Proceedings of the World Congress on Engineering and Computer Science 2008
WCECS 2008, October 22 - 24, 2008, San Francisco, USA

Neural Network Modeling and HDP for Neutralized pH Value Control in the Clarifying Process of Sugar Cane Juice

Xiaofeng Lin, Shengyong Lei and Huixia Liu

***Abstract*—Neutralizing pH value of sugar cane juice is the important craft in the control process in the clarifying process of sugar cane juice, which is the important factor to influence output and the quality of white sugar. On the one hand, it is an important content to control the neutralized pH value within a required range, which has the vital significance for acquiring high quality purified juice, reducing energy consumption and raising sucrose recovery. On the other hand, it is a complicated physical-chemistry process, which has the characteristics of strong non-linearity, time-varying, large time-delay, and multi-input. Therefore, there has not a very good solution to control the neutralized pH value. Firstly, in this paper, neural network model for the clarifying process of sugar juice is established based on gathering 1200 groups of real-time sample data in a sugar factory. Then, HDP (Heuristic Dynamic Programming) method is used to optimize and control the neutralized pH value in the clarifying process of sugar juice. The simulation results indicate that this method has the good control effect. This will build a good foundation for stabilizing the clarifying process and enhancing the quality of the purified juice and lastly enhancing the quality of white sugar.**

***Index Terms*—Adaptive dynamic programming (ADP), heuristic dynamic programming (HDP), clarifying process of sugar cane juice, neutralized pH value.**

I. INTRODUCTION

Clarifying process is a core link in the course of sugar production. As we know, it has the characteristics of strong non-linearity, multi-constraint, strong coupled, time-varying, large time-delay, and multi-input. The technology is complicated, which results in great difficulty in the course of modeling and optimization control. With the existing technological process and equipment, it is a key problem how to utilize omni-directional information and adjust processing parameters in real time on site to keep the optimum state of production, improving the quality of the purified juice. It is a complicated physical-chemistry process to neutralize the juice, and the pH value needs the manual regulation in the actual production process, so its control effect is insufficiently stable, i.e. sometimes pH excessively is high and sometimes it excessively is low, and the result is not good[1][2][3].

Manuscript received May 27, 2008. This work was supported in part by the Science and Research Foundation of Guangxi University, China under Grant X051023.

X. Lin and S. lei are with the College of Electric Engineering, Guangxi University, Nanning 530004, China (E-mail: gxulinxf@163.com; aleismart@163.com).

H. Liu is with the Light Industry and Food Engineering Institute, Guangxi University, Nanning 530004, China (sugarliu@gxu.edu.cn).

Adaptive Dynamic Programming (ADP) was proposed by Werbs[4] in the 1970s. It is a neural network-based approximation dynamic programming. Dynamic programming is the only method which can precisely solve general nonlinear long-term optimization problems with stochastic and fluctuant characteristics, but with curse of dimensionality in the implementation process. ADP can improve the numerical process and avoid curse of dimensionality by using action-critic. In the mean time, it can obtain the optimal or sub-optimal control strategy. Therefore, for dynamic systems like sugar factories with massive uncertain factors, but must maintain at a certain running stability, adaptive dynamic programming is a feasible scheme.

In this article, the technology using popular sulfitation method which is very popular in most Chinese sugar factories is served as the research background, in the foundation of qualitatively analyzing the technical principle of the clarifying process of sugar juice, neural network model for the clarifying process of sugar juice is established. This model is regarded as controlled object and the model network in HDP controller. Then, HDP (Heuristic Dynamic Programming) is used to control the neutralized pH value in clarifying process of sugar refineries [5]. This will build a good foundation for stabilizing the clarifying process and improving the quality of the purified juice and eventually improving the quality of the finished sugar.

II. NEURAL NETWORK MODELING OF THE CLARIFYING PROCESS OF SUGAR CANE JUICE

A. Clarifying process of sugar juice[1][2]

At present, sulfurous acid method is very popularly used in most sugar factories in China. In this craft the process of neutralizing the pH value is very important and it directly influences the output and the quality of white sugar.

The mixed juice coming from the milling section is processed by working procedures such as predefecation, heating, neutralization reaction, sedimentation and filtering and so on. The aim is to put out the high-quality sugar in the course of crystallization by eliminating the non-sugar elements and eventually obtain the high quality of the granulated sugar. The sulfitation process is mainly adopted at present. It is a complicated physical-chemistry process to clarify the juice, and is divided into four stages which are predefecation, heating, neutralization reaction, sedimentation

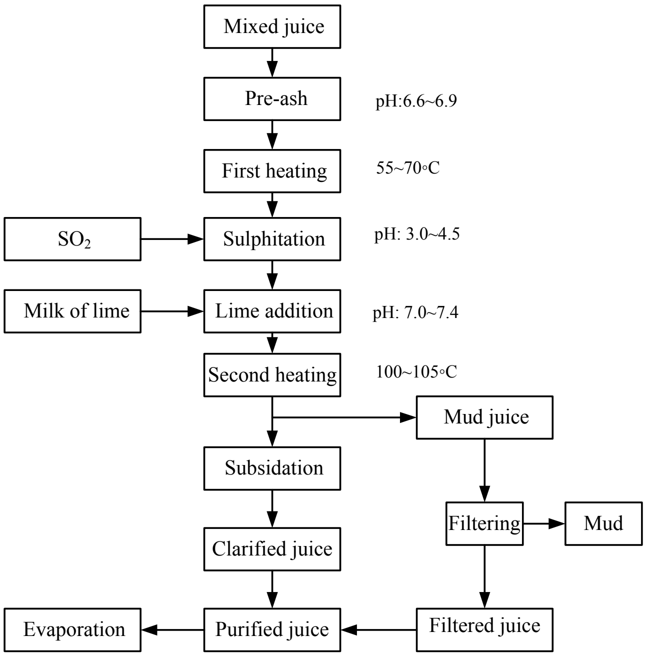

Fig.1. Flow diagram of the clarifying process of sugar cane juice

and filtering, as shown in Fig.1. Clarifying agents commonly used in sugar factories mainly include lime, sulfur dioxide, industrial phosphoric acid etc. At first a small amount of lime is put into the mixed juices, and at the same time, phosphoric acid is also put into the mixed juices to adjust pH to a low-grade acidity or neutralization. And then the mixed juice is heated, for the first time, with the temperature controlled within the range of 55-70℃. After that the mixed juice is sent into the neutralization device. In neutralization device, the lime liquid and sulfur dioxide gases are added to mixed juices. Then sulfurous acid and calcium hydroxide neutralize in the join, which produces calcium sulfurous to be separated out, synchronously colloid is coagulated. Then the neutralized juice is heated for the second time to accelerate reaction of phosphoric acid and sulfurous acid. Finally the neutralized juice is going to the subsider for subsiding.

The main factors affecting the sulphitation neutralization are:

(1)The instability of flow of juice will directly influence the following operations such as adding lime, sulfur dioxide and the phosphoric acid.

(2) Either pre-ash's pH value too high or too low will result in the increased difficulty of the sulphitation neutralization control.

(3)Influence of the lime milk and sulfur dioxide flow. If the amount of lime put into the juice is too small or the amount of sulfur dioxide is too large, pH value in the sugarcane juice will become acid, which will affect neutralization reaction and cause high SO_2 and calcium contents in the purified juice, and inevitably decrease the purity of juice. If too large amount of lime or too small amount of sulfur dioxide is put into the juice, it will cause the reducing sugar resolving and increase Color Value of the purified juice, and inevitably decrease the purity of juice.

It has the vital significance to control pH value stability in the clarifying process of sugar juice, which affects directly the quality of the purified juice, and inevitably the product's quality. If the neutralized pH value is too low, this will speeds up the sucrose transformation, which results in loss of sucrose and cause the juice containing higher dissoluble calcium, and inevitably cause a lot of scale formed in the evaporation station and boiling house, thus it increases energy wastage. Contrarily, when the neutralized pH value is too high, the original sugar decomposes the new pigment so that its color becomes depth, these can increase color value of the product sugar, and affects the quality of the granulated sugar. Moreover, instability of the pH value can increase the amount of use of the clarifying agent, and increase the cost.

B. Neural network modeling for clarifying process of sugar cane juice

There are mainly two purposes to build the NN model for clarifying process of sugar cane juice. One is the NN model acting as the controlled object, which is simulated in computer before implementation in real-time control. The other is the NN model using as model network of HDP controller designed by us, which simulates the characteristics of controlled object and predicts its new state parameters. As we all know, a three layer neural network can approximate any nonlinear functions with any desired precision, so the artificial neural networks trained with BP algorithm are used to establish the model for clarifying process of sugar cane juice in this paper. After qualitative analysis on various variables affecting the neutralized pH value as well as on the interrelations among different neutralized pH values, we can control the neutralized pH value through adjusting the flows of sugar juice, the pre-ash pH value, the intensity of sulfur and the current capacity of the milk of lime. We have gathered 1200 groups of data in a sugar factory, part of data as shown in table 1. This NN model can be established with the neural network in terms of the input/output behavior of these data[6][7], which is shown in Figure 2.

The NN model trained with BP algorithm is chosen as a 4-36-1 structure. The numbers of neurons in the input, hidden and output layers are chosen to be four, thirty-six and one respectively. The inputs to the model are 4 control variables (or input variables): the flows of sugar juice, the pre-ash pH value, the intensity of sulfur and the current capacity of the milk of lime and the output of the model is state parameter: the neutralized pH value. The neutralized pH value is controlled by 4 control variables, and one or more control variables' change will influence the pH value. Optimizing and controlling the pH value, we use HDP method to complete the control for the plant to generate the appropriate 4 control quantities and make the neutralized pH value stabilize in the required scope. This work will build the good foundation for implementation in real-time control in the future.

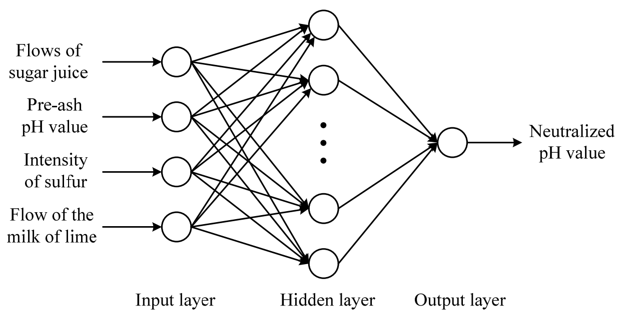

Fig. 2. BP neural network model for the clarifying process of sugar cane juice

TABLE I
THE PARTIAL REAL-TIME DATA IN THE CLARIFYING PROCESS OF NATONG SUGAR FACTORY, COUNTY OF LONGAN, GUANGXI, CHINA

No.	Flow of sugar cane juice (t/h)	Pre-ash pH	Intensity of sulfur (ml)	Flow of the milk of lime (l/min)	Neutralized pH
1	158.55	6.55	22.34	50.60	7.51
2	196.3	6.90	21.50	52.60	7.64
3	156.84	6.88	20.93	46.70	7.66
4	171.5	7.14	19.21	46.00	7.58
5	172.34	6.91	18.89	44.70	7.46
6	153.81	7.63	19.93	44.10	7.56
7	178.28	7.21	16.78	47.60	7.58
8	142.27	7.08	17.43	42.80	7.66
9	165.59	6.92	17.53	33.50	7.41
10	150.28	7.09	17.25	33.60	7.56
…	…	…	…	…	…

The neural network modeling mainly has several important links: sample data pretreatment, data normalization, network design, network training and network test and so on. When processing the sample data, summarizing the operation range of sampled variables based on technical requirements and operation experiences, parts of the data can be primarily eliminated. After being processed, 800 sets of data are used as training samples, and 200 sets of data are used as testing samples, the data become numerical values between (-1,1) after a naturalized process. Our designed neural network is chosen as a 4-25-1 structure with 4 input neutrons, 25 hidden neutrons and 1 output neutron. For this neural network, the hidden layer and output layer use the sigmoidal function. We have applied trainlm (the Levenberg-Marquardt algorithm) for the training of the netwok, and the trained model is shown in Fig. 3.

III. THE DESIGN OF HDP CONTROLLER

A. background

Adaptive dynamic programming (ADP) is neural network design capable of optimization over time under conditions of noise and uncertainty. It was proposed as new optimization technique combining the concepts of reinforcement learning and approximates dynamic programming. Dynamic programming is a very useful tool in solving non-linear system optimization problems. However, it is often computationally untenable to run true dynamic programming due to the backward numerical process required for its solutions. So it can only be applied to simple, small-scale control problems. Therefore, many researchers started to find approximate solutions to dynamic programming. The key step is to estimate the cost function in dynamic programming by using a function such as neural networks and it can avoid the so-called “curse of dimensionality” problem[8][9] in finding approximate solutions to dynamic programming. Then the optimal control signal can be obtained by minimizing the cost function. The implementation of adaptive dynamic programming usually requires the use of three networks: Critic

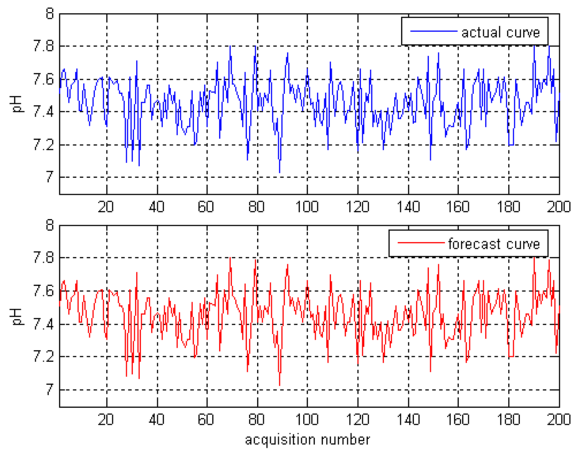

Fig. 3. The neural network model for the clarifying process of sugar cane juice

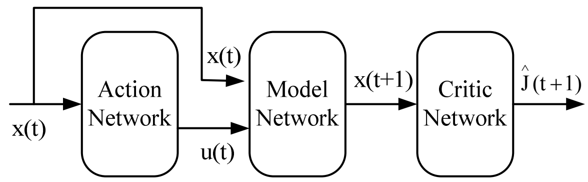

Fig.4. Typical schematic diagram for ADP

network, Model network, and Action network [10]. These three networks perform the function of evaluation, prediction, and decision, respectively (Figure 4). The action network outputs the control signal, the model network simulates the characteristics of controlled object and outputs new state parameter, and the critic network outputs an estimate of cost function given by the Bellman equation associated with optimal control theory in order to guide the action network toward the optimal solution. To obtain the optimal control decision, we need to adjust the weights of the critic and action networks, which can be completed by training the critic and action networks. Existing adaptive dynamic programming [11] can be categorized as: (1) heuristic dynamic programming (HDP); (2) dual heuristic dynamic programming (DHP); and (3) globalized dual heuristic dynamic programming (GDHP). In this article we use the HDP method to control the neutralized pH value in clarifying section of sugar mills.

B. General Structure of HDP controller

HDP controller involves three networks: action network, model network and critic network. Each of these networks includes a feedforward and a feedback component. The action network outputs the control signal, the model network simulates the characteristics of controlled object and outputs new state parameter, and the critic network outputs an estimate of cost function given by the Bellman equation associated with optimal control theory.

Fig.5 is the schematic diagram for implementation of our designed HDP controller [12]. In this figure, the solid lines represent signal flow, while the dashed lines are the paths for parameter tuning of the critic network and the action network. It is noted that the signal parameters with thick solid present

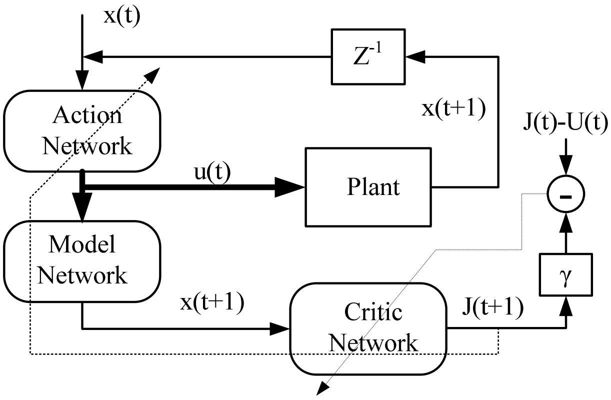

Fig.5. Schematic diagram for implementations of HDP Controller

vector parameters. It will generate control signal u(t) when the action network accepts the system state x(t), then u(t) adds to the model network which will predict new state parameter x(t+1); x(t+1) is only input parameter of the critic network which will output an approximate value of J function given by the Bellman dynamic programming equation. In Fig.5, Plant is the neural network model for the clarifying process of sugar juice as discussed in section 2.2 as well as the model network, which accepts the control signal u(t) from the action network outputs and generates the new state x(t+1). In addition, U(t) is the utility function, γ is the discount factor and Z^{-1} is the time-delay operator.

C. The design of Critic network

The critic network is chosen as a 1-8-1 structure with 1 input neutron, 8 hidden layer neutrons and 1 output neutron. The 1 input is one state x(t) from output of the model network, and the output of the critic network is the estimated cost-to-go (J) function in the Bellman equation of dynamic programming, which is defined as:

$$J(t) = \sum_{k=0}^{\infty} \gamma^k U(t+k) \quad (1)$$

Where γ is the discount factor for finite horizon problems with the range of [0, 1] and is chosen to be 0.95 in this design. U(t) is the utility function or the local cost, which is related to the control object during training the controller. How to determine U(t) in fact is the process to determine the optimal controller of dynamic programming. U(t) must be able to reflect all kinds of problems of controlled systems in order to design the optimal controller which can meet requirements of system. In view of the different control problem, the utility function's form is also different. In this paper, the control problem is the control of neutralized pH value in sugar the clarifying section, and the aim is to stabilize the neutralized pH value in the range of 7.0 to 7.4. Therefore, the utility function chosen is as follows:

$$U(t) = \begin{cases} \left(\dfrac{X(t)-7.2}{8}\right)^2, |X(t)-7.2| \le 0.2 \\ 1, otherwise \end{cases} \quad (2)$$

Where x(t) is the neutralized pH value, U(t) is the utility function.

The hidden layer of the critic network uses the sigmoidal function given by:

$$f(x) = \frac{1-e^{-x}}{1+e^{-x}} \quad (3)$$

To do this we can use the *tansig* function in MATLAB 7.0 and also write the codes in terms of the equation (3). The critic network's output layer is linear. There are two processes for training the network, one is the forward computation process and the other is the error backward propagation process which updates the weights of the critic network (figure 5). We use the critic network to output the estimate of J in the equation (1), and our aim is minimizing the following error function:

$$e_c(t) = J(t) - [\gamma \cdot J(t+1) + U(t)] \quad (4)$$

$$E_c(t) = \frac{1}{2} \cdot e_c^{\,2}(t) \quad (5)$$

The weight update rule for the network is gradient descent rule, which is given by the following equations,

$$w_c(t+1) = w_c(t) + \Delta w_c(t) \quad (6)$$

$$\Delta w_c(t) = l_c \cdot \left(-\frac{\partial E_c(t)}{\partial w_c(t)}\right) = l_c \cdot \left(-\frac{\partial E_c(t)}{\partial J(t)} \cdot \frac{\partial J(t)}{\partial w_c(t)}\right) \quad (7)$$

Where l_c is the learning rate of the critic network, γ is the discount factor and w_c is the weight vector in the critic network.

D. The design of Action network

The structure of the action network is chosen as 1-8-4 with 1 input neutron, 8 hidden layer neutrons and 4 output neutrons. The one input is the state x(t), which is the neutralized pH value. The 4 outputs are u1(t), u2(t), u3(t) and u4(t). They represent the flows of sugar juice, the pre-ash pH value, the intensity of sulfur and the current capacity of the milk of lime, respectively. For this network, both hidden layer and output layer use the *sigmoidal* function as shown in the equation (3). The aim of training the action network is minimizing the output of the critic network J, and the weights updating equations in the action network are as follows:

$$e_a(t) = J(t+1) \quad (8)$$

$$E_a(t) = \frac{1}{2} \cdot e_a^{\,2}(t) \quad (9)$$

$$w_a(t+1) = w_a(t) + \Delta w_a(t) \quad (10)$$

$$\Delta w_a = l_a \cdot \left(-\frac{\partial E_a}{\partial w_a}\right) = l_a \cdot \left(-\frac{\partial E_a}{\partial J(t+1)} \cdot \frac{\partial J(t+1)}{\partial x(t+1)} \cdot \frac{\partial x(t+1)}{\partial u(t)} \cdot \frac{\partial u(t)}{\partial w_a}\right) \quad (11)$$

Where l_a is the learning rate of the action network, and w_a is the weight vector in the action network.

E. The design of Model network

The structure of the model network is chosen as 4-36-1 with 4 input neutrons, 36 hidden layer neutrons and 1 output neutron. This network is the same as the neural network model of sugar clarifying section detailed in section 2.2. It is not necessary to train the model network due to the fact that the weights (W_{m1} and W_{m2}) of the neural network model of sugar clarifying section are fixed.

IV. Simulation Results

The parameters and their initial values used in the simulations of HDP controller are summarized in the following:

The initial state of neutralized pH value: x(0)=7.0;

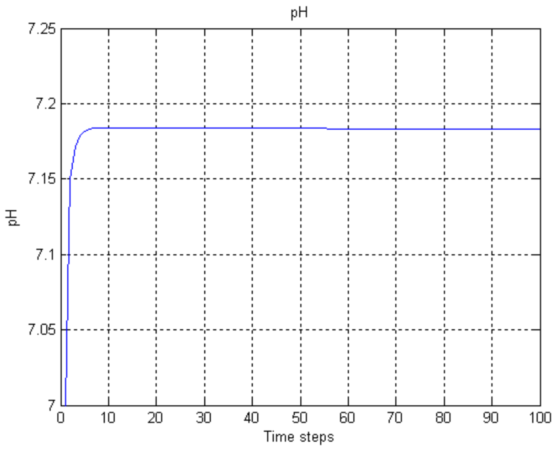

Fig.6. Result for the pH value control in the clarifying process of sugar juice

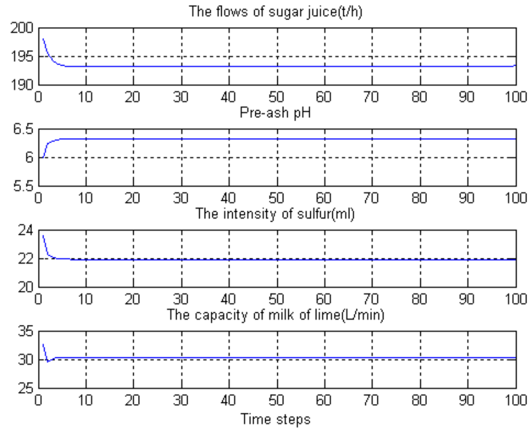

Fig.7. Results for the pH value control in the clarifying process of sugar juice: u1: the flows of sugar juice, u2: the pre-ash pH value, u3: the intensity of sulfur and u4: the current capacity of the milk of lime respectively.

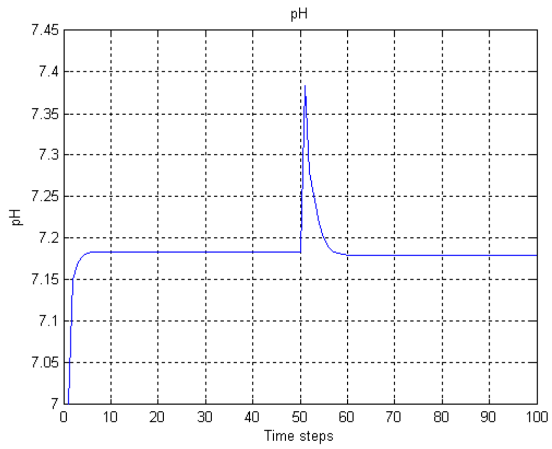

Fig.8. Control objective curve of the pH value added the noises

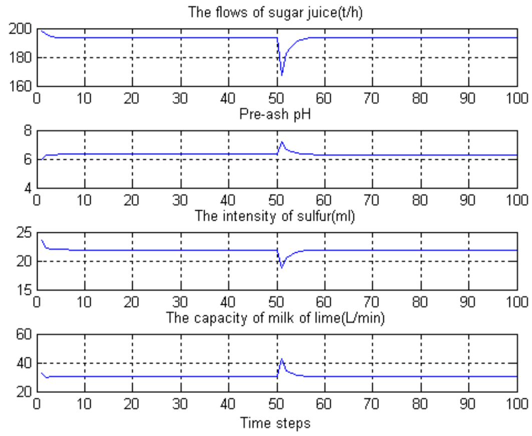

Fig.9. Curves of the four control variables with added the noises

The initial weights of the critic network: W_{c1} and W_{c2} are random in the range of -0.1 to +0.1;

The initial weights of the action network: W_{a1} and W_{a2} are random in the range of -0.1 to +0.1;

The weights of the model network: W_{m1} and W_{m2} are fixed;

The learning rate of the critic network: l_c=0.3;

The learning rate of the action network: l_a=0.3;

The discount factor: γ=0.95;

The desire error training the critic network：T_c=0.05;

The desire error training the action network：T_a=0.005;

The maximum of cycle-index of the critic network: N_c =50 （to avoid endless loop）;

The maximum of cycle-index of the action network: N_a =50 （to avoid endless loop）;

The training rules of the critic and the action networks are based on the gradient descent rule. Our control goal for the HDP controller is to control the neutralized pH value within the range of (7.0, 7.4). Fig. 6 shows a typical movement or trajectory of the pH value in the clarifying process of sugar juice under HDP controller for a successful learning trial. In the first experiment, the neutralized pH value can be controlled in the range of (7.0, 7.2). As time goes by, after about 10 steps, pH was stabilized at about 7.18. Moreover, pH stays the same after passing through 500 steps. So this experiment was successful. It is noted that the display in Fig. 6 is only for 100 steps. Fig. 7 shows a typical movement or trajectory of the four control variables with the neutralized pH value stabilized in 7.18. We then performed a similar experiment in the case of some added noise signals when the training was at the 50th step in order to test the controller's ability for anti-disturbances. As can be seen in Fig.8, the neutralized pH value can return to the original stable state after about 10 steps. Fig. 9 shows a corresponding movement or trajectory of the four control variables with some noises.

V. Conclusions

To overcome the difficulty of neutralized pH value stable control for the clarifying process in the sugar refineries, a HDP controller used to control neutralized pH value is designed in this paper. HDP method, with model network, is able to guide the controller to learn and train better with partial prior knowledge of the controlled system known. HDP combining the concepts of dynamic programming and reinforcement learning is used to optimize and control the neutralized pH value for sugar clarifying section. The research indicates that this method has good control results and abilities for anti-disturbances. This will build a good foundation for implementation in real-time control in the future.

ISBN: 978-988-98671-0-2

REFERENCES

[1] Cane sugar technology. Guangdong Light industry Institute and Sichuan light industry institute Combined in one volume[M]. Light industry publishing house, Beijing, 1982.

[2] Chen Weijun, Xu Sixin, et al. Sugar cane production principle and technology (the fourth volume)[M]. Chinese Light industry publishing house, Beijing, 2001.

[3] Huang Xueying. Improvement and its application of Neutralized pH online control system of survey[J]. Sugar cane sugar industry, 2002(2) : 42-45.

[4] Paul J.Werbos. Advanced forecasting methods for global crisis warning and models of intelligence[J]. General System Yearbook, 1977, 22: 25–38.

[5] O. Kovalenko, D. Liu, H. Javaherian . Neural network modeling and adaptive critic control of automotive fuel-injection systems[C]. Proceedings of the 19th IEEE International Symposium on Intelligent Control, Taipei, Taiwan, Sept. 2004, 368-373.

[6] Zhou Kaili, Kang Yaohong. Neural network model and its MATLAB simulation program design[M]. Tsinghua University publishing house, Beijing, 2005.7.

[7] Han Liqun. Artificial neural networks theory, design and application (second edition)[M]. Chemical industry publishing house, Beijing, 2007.7.

[8] Paul J. Werbos. Stable Adaptive Control Using New Critic Designs[OL]. http: //arxiv.org/abs/adap-org/9810001v1.

[9] Si J, Barto A, Powell W, et al . Handbook of learning and approximate dynamic programming[M]. New York: John Wiley&Sons2004.

[10] Danil V. Prokhorov, Donald C. Wunsch, Adaptive Critic Designs[J]. IEEE Transactions on neural networks, 1997,8(5): 997-1007.

[11] Paul J. Werbos. Tutorial on neurocontrol, control theory and related techniques: from back propagation to brain-like intelligent systems[C]. 12th ICMCM & SC, 1999. http: //www.iamcm.org/pwerbos/

[12] Wenxin Liu ,Venayagamoorthy,G. K , Wunsch D.C. A heuristic-dynamic-programming-based power system stabilizer for a turbogenerator in a single-machine power system[J]. IEEE transactions on industry applications, 2005, 41: 1377-1385.