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A NEUROMORPHIC CONTROLLER FOR A DISTILLATION COLUMN

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ABSTRACT

This paper investigates the design of a neural network based controller to control the concentration of the overhead and bottom product in the model of a distillation column. Satisfactory computer simulation results of this approach are obtained.

Keywords – distillation column, neural networks, nonlinear control

I. INTRODUCTION

Distillation columns are widely used in chemical processes, such as crude oil refinery and hydrocarbon processing industries. The control of the overhead and bottom compositions in a binary distillation column using reflux and steam flow rates has shown to be a particularly difficult problem, due to the significant time delays and nonlinear inherent interaction in the process. Different control approaches have been proposed, such as PID controller with decoupling [1], IMC (internal model control) with diagonal factorization [2], and two-point control [3].

Artificial neural networks have been successfully applied to the identification and adaptive control of dynamic systems in recent years. The approach based on neural networks has some significant advantages over conventional methods such as adaptive learning ability, nonlinear mapping ability, as well as fault tolerant ability, etc.; thus it is more flexible and easily to be implemented in practice. In this research, a sampled discrete-time dynamic model of a methanol/water column is derived based on the transfer function given in [2]; then a neural network based controller is designed to control the concentration of the overhead and bottom compositions. Computer simulation results are also presented.

II. THE MODEL OF A DISTILLATION TOWER

A typical binary distillation column model is a nonlinear MIMO (multi-input, multi-output) system with the following transfer function [2]:

$$\begin{bmatrix} y_1(s) \\ y_2(s) \end{bmatrix} = \begin{bmatrix} \dfrac{12.8e^{-s}}{16.7s+1} & \dfrac{-18.9e^{-3s}}{21.0s+1} \\ \dfrac{6.6e^{-7s}}{10.9s+1} & \dfrac{-19.4e^{-3s}}{14.4s+1} \end{bmatrix} \begin{bmatrix} m_1(s) \\ m_2(s) \end{bmatrix} + \begin{bmatrix} \dfrac{3.8e^{-8s}}{14.9s+1} \\ \dfrac{4.9e^{-3s}}{13.2s+1} \end{bmatrix} d(s) \tag{1}$$

where y_1 represents the overheads composition (mol % methanol), y_2 represents the bottoms composition (mol % methanol), m_1 is the reflux rate (Ib/min), m_2 is the steam flow rate (Ib/min), and d is the feed flow rate (Ib/min). A diagram of the Wood/Berry column is shown in Fig. 1 [1].

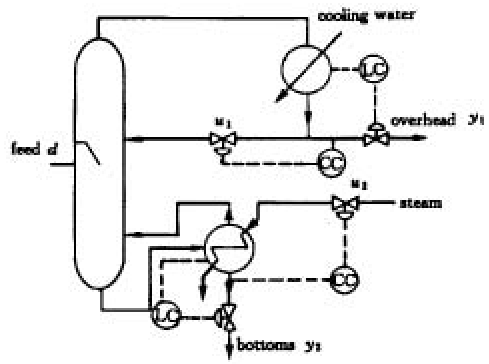

Fig. 1. The Wood/Berry distillation column

The above continuous-time system model can also be written as:

$$\begin{bmatrix} y_1(s) \\ y_2(s) \end{bmatrix} = \begin{bmatrix} \dfrac{0.7665e^{-s}}{s+0.05988} & \dfrac{-0.9e^{-3s}}{s+0.0476} \\ \dfrac{0.6055e^{-7s}}{s+0.0917} & \dfrac{-1.3472e^{-3s}}{s+0.0694} \end{bmatrix} \begin{bmatrix} m_1(s) \\ m_2(s) \end{bmatrix}$$

$$+ \begin{bmatrix} \dfrac{0.2550e^{-8s}}{s+0.0671} \\ \dfrac{0.3712e^{-3s}}{s+0.0758} \end{bmatrix} d(s) \tag{2}$$

If the above process is sampled with the sampling rate equal to unit time delay and considering the relationship $z = e^{sT}$, then a discrete-time system model can be obtained:

$$\begin{bmatrix} y_1(z) \\ y_2(z) \end{bmatrix} = \begin{bmatrix} \dfrac{0.7665}{z-0.9419} & \dfrac{-0.9z^{-2}}{z-0.9535} \\ \dfrac{0.6055z^{-6}}{z-0.9124} & \dfrac{-1.3472z^{-2}}{z-0.9311} \end{bmatrix} \begin{bmatrix} m_1(z) \\ m_2(z) \end{bmatrix}$$

$$+ \begin{bmatrix} \dfrac{0.2550z^{-7}}{z-0.9351} \\ \dfrac{0.3712z^{-2}}{z-0.9270} \end{bmatrix} d(z) \tag{3}$$

i.e.,

$$\begin{aligned} y_1(k+10) = {} & 2.8305y_1(k+9) - 2.6705y_1(k+8) \\ & + 0.8398y_1(k+7) + 0.7665m_1(k+9) \\ & - 1.4476m_1(k+8) + 0.6834m_1(k+7) \\ & - 0.9m_2(k+7) + 1.6893m_2(k+6) \\ & - 0.7927m_2(k+5) + 0.2550d(k+2) \\ & - 0.4833d(k+1) + 0.2290d(k) \end{aligned} \tag{4}$$

$$\begin{aligned} y_2(k+9) = {} & 2.7724y_2(k+8) - 2.5620y_2(k+7) \\ & + 0.7891y_2(k+6) + 0.6055m_1(k+2) \\ & - 1.1262m_1(k+1) + 0.5237m_1(k) \\ & - 1.3472m_2(k+6) + 2.4780m_2(k+5) \\ & - 1.1384m_2(k+4) + 0.3712d(k+6) \\ & 0.6850d(k+5) + 0.3160d(k+4) \end{aligned} \tag{5}$$

where k is time index.

III. ON THE DESIGN OF A NEURAL NETWORK CONTROLLER

It has been proved that a multi-layer feedforward artificial neural network is capable of representing any measurable function within any desired degree of accuracy with the correct values of weights and sufficient number of hidden units; thus it has been widely used for system identification and adaptive control in recent years.

Neuromorphic control is an adaptive learning approach, in which artificial neural networks can be chosen as either a controller, or an identification model, or both of them. In this research, a multi-layer feed-forward neural network will be employed to keep the overheads composition and bottoms composition to be constants (i.e., set-point control). The input layer of the neural network contains three input nodes; one for the feed flow rate d and the other two for the overheads/bottoms composition. There are two nodes in the output layer for the reflux flow rate and the steam flow rate. The neural network has two hidden layers. Hyperbolic tangent function is chosen to be the activation function of the neurons, i.e.,

$$f(x) = \frac{1-e^{-x}}{1+e^{-x}} \tag{6}$$

First, the neural network is trained to minimize the difference between the desired and actual output in noise-free situation. When the disturbance on feed flow rate occurs, the weights of the neural network controller are fine-tuned on-line to pull the outputs of the system back to the desired value. Modified back-propagation algorithm with adaptive learning rate will be used in computer simulation examples. Fig. 2 shows the block diagram of the controller and the system model.

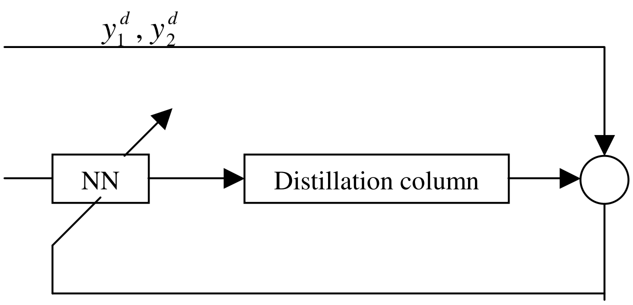

Fig. 2. The block diagram of the overall system

The objective function is defined as:

$$J = \sum_{i=1}^{2} (y(i) - y_d(i))^2 \tag{7}$$

where y(i) is the actual composition value and $y_d(i)$ (i = 1, 2) represents the desired compositions in the system. The weights of the neural network are initialized by a random number generator; then all the weights are adjusted at the same time during the training process:

$$W(k+1) = W(k) + \Delta W(k) \tag{8}$$

where $$\Delta W(k) = \eta \frac{\partial J}{\partial W} \tag{9}$$

Note the k here is the training iteration; and η is the learning/training rate. The outputs of the neural network are calculated in a forward way, from the input layer to the output layer; while the gradient of the objective function with respect to the weights are back propagated from the output layer to the input layer, using the chain rule. Let σ_i^l the output of the i-th neuron in the l-th layer in the network, then:

$$\frac{\partial \sigma_i^l}{\partial w_{ji}^l} = \frac{1}{2}\left[1 - (\sigma_i^l)^2\right]\sigma_i^{l-1} \tag{10}$$

$$\frac{\partial \sigma_i^l}{\partial w_{ji}^{l-1}} = \frac{\partial \sigma_i^l}{\partial \sigma_i^{l-1}} \cdot \frac{\partial \sigma_i^{l-1}}{\partial w_{ji}^{l-1}} \tag{11}$$

The training procedure can be repeated until the error function reaches its minimum value or an acceptable level.

The computer simulation result is shown in Fig. 3. The solid line represents the overheads composition of the column controlled by nominal controller, and the dashed line shows the result of a neural network controller. From the simulation result, we conclude that the performance of the neural network controller is satisfactory.

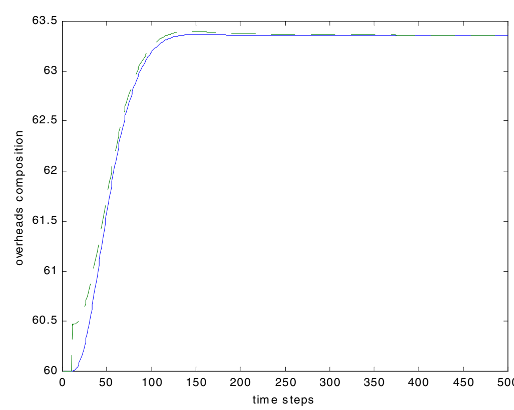

Fig. 3. Computer Simulation Result

IV. CONCLUSION

The control of a binary distillation column is generally a difficult problem, due to the nonlinearity and time-delay properties in the process. In this paper, an approach based on artificial intelligence is presented and the design of a neuromorphic controller is investigated. Computer simulation results are also presented.

V. REFERENCES

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