Application of artificial neural networks in analysis of CHF experimental data in round tubes

HUANG Yan-Ping,[1,2] SHAN Jian-Qiang,[2] CHEN Bing-De,[1] LANG Xue-Mei,[1] JIA Dou-Nan,[2] WANG Xiao-Jun[1]
([1]Nuclear Power Institute of China, Chengdu 610041; [2]Xi'an Jiaotong University, Xi'an 710049)

Abstract Artificial neural networks (ANNs) are applied successfully to analyze the critical heat flux (CHF) experimental data from some round tubes in this paper. A set of software adopting artificial neural network method for predicting CHF in round tube and a set of CHF database are gotten. Comparing with common CHF correlations and CHF look-up table, ANN method has stronger ability of allow-wrong and nice robustness. The CHF predicting software adopting artificial neural network technology can improve the predicting accuracy in a wider parameter range, and is easier to update and to use. The artificial neural nefwork method used in this paper can be applied to some similar physical problems.

Keywords Artificial neural networks, Critical heat flux, Thermal-hydraulics, Reactor engineering, Reactor safety
CLC number TL331

1 Introduction

The critical heat flux (CHF) is one of the main factors, which limit the heat transfer capability of the boiling heat transfer facilities such as reactor and boiler. A large amount of experimental and theoretical researches for CHF has been performed so far, while some credible predicted models and correlations have been obtained.[1] However all experiments were performed for special objects and based on a special condition. The application ranges of CHF correlations were limited. If the operational parameters of a new heat transfer equipment go beyond the effective ranges of the experimental correlation, a new CHF experiment must be carried out over again. These correlations were gained by the general polynomial regression, so it is hard to know more comprehensive effects of the systemic parameters.

Groeneveld *et al*.[2] have put forward a CHF look-up table based on 30,000 experimental data by the general statistical method and the way of the parameter prediction. The hypothesis of local condition was accounted for and the factors such as system pressure, tube diameter, mass flux and vapor quality were considered, but the tube length effect was neglected. General speaking, the CHF look-up table is a good method for its abundant data, the widest predicting range and higher predicting precision.

With the experimental data obtained by different labs increasing, the big error and even wrong data also increase inevitably because of the measuring technique, unit and data transfer. So if the analysis method has a stronger ability of allow-wrong and a nice robustness when a large amount of experimental data was produced, precision of the predicting system would be improved rationally.

Therefore, with the new experimental data producing constantly, it is necessary for us to pay more attention to the analysis of the present CHF experimental data in order to improve CHF predicted ability within the range of possibilities. A kind of method or model with a stronger ability of allow-wrong and a nice robustness is needed to improve the predicting accuracy in a wider or full-parameter range, and it is easier to be updated for the system structure and parameters to describe the complicated correlations. This paper aims at developing a theoretical approach by means of artificial neural network theory and based on enough CHF experimental data.

2 BP networks and BP arithmetic

A BP (Back Propagation) network of ANN is a

Received date: 2003-05-15

kind of multi-layer and feed forward networks. It consists of an input layer, one or several hidden layers and an output layer. Each layer is made up of a certain number of nodes.[3] The error back transmitting arithmetic was employed as the training arithmetic of BP network. For a three-layer network, I, J, K, denote the nodes of input layer, hidden layer and output layer respectively. The training set is composed of M samples. $m = \{1, 2, \ldots, M\}$, $i = \{1, 2, \ldots, I\}$, $j = \{1, 2, \ldots, J\}$, $k = \{1, 2, \ldots, K\}$. The feed forward calculating formula of BP network are written as:

$$O_{mj} = \left\{1 + \exp\left[-\left(\sum_i W_{ij} O_{mi} - \theta_j\right)\right]\right\}^{-1} \tag{1}$$

$$O_{mk} = \left\{1 + \exp\left[-\left(\sum_j W_{jk} O_{mj} - \theta_k\right)\right]\right\}^{-1} \tag{2}$$

While adjusting the weight value and the threshold value by back forward method, the formula to evaluate the modified amount for the n-th iterative calculation are:

$$\Delta W_{jk}^{(n)} = \eta \sum_m \delta_{mk} O_{mj} + \alpha \Delta W_{jk}^{(n-1)} \tag{3}$$

$$\Delta W_{ij}^{(n)} = \eta \sum_m \delta_{mj} O_{mi} + \alpha \Delta W_{ij}^{(n-1)} \tag{4}$$

$$\Delta \theta_k^{(n)} = -\eta \sum_m \delta_{mk} + \alpha \Delta W_k^{(n-1)} \tag{5}$$

$$\Delta \theta_j^{(n)} = -\eta \sum_m \delta_{mj} + \alpha \Delta W_j^{(n-1)} \tag{6}$$

where $\delta_{mk} = (t_{mk} - O_{mk}) O_{mk} (1 - O_{mk})$ and $\delta_{mj} = \sum_k \left(\delta_{mk} W_{jk}^{(n)}\right) O_{mj} (1 - O_{mj})$; η takes a value between 0 and 1; α takes a value between 0 and 1.

3 CHF database

According to different researching aims, the following two CHF sub-databases are derived:

(1) CHF sub-database based on inlet condition

This sub-database based on inlet condition in round tubes makes sequence in a row and arranges in the following order: p, D, L, G, SC and q_{CHF}. 6,942 data were employed in this sub-database and the parameter ranges were as follows: p: 0.1 to 20 MPa; D: 0.01 to 0.0375 m; L: 0.0254 to 4.966 m, G: 13 to 18580 kg/(m^2·s), SC: 0 to 1667 kJ/kg and q_{CHF}: 9 to 2152 W/cm^2.

(2) CHF sub-database based on local condition

This sub-database based on local condition in round tube makes sequence in a row and arranges in the following order: D, L, p, G, x and q_{CHF}. 4877 experimental data were employed in this sub-database, and the parameter ranges were: p: 0.14 to 20 MPa; D: 0.0019 to 0.0375 m; L: 0.0351 to 4.966 m; G: 40 to 17089 kg/(m^2·s); x: –0.85 to 1.0 and q_{CHF}: 9 to 1483 W/cm^2.

4 Applied research

4.1 Research on the feasibility and reliability of ANN

The BP model with a four-layer network and the S form function was adopted as the structure model of CHF-ANN to study the feasibility and reliability of ANN in analyzing a large amount of CHF experimental data.[4] The input neurons were pressure, mass flux and mass quality. Two hidden layers included 20 neurons respectively. The output was CHF value. The most sharply dropping way was used as the convergence mode. The absolute error was used as the determining criterion of the systemic error for the objective function. The input and output neurons were normalized. The input and output samples were also normalized between 0.1 and 0.9. The initial weight value was random. The training database came from the CHF look-up table established by Groeneveld *et al*.[2] The comparison between the predicted results obtained by training networks and by other ways was shown in Table 1. In Table 1, the error of AECL-UO was the testing result for the look-up table in Ref.[5], in which 465 data (their parameters fell in the parameter range of the look-up table) were used.

Thus it is seen that ANN can be applied effectively to analyze and predict a large amount of CHF experimental data in a wide parameter range. The comparison with other general ways shows that ANN enlarges greatly the effective predicting range and the predicting precision is improved distinctly. Due to the allow-wrong ability of ANN itself, CHF predicting system based on ANN has a nice robustness. At the same time, it can be found that the training speed of the most sharply dropping way is very low and the normalized method adopted cannot extend easily. In addition, it has been known that CHF experimental database with better performance is a key of training CHF-ANN predicting system with fine performance.

Table 1 Researching results of feasibility and reliability

Name of formula	Average error	Mean square deviation	Maximum error
Biasi	0.282	0.518	3.659
Bowring	0.47	0.776	3.490
Macbeth	>>1.	>>1.	>>1.
Levitan	0.321	0.388	1.442
AECL-UO[5]	0.165	0.349	2.744
ANN in Section 4.1	0.07	0.149	1.339

4.2 Modification of CHF-ANN model

According to the above research, the structure model of CHF-ANN predicting system was modified as follows.

The output neuron function is represented as:

$$O_{mk}=\frac{C}{1+\exp\left[-\left(\sum_j W_{jk}O_{mj}-\theta_k\right)\right]} \tag{7}$$

where C depends on the problem under consideration. In this paper, C=3000.

Normally the absolute error is used to set the output criterion of network. But as a result of this way, when the absolute error is smaller, the relative error is bigger. In this study, the relative error is adopted as the objective function:

$$E=\sum\frac{\left(t_i-O_{\mathrm{m}k,i}\right)^2}{t_i^2} \tag{8}$$

To avoid the training paralysis caused by computing overflow with no normalization, the method in which the random weight value of the input layer is divided by the maximum input is adopted, namely:

$$W_o\left(1,i\right)=\frac{y_{\mathrm{rands}}}{y_{\max}} \tag{9}$$

On the basis of CHF database characteristic and demand of prediction, after training and test for many times, the network structure adopted in this paper is depicted in Fig.1, where number of the input layer neuron is 5; the neuron numbers of the two hidden layers are 30 and 40, respectively; and the neuron number of the output layer is 1, namely CHF value.

On account of defect and shortage of the most sharply dropping way adopted in the research of feasibility and reliability, the training arithmetic has also been improved and tested. At last a kind of combined arithmetic, the integration of BP arithmetic and simulated annealing algorithm,[6] is employed as the training network algorithm in this paper.

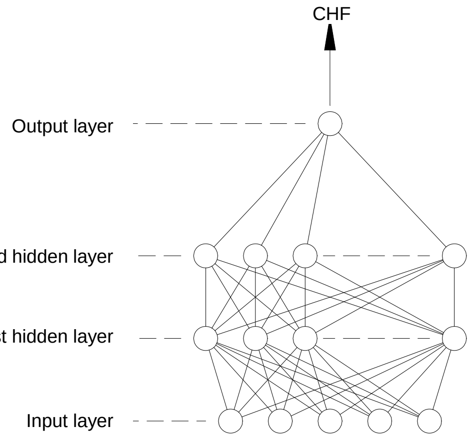


Fig.1 Schematics of CHF-ANN networks structure.

4.3 CHF-ANN predicting system and assessment

4.3.1 CHF-ANN predicting system

(1) CHF-ANN predicting system based on inlet condition in round tubes:

The training database is the CHF sub-database based on inlet condition. Experimental data such as p, D, L, G, SC are input neurons, the CHF value is output neuron. The neuron numbers of two hidden layers are 30 and 40 respectively; the final training RMS (root-mean-square) value is 10.15%.

(2) CHF-ANN predicting system based on local condition in round tubes:

The training database is the CHF sub-database based on local conditions. Experimental data such as D, L, p, G, x are input neurons. The neuron numbers of two hidden layers are 30 and 40 respectively; the final training RMS value is 14.46%.

4.3.2 Assessment of predicting results

Four methods are employed to assess the predicting result of CHF-ANN. They are Biasi, Bowring, Katto correlation and AECL look-up table.

4.3.2.1 Comparison between different methods under the same database

340 experimental data are adopted in this comparison, and the parameter ranges are as follows: D: 6.2 to 37.5 mm; L: 0.61 to 1.972 m; p: 3.45 to 10.34 MPa; G: 637 to 5 683 kg/(m^2·s); x: 0.11 to 1.00 and SC: 47.4 to 1 198 kJ/kg, which belongs to the intersection of the effective parameter range of above four methods. The predicting statistic results of all methods is shown in Table 2, where SC represents the CHF-ANN method based on inlet condition, X represents the CHF-ANN method based on local condition. The comparison results show that the method brought forward in this study has the highest predicting precision among Bowring, Katto and Biasi CHF predicting correlation, CHF look-up table of AECL and CHF-ANN method developed in this study on the basis of the same database. In general methods, Bowring correlation is the best; Katto and AECL correlations are better; and the predicting result of Biasi correlation is the worst because Biasi correlation is based on local condition and its parameter range is very narrow. The error range of AECL look-up table is from –70% to 30%, for the data used in this comparison are located in the uncertain area of AECL look-up table. While the error ranges of CHF-ANN are ±30% for the local condition CHF-ANN and ±15% for the inlet condition CHF-ANN, respectively, comparing the mean error, RMS, maximum error and error range of all methods, it is clear that the predicting precision of CHF-ANN method is distinctly higher than other methods.

Table 2 Comparison between different methods under the same database

Method	Average error	Mean square deviation	Error range	Maximum error
Biasi	-0.044	0.203	-100%~60%	-0.941
Bowring	0.057	0.103	-15%~25%	0.242
Katto	-0.046	0.108	-35%~20%	-0.330
AECL table(X)	-0.364	0.455	-70%~30%	-0.677
CHF-ANN(SC)	-0.001	0.041	-15%~15%	0.181
CHF-ANN(X)	-0.005	0.088	-25%~30%	0.290

4.3.2.2 Comparison between different methods under different databases

“Different database” here means that the data used to assess are different, but these data are selected from the CHF-ANN database, and their parameter range belongs to the effective parameter range of the above five methods. Apparently the parameter range of CHF-ANN method is the widest. The comparison aims at verifying fairly if CHF-ANN method has apparent advantage in both predicting range and predicting precision or not. The predicting statistic results of all methods are shown in Table 3. The comparison results show that the method brought forward in this study has the widest predicting range and the highest predicting precision among Bowring, Katto and Biasi CHF predicting correlation, CHF look-up table of AECL and CHF-ANN method developed in this study under their own effective range of different CHF predicting methods. Among four kinds of general methods, Bowring correlation is still the best, Biasi correlation and AECL look-up table are both poor, the reason is the same as described in 4.3.2.1.

Table 3 Comparison between different methods under different databases

Method	Average error	Mean square deviation	Number of data points
Biasi	0.054	0.353	2820
Bowring	0.022	0.153	5993
Katto	0.030	0.170	6905
AECL table(X)	0.016	0.455	3320
CHF-ANN(SC)	-0.013	0.1015	6942
CHF-ANN(X)	-0.030	0.1446	4877

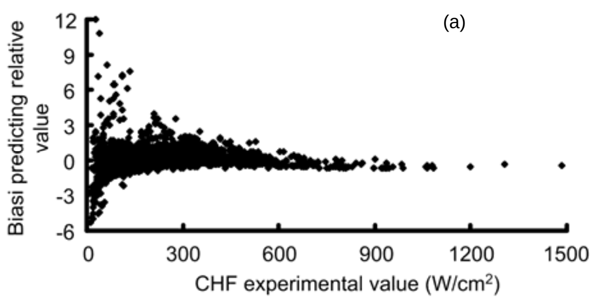
4.3.2.3 Comparison between different methods under full-parameter range

“Full parameter range” here means that all data of CHF experimental database built in this study are used to assess the above five methods. It means that some data do not belong to the effective parameter range of Biasi, Bowring, Katto and AECL lookup table, but all data are in the effective parameter range of CHF-ANN method. The comparison aims at verifying the predicting characteristic of all methods in the full-parameter range. The predicting statistic results of all methods are shown in Table 4. The distribution of predicting error with CHF experimental value is shown in a set of Fig.2. In these figures, the *Y*-coordinate represents the relative predicting values of different methods ((predicting CHF value−experimental CHF value) / experimental CHF value), and the *X*-coordinate represents the experimental CHF values.

The comparison results show that CHF-ANN method has the widest effective range and the highest predicting precision among the above five methods under the full-parameter range. Because predicting range goes beyond the range of four kinds of general methods, their predicting precisions have been distinctly influenced.

Table 4 Comparison between different methods under full-parameter range

Method	Average error	Mean square deviation	Number of data points
Biasi (X)	0.073	0.872	4877
Bowring (SC)	0.025	0.162	6942
Katto (SC)	0.040	0.181	6942
AECL Loop-uptable (X)	0.026	0.567	4877
CHF-ANN (SC)	-0.013	0.1015	6942
CHF-ANN (X)	-0.030	0.1446	4877



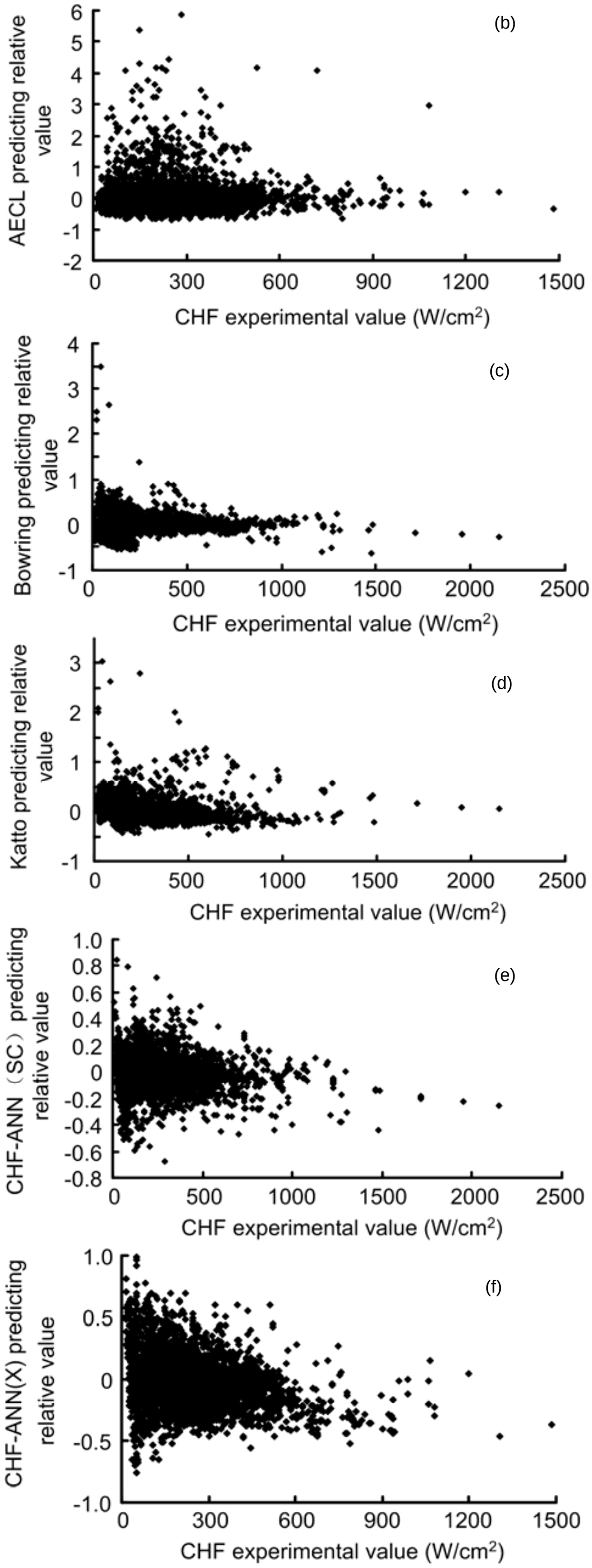


Fig.2 (a) Predicting results of Biasi correlation in full-parameter range; (b) predicting results of AECL look-up table in full-parameter range; (c) predicting results of Bowring correlation in full-parameter range; (d) predicting results of Katto correlation in full-parameter range; (e) predicting result of CHF-ANN based inlet condition in full-parameter range; (f) predicting result of CHF-ANN based local condition in full-parameter range.

4.3.2.4 Test using the experimental data out of the database

To examine the comprehensive characteristic of CHF-ANN, two groups of totally 283 experimental data, produced in 1998 by Nuclear Power Institute of China, were employed to test the predicting characteristic of CHF-ANN method. The 283 experimental data were not in the training database of this study.

(1) Test of CHF-ANN based on inlet condition in round tubes

For 24 data in all, the parameter ranges are as follows: p: 13.4 to 14.8 MPa; D: 0.008 m; L: 1.0 m; G: 572 to 4143 kg/(m^2·s), SC: 97.2 to 692 kJ/kg and the CHF experimental value is from 82 to 451 W/cm^2. The predicting RMS value is 6.21%, the maximum error is 15.2% and the average error is 2.31%. The comparison between the experimental and predicting results is shown in Fig.3.

(2) Test of CHF-ANN based on local condition in round tubes

For 259 data in all, the parameter ranges are as follows: p: 4.2 to 11 MPa, D: 0.006 to 0.012 m, L: 0.2195 to 2.0 m, G: 679 to 4 426 kg/m^2.s, x: 0 to 0.91 and the CHF experimental value is from 111 to 811 W/cm^2. The predicting RMS value is 14.75%, the maximum error is 44.8%, and the average error is –0.6%. The comparison between the experimental and predicting results is shown in Fig.4.

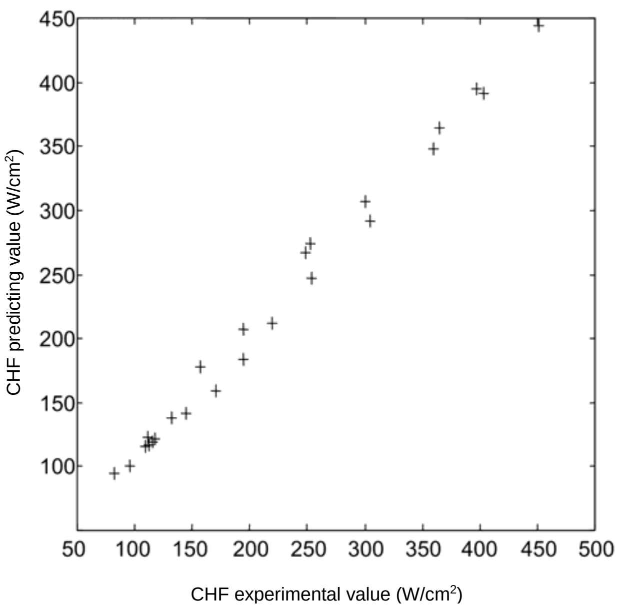


Fig.3 Test results of CHF-ANN based inlet condition.

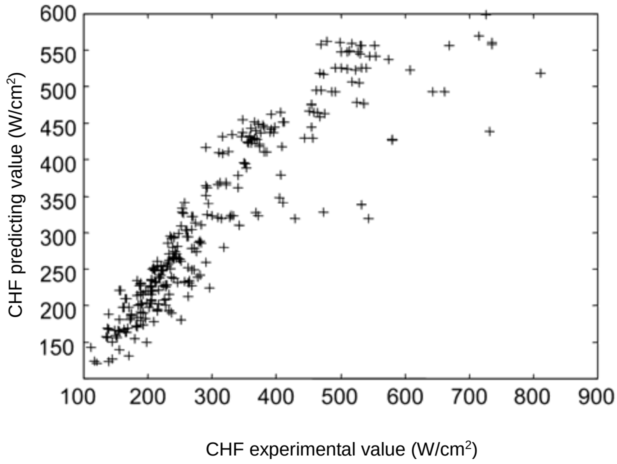


Fig.4 Test results of CHF-ANN based local condition.

From the test result, it can be found that the predicting characteristic of CHF-ANN is excellent. The predicting precision of the inlet condition CHF-ANN software is better than that of the local condition CHF-ANN software.

5 Conclusions

(1) The predicting precision indexes of ANN method are all better than those of four kinds of general methods, which shows that ANN method is better than general methods in dealing with the dispersed experimental data and is specially suitable for the analyzing and reducing of experimental data group with a great quantity, wide parameter range and complicated data distribution.

(2) Comparisons and analyses under different effective range and full-parameter range show that the predicting precision and effective predicting range of CHF-ANN are improved distinctly as compared with four kinds of general methods.

(3) The predicting results of CHF-ANN based on two conditions (inlet and local condition) show that the predicting precision of the former is greatly better than that of the latter.

(4) ANN method has strong ability of allow-wrong and nice robustness, so it can reduce data eliminating wrongly and improve the predicting precision.

(5) Since CHF-ANN after being trained is a small software package and is easy to be called by other codes, it is very convenient to use.

Nomenclature

C: a constant in Eq.(7)
D: diameter of tube……………(mm)
E: relative error ……………...(%)
G: mass flux………………..[kg/(m^2·s)]
I: node number of input layer
J: node number of hidden layer
K: node number of output layer
L: heated length……………...(m)
O_{mi}: output of input layer
O_{mj}: output of hidden layer
O_{mk}: output of output layer
M: total number of samples
p: system pressure……………(MPa)
q_{CHF}: critical heat flux…………(W/cm^2)
SC: inlet subcooling……….(kJ/kg)
t: ideal output value
$W_{o(i,j)}$: initial weighting value
W_{ij}: weighting value of input to hidden layer
W_{jk}: weighting value of hidden to output layer
x: mass quality
y_{max}: maximum input
y_{rands}: random weighting value
α: coefficient of inertia
η: learning efficiency
θ_j: threshold value of hidden layer
θ_k: threshold value of output layer

References

1 Collier J G. Convective boiling and condensation, McGraw-Hill Book Company, UK, 1994
2 Groeneveld D C, Leung L K H, Kirillov P L *et al*. Nucl Eng Des, 1996, **163**: 1-23
3 Yang X J, Zheng J L. Artificial net works (in Chinese), Beijing: Chinese Higher Education Press, 1992
4 Shan J Q, Huang Y P, Chen B D. in: Ray H B, Kunio Hamada, Bertrand Barre (eds), 6th international conference on nuclear engineering ICONE-6, San Diego, California, USA, May 10-14, 1998
5 Moon S K, Baek W P, Chang S H. Nucl Eng Des, 1996, **163**: 29-49
6 Tang L S. Simulated annealing algorithm (in Chinese), Beijing: Chinese Science Press, 1997