V_{jk}) = \eta \cdot \delta_k \cdot b_j$$
$$\Delta W_{ij} = -\eta (\partial E/ \partial V_{jk}) = \eta \cdot e_j \cdot X_i$$

Where X_i is the input of input layer, b_j is the output of the hidden layer, e_j is the error of the hidden layer, δ_k is the error of the output layer, η is the step size of the study, ΔW_{ij} and ΔV_{jk} are the weight changes.

In order to accelerating convergence rate and avoiding oscillating, Hoskine[13] gave momentum strategy methods by adding momentum strategy to weights updating rule. The new equations are given by:

$$\Delta V_{jk}(n + 1) = -\eta (\partial E/ \partial V_{jk}) + \alpha \cdot \Delta V_{jk}(n)$$
$$\Delta W_{ij}(n + 1) = -\eta (\partial E/ \partial V_{jk}) + \alpha \cdot \Delta W_{ij}(n)$$

Where α is the momentum coefficient, n is the cycle index.

In the BP algorithm, training is carried out by repeatedly presenting the entire set of training patterns until the error functions over all the trainings are minimized and within the preset training precision.

3.2 Training BP neural network

3.2.1 Data initialization of BP neural network

Lithium bromide concentrations between 55 % and 65 % are commonly used in absorption chiller. This range provides maximum efficiency for absorption of the flash-evaporated water. Working temperature varies between 145 and 173 since LiBr concentration ranges from 55 % to 65 % in the absorption system. Recently, the triple-effect absorption cycle has attracted much interest to replace the conventional machine as the more efficient one. In high generator, the

temperature of lithium bromide solution is raised to 200 . In industry ,LiOH and Na_2MoO_4 are the popular inhibitors.

In principle ,it has been proved that any continuous function can be uniformly approximated by a neural network model with only one hidden layer. So a three layer BP network is employed in our study. It is easy to determine the number of neurons in the input layer and the output layer during applications. There are four neurons in the input layer denoting temperature and the content of LiBr ,LiOH ,Na_2MoO_4 in absorption chiller ,respectively. However it is not easy to choose the appropriate number of neurons in the hidden layer for there is currently no definite rule to determine it. Using too many neurons impedes generalization and increases training time. Using too few neurons impairs the neural network and prevents the correct mapping of input to output. In this study ,the number of neurons in the hidden layer is determined according an empirical formula[14]and is eight. There is only one neuron in the output layer representing the corrosion rate.

Data of 79 typical corrosion rate samples are gathered for use in training and testing the BP network. The number of corrosion rate in 55 % LiBr solution is 20. 30 patterns are the data in 60 % LiBr solution. The rest patterns are the data in 65 % LiBr solution. The database is divided into two data sets :training sets and test sets ,containing 88 % and 12 % data of database ,respectively. Preprocessing of the data is usually required before presenting the patterns to BP neural network. It is necessary because the Sigmoid activation function modulates the output of each neuron to values between 0 and 1. The following normalization procedure is commonly adopted and is used in our work.

$$X_i = \frac{1}{2} \cdot \frac{X_{max} - X_i}{X_{max} - X_{min}}$$

Where X_{max} and X_{min} are the maximum and minimum values of a variable ,X_i is the normalized value of the variable.

Initial weights and threshold values are randomly initialised with a uniform distribution over [- 1 ,1]. Step size and momentum coefficient are chosen to bo 0. 1 and 0. 9 ,respectively. During the training of the BP network ,the error function for all training patterns is monitored. The training course is stopped when the error function reduces within a given tolerance. And then the fixed structure of BP network is obtained.

3.2.2 Validating BP neural network

Of the total training patterns ,10 are randomly chosen and are used to validate whether the trained BP network has mapped the nonlinear relationship of these factors. The tested results are shown in Tab. 2. As shown ,the relative errors of predicted values of corrosion rate are within 10 % ,and the maximum absolute error is 8. The predicted results agree with the actual data to within reasonable experimental error. Thus ,the results indicate that the trained BP network estimates corrosion rate with and accuracy similar to that in the experimental measurement and can be used to predict the corrosion behavior of carbon steel.

Tab. 2 Results of validating BP network using training samples

LiBr Concn. / %	Temperature /	LiOH Concn. / mol·L^{-1}	Na$_2$MoO$_4$ Concn. mg·L^{-1}	Experimental data/μm·y^{-1}	Predicted value/μm·y^{-1}	Absolute error/μm·y^{-1}	Relative error/ %
55	145	0	150	536.4366	535.0343	1.4023	0.26
55	145	0.07	150	36.6015	34.0258	2.5757	7.04
55	175	0.07	150	49.0591	49.6773	0.6182	1.26
60	145	0.07	150	39.5889	39.6806	0.0917	0.23
60	150	0.02	200	364.7655	372.6786	7.9131	2.17
60	150	0.10	150	40.6374	37.0702	3.5672	8.78
60	200	0.07	150	121.7986	125.8548	4.0562	3.33
65	173	0.07	1000	51.3772	50.5059	0.8713	1.70
65	173	0.10	0	406.4175	407.2542	0.8367	0.21
65	240	0.10	300	373.5200	368.5536	4.9663	1.33

3.3　Predicted results of BP network and discussion

The predicted values of the test sets ,which are obtained with trained BP network ,are shown in Tab. 3. The relative errors of the others are within 5 % except that one pattern has larger relative errors in 55 %LiBr solution ,which is 18.30 %. The reason is that the amount of corrosion data in 55 %LiBr in input patterns is less than that in other cases ,resulting in higher relative errors in less concentrated LiBr solutions. So far as absolute errors are concerned ,the absolute error of the pattern having large relative error is less than 7. The accuracy still meets the requirement. The results indicate that trained BP network can be used to predict the corrosion behavior of carbon steel in different concentrations of LiBr solutions with various inhibitors at different temperatures.

Tab. 3　Predicted results of trained BP network

LiBr Concn. / %	Temperature /	LiOH Concn. / mol·L^{-1}	Na$_2$MoO$_4$ Concn. mg·L^{-1}	Experimental data/μm·y^{-1}	Predicted value/μm·y^{-1}	Absolute error/μm·y^{-1}	Relative error/ %
55	145	0	150	36.6100	29.9105	6.6995	18.03
55	160	0.07	150	41.0428	39.6497	1.3931	3.39
55	200	0.07	150	84.8376	81.0565	3.7811	4.46
60	150	0.02	200	364.7655	372.6786	7.9131	2.17
60	150	0.07	150	42.3084	44.4279	2.1195	5.01
60	240	0.07	150	242.5900	240.2126	2.3774	0.98
65	173	0.10	300	74.6300	72.7456	1.8844	2.53
65	173	0.15	150	302.0973	291.4716	10.6257	3.52
65	220	0.07	150	444.4600	466.5221	22.0621	4.96

4   Conclusions

BP neural network was trained using obtained corrosion data and was tested with the remaining patterns. The predicted values agree with experimental data. The trained BP network can be used to predict corrosion rate of carbon steel in LiBr solutions having different concentrations with different inhibitors at different temperatures. Predicted accuracy of neural network relates to the selection and the number of training patterns. The model provides a novel method for studying the corrosion of metallic materials and field monitoring in LiBr absorption chiller. .

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LiBr   Na$_2$MoO$_4$,   ,

LiBr   ,   ,

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