Diagnosis System for Alumina Reduction Based on BP Neural Network

Shuiping Zeng
North China University of Technology, Beijing, China
zshp@ncut.edu.cn

Lin Cui and Jinhong Li
North China University of Technology, Beijing, China
cuilin880718@sina.com; ljh@ncut.edu.cn

***Abstract*—The diagnosis system for the alumina reduction was developed on the basis of BP neural network with optimization by genetic algorithm. The neural network used the characteristic vectors composed of the frequency energy calculated from cell resistance as 10 inputs and three cell statuses as 3 outputs. The neural network was certified by industrially sampling data. The results showed the accuracy ratio was larger than 80%, which can meet the requirements in the aluminum production. The diagnosis software was designed and applied in an aluminum smelter.**

***Index Terms*—Alumina reduction, diagnosis, neural network**

I. INTRUCTION

Aluminum electrolysis is a big energy-consuming process. Usually producing 1000 kilogram aluminum would consume 15000 kilowatt-hours electricity. Saving energy in the production has been getting more and more important. In aluminum production, alumina is used as raw material, cryolite-alumina melts as solvent，carbon block as anode and liquid aluminum covered on the carbon as cathode. Direct current is led from anode to cathode. Carbon dioxide mixed with carbon monoxide evaporates from anode and aluminum deposits on cathode. The process control of the aluminum production has been developed fast, but the diagnosis of cell status has not been investigated intensively. According to industrial experiments, the cell status much affects the cell control system, because the different cell status should adopted different control policy. It is a bottleneck for aluminum production to improve the economic index and its automation [1]. The cell is the major equipment for Aluminum electrolysis, which status of is not only related to the economic technical indexes, but also affected the cell life and usual production. Aluminum production is a nonlinear, more coupling, and time-varying and large delay process. In this process, the material balance and energy balance are constantly changing, and restraining each other, and some cases maybe happens, such as anode effect, anode lesion, cold cell, hot cell, etc. Once some of them happen, the losses of material and energy would be caused. It has been an urgent problem to reduce the energy consumption of aluminum electrolysis, to increase cell age, and to reduce the material loss in the world [2].

Till now, fault diagnosis technology in aluminum production mainly concerned with the fuzzy expert system, neural network, wavelet transform and the combination of some technology methods [3-4]. Good results have been achieved in some extent according reports, but diagnosis systems with good performance in industry process are not reported [5-6].

II. SYSTEM DESIGN

A. Classification of the Cells Status

Because the situation of anode and cathode was critical in the production, the three cell conditions, which are anode lesion, liquid aluminum fluctuation and normal condition was considered in the process. The structure of aluminum production cells status analysis was shown in the Fig. 1.

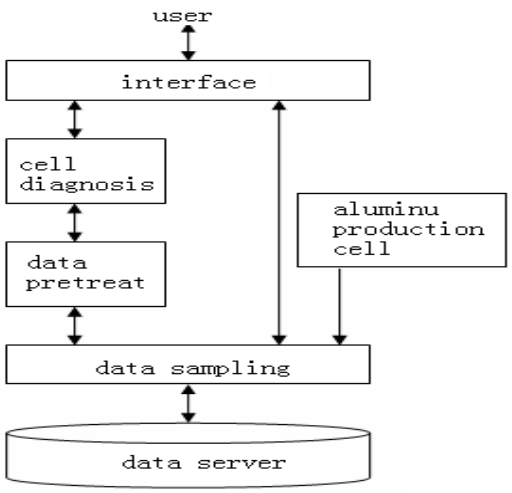

Figure 1. System structure

From the Fig. 1, the general structure of the system can be divided into three levels. The top is man-machine interface, namely interface layer, including all sorts of man-machine interface, menus, command buttons,

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graphic display, etc. The middle layer is the body of signal analysis, status diagnosis algorithm and parameters pre-treating, namely logic layer, including various coefficient computation, realization of cell status diagnosis algorithm, parameters setting and online data acquisition, etc. The low level is the database server, namely the data layer, storing the magnums data sampling on site, measuring and inputting manually, etc.

III. NEURAL NETWORK SYSTEM

A. Determination of Inputs and Outputs

Reference [7] collected and discussed the cell resistance signal under the normal and abnormal circumstance. The cell resistance signal was sampled and treated by frequency analysis. According their results, we find that the three kinds of status mentioned above behave different in their resistance signal frequency and the amplitude of spectrum. The characteristic of different kinds of cell status are shown in the table 1.

On the basis of Ref. [7], cell status samples are established by using the frequency energy as the characteristic vectors. The input characteristic vectors are P0, P1, P2, P3, P4, P5, P6, P7, P8, P9. They represent the total energy and stage energy with the frequency between *0~0.01Hz*，*0.01~0.02Hz*，*0.02~0.03Hz*，*0.03~0.04Hz*，*0.04~0.05Hz*，*0.05~0.06Hz*，*0.06~0.07Hz*，*0.07~0.08Hz* and *0.08~0.09Hz* respectively.

We take three kinds of cell status as the network outputs. The following vectors can represent them. *Y1*：（1 0 0） donates the cell status is normal; *Y2*：（0 1 0） donates the liquid aluminum is fluctuating; *Y3*：（0 0 1） donates the anode is abnormal.

TABLE I.

Characteristic of aluminum production cells under the diffident status

Cell status	characteristic			
	Frequency energ	Low-frequency (< 0.01Hz)	Intermediate-frequency (0.01～0.1Hz)	High-frequency (>0.1Hz)
Normal	Low	A control signal	No obvious peak-value	No obvious peak-value
Liquid aluminum fluctuation	High	A control signal	An obvious peak-value at the frequency of 0.02~0.03Hz	No obvious peak-value
Anode abnormal	High	A control signal	Tow obvious peak value at the frequency of 0.03~0.04Hz and 0.06~0.07Hz	No obvious peak-value

B. Selection of the Other Network Parameters

Neurons at the input layer are determined by the dimensions of input characteristic vectors. By reference of the discussion above, the dimensions are 10. That is to say the nodes are also 10. Neural nodes at the output layer are determined by the different kinds of status. In this paper we treated only the three circumstances, so that the nodes of output layer are 3. According to the rule of determining the hidden nodes under 3 layers of BP neural network, taking the number of hidden nodes for 8. After repeat experiments, the learning rate was selected as 0.08 and expectative error as 0.005.

C. The Neural Network Model

According to the analysis above, the BP neural network model has 10 input neurons, 3 output neurons and 8 hidden neurons. Here the BP neural network has three layers: input layer (*I*), hidden layer (*H*) and output layer (*O*). Among them I_i is the output of *ith* node at input layer, H_j is the output of *jth* node at hidden layer, O_k is the output of *kth* node at output layer. WIH_{ij} is the weight between the *ith* node of input layer and the *jth* node of hidden layer, WHO_{jk} is the weight between the *jth* node of hidden layer and the *kth* node of output layer, h_j is the threshold value of *jth* node at hidden layer. Where $1 \le i \le 10$, $1 \le j \le 8$, $1 \le k \le 3$.

The structure of BP neural network is shown in the Fig. 2.

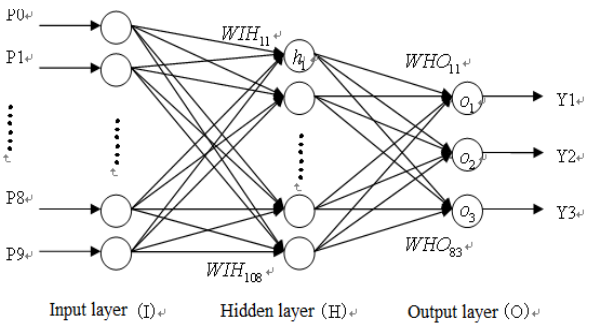

Figure 2. BP neural network

IV. OPTIMIZATION OF THE BP NEURAL NETWORK BY GENETIC ALGORITHM

A. Optimization Processes

(1) Parameter initialization

Some parameters: were set as follows. The initial population *G* is 30, maximum genetic algebra *T* is 100, crossover rate $P_{crossover}$ is 0.6, and mutation rate $P_{mutation}$ is 0.09. The fitness function f_i is realized by the software MATLAB.

(2) Coding and generating initial population.

The weights and threshold values were coded with real number, and a code chain was constructed. Every chain is a collection of weights and threshold values in the BP neural network. Finally an initial population which contains 30 individuals is generated randomly.

(3) Computing the adapters of every individual

According to the fitness function, the adapters of every

individual were calculated. And it was judged whether it meets the requirements or not. If not, the genetic operation was executed and the new individuals were given out. Then we compute the sum of error squares of the artificial neural network. If the result does not reach the expectation, where the expectation value ε_{GA} is 5.0, the genetic operation went on. If it is satisfied within 100 times operation, we get the optimal solution finally.

(4) Decomposing the optimal solution into the weight and threshold value of BP neural network.

B. Training the Network

Genetic algorithm was used to optimize neural network weights and thresholds, and then the neural network was trained from the practice with *BP* algorithm. The software MATLAB is used for programming in the design. With genetic optimization, the neuron network can be reached the indicated error, where expected precision ε_{BP} is 0.005, after 2571 training times; otherwise it should be 3131 times. Fig. 3 showed the corresponding errors with training times in the two situations.

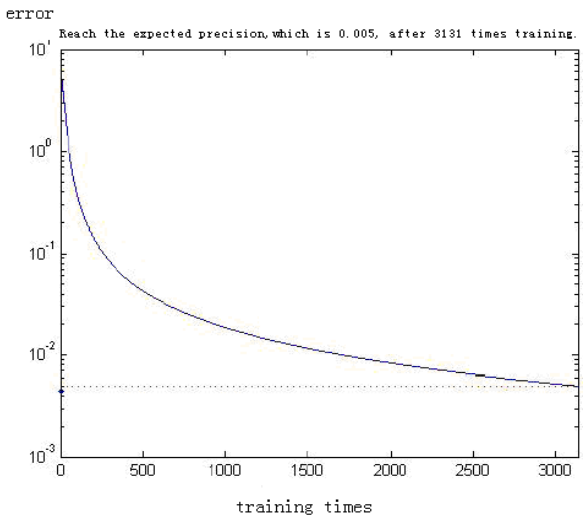

Figure 3. Corresponding error with training times without genetic optimization

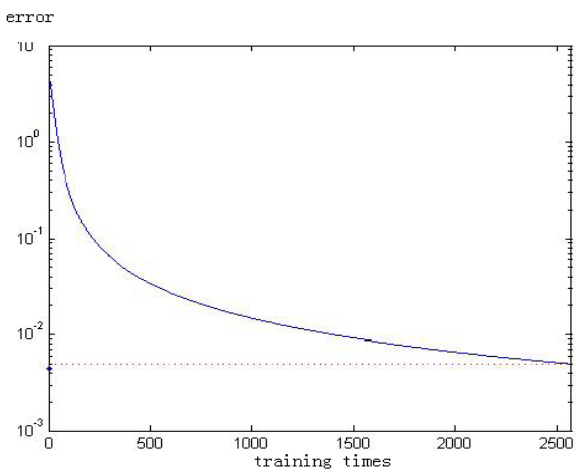

Figure 4. Corresponding error with training times with genetic optimization

C. Software for the Optimization

The flowchart of genetic algorithm is shown in Fig. 4.

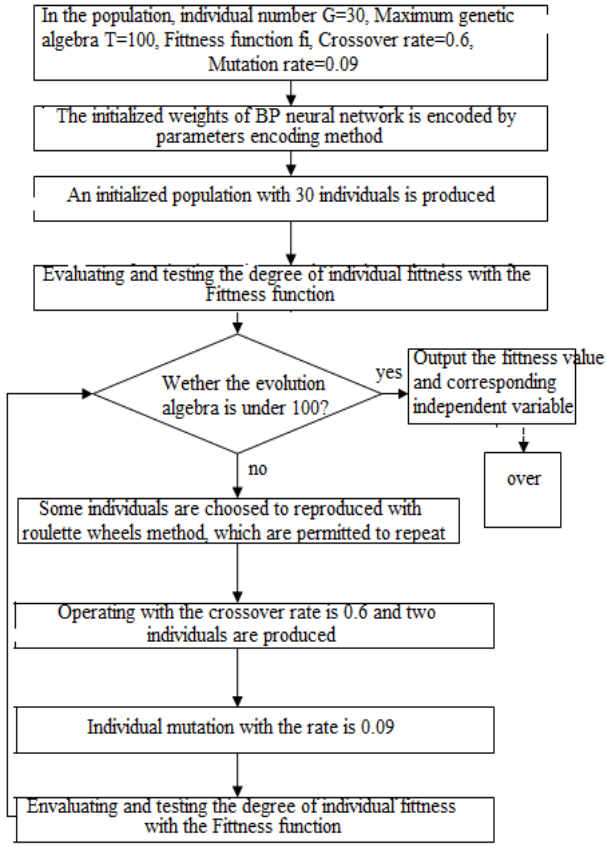

Figure 5. Genetic algorithm flowchart

The results from the computer are as following:

0.9832	0.9952	0.9855	0.0091	0.0162	0.0126
0.0199	0.0108	0.0102	0.0147	0.0106	0.0142
0.9925	0.9895	0.9813	0.0116	0.0162	0.0130
0.0185	0.0072	0.0144	0.0119	0.0095	0.0188
0.9838	0.9858	0.9902			

The ideal values should be

1	1	1	0	0	0	0	0	0
0	0	0	1	1	1	0	0	0
0	0	0	0	0	0	1	1	1

With comparison of the outputs from computer with the ideal values from the real cell status, the results can be satisfied for diagnosis in aluminum production.

.D. Examination of the Network

We used the 30 sets of data acquired on site to test the well-trained BP neural network. As a result, 25 sets of them could diagnose the status correctly. That is to say the accuracy rate is larger then 80%. Because alumina reduction process is not full automation, this accuracy can meet the requirements in industrial process. This cell diagnosis model can be run into practice.

V. SYSTEM APPLICATION

A. Software Design

Aluminum production cells status diagnosis system was designed with Microsoft VB6.0, which can display and search the parameters of the cell which saved in the SQL database, including voltage, electric current, alumina concentration and temperature. Also this system could diagnose the cell status during the electrolytic process, and display the results. Fig. 6 is the system structure. The system is called ACSD.

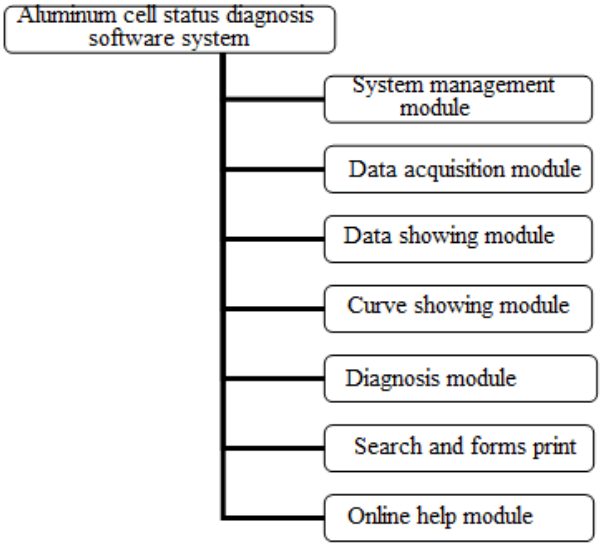

Figure 6. System function module chart

B. System Operation

ACSD is setup in windows operation system. Then the SQL2000 database should be linked with the ACSD, because all the data needed in the diagnosis must come from the database. The system starts with pressing the button marked ACSD on the desktop and input the password. Fig.7 is the interface of the software. Fig.8 is the output for the diagnosis, which displays the cell status and the technical parameters.

C. Discussions

This ACSD has been running in an aluminum plant western China three mouths, which was embedded in the control system. The control system makes the decision based on the cell status reported by ACSD. The operation of the cells was improved comparing with the old control system, but some problems were exposed. The system should be expiated in several aspects, as following.

(1) The anode lesion status can be diagnosed, but the cell has 20 anodes, the system does not know which one caused the anode lesion. Consequently the controller does not indicate the default position.

(2) Neural network can just give the controller three kinds of status. There are other kinds of status in the process can not be detected, which would affect the control of the aluminum production.

(3) The cell age and fed material changed constantly, how to make the ACSD match various circumstances?

Above problems must be taken into consideration in next generation model

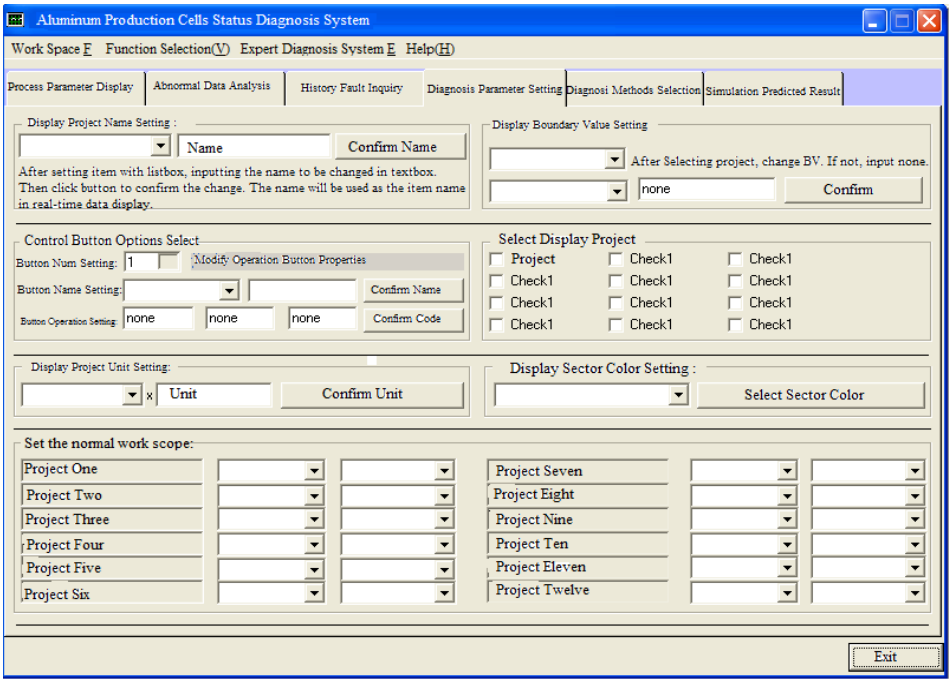

Figure 7. Main interface of the software.

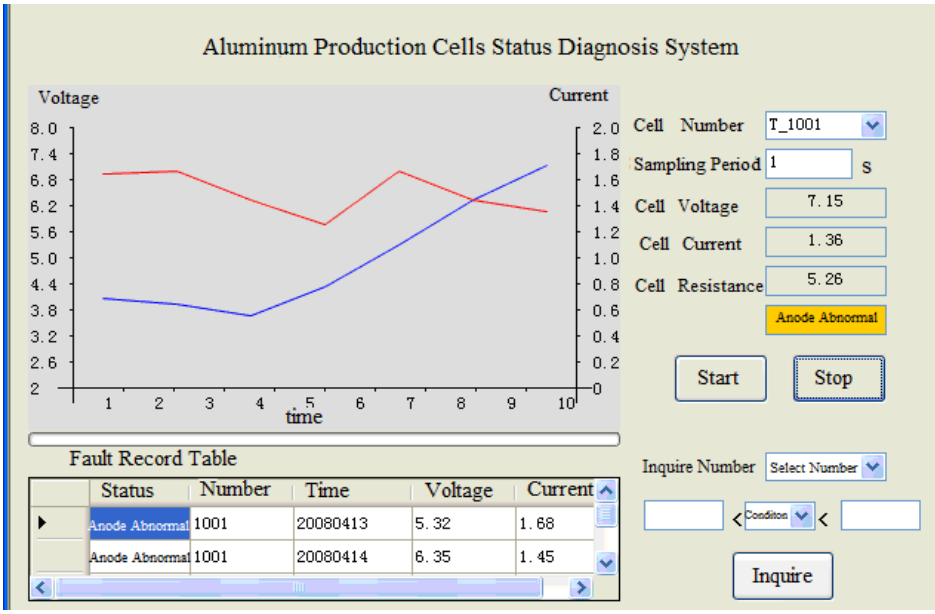

Figure 8. The output of diagnosis

VI. CONCLUSIONS

(1) The characteristics of the aluminum electrolysis in several cell statuses were analyzed and the frequency spectrum energy was used as inputs and three kinds of cell status used as outputs to design the diagnosis system.
(2) Neural network model was established for the cell status diagnosis, and genetic algorithm is applied to optimize the initial weights and thresholds of the BP neural network.
(3) By experiments with the actual production data, the results are consistent with the actual situation and the diagnosis system was embedded in the cell control system and applied in the aluminum electrolysis.

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Shuiping Zeng (birth place is Jiangxi Province China and birth day is 10th December, 1961) received the Ph.D. degree in control of aluminum production from Central South University of Technology, Changsha, PRC in 1996. Previously he was a M.Sc. student in non-ferrous metallurgy in Kunming University of Technology, Yunnan, PRC from Aug. 1984 to April 1987, a undergraduate student in Northeast University, Shenyang, PRC from Sept. 1979 to July 1983.

He is currently a research professor specialized in automation at North China University of Technology, Beijing, PRC. Previously he worked as a lecturer specialized in light metals in Jiangxi University of Science and Technology, PRC from May 1987 to Aug. 1993, as a teaching assistant specialized in metallurgy, Kunming University of Technology from Aug. 1983 to Aug. 1984.

Dr Shuiping Zeng is a TMS membership (USA). And he was awarded the first class prize of science and technology in Luoyang city, China in 2010.