CONTROL OF DISTILLATION PROCESS USING NEURO- FUZZY TECHNIQUE

1AASTHA GUPTA, 2ASHA RANI, 3VIJANDER SINGH

Instrumentation and Control Engineering Division, Netaji Subhas Institute of Technology, University of Delhi, Sector-3, Dwarka, New Delhi
Email: gupta.aastha3@gmail.com, ashansit@gmail.com, vijaydee@gmail.com

Abstract—Distillation is an essential separation process in the chemical and petrochemical industry. The distillation process is a highly nonlinear, complex, interactive and non-stationary therefore its control is difficult. In the present work an adaptive neuro-fuzzy controller is designed to control a binary distillation process. A conventional PID controller is also designed for comparison purpose. The comparison of performance analysis shows the effectiveness of the designed controller.

Keywords—Adaptive neuro-fuzzy controller, Binary Distillation process, Intelligent Controller, PID controller.

I. INTRODUCTION

Distillation is an important separation process in chemical industries and plays an important role in economical growth of a country. The difficulties in control of distillation process are due to their highly non-linear characteristics, multiple input multiple output (MIMO) structure and the presence of severe disturbances during operations. As discussed the distillation column is a typical example of a MIMO system in which there are strong interactions between the variables. The interactions occurring between the inputs and the outputs are difficult to identify. The disturbances to a distillation column from many sources such as feed (feed flow rate, feed composition), reflux and heat input/vapour flow rate. These difficulties pose numerous challenging control problems and also attract a large number of researchers from different disciplines.

J.S. Yang [1] proposed the PI/PID control of a binary distillation column via a genetic searching algorithm (GSA) and indicated that GA can provide better results as compared to those using single-loop and multi-loop Zeigler-Nichols tuning methods. Xueimei Zha [2] proposed the rigorous dynamic model of a distillation process to realize its dynamic optimization and advanced control. The proposed model achieved high precision and the maximum error obtained is less than 3%.

Murad et al. [3] introduced a 2-DOF IMC (Internal Model Control) controller for distillation column and is found to be significantly better than traditional single loop PI controllers. Wong et al. [4] proposed the new approach for developing low-order, non-linear, dynamic models for distillation column. Simple relationship in non-linear state-space models provided excellent low order models for three distillation columns, two simulated and one experimental. Zou et al. [5] developed a linear discrete state-space model of a methanol/water binary batch distillation column and the state-space model is used to design a Model Predictive Control (MPC) strategy. The control experiments shows that MPC gives smooth and accurate control results as compared to commonly used PI control.

Lee et al. [6] presented a number of robust control theories to develop systematic methods for control structure selection and controller design. Basualdo et al. [7] proposed the neural network to model the plant and its inverse, and directly included as a part within the internal model control structure. The combined structure of conventional controllers (P, PD) with the inverse model is then implemented in order to improve the performance of the controlled system.

Santhanam et al. [8] proposed a new fuzzy adaptive technique to adapt the feed forward model and decoupling model in a binary distillation column so that it can reject the feed flow disturbances which affect the distillate composition. Z. Abdullah et al. [9] provided a review of the models that have been implemented in continuous distillation columns and it reveals a remarkable prospect of developing a non-linear model in this research area.

Jang et al. [10] defined an adaptive multilayer feed forward network wherein each node applies a particular function on incoming signals as well as a set of parameters of that node. Sugeno et al. [11] formulated problems of structure identification of a fuzzy model and the verification of structure is also described. An algorithm for identifying structure is made and parameters of identification algorithm are determined. Takagi et al. [12] presented a mathematical tool to build a fuzzy model of a system which uses fuzzy implications and reasoning.

Lee [13] presented a survey of fuzzy logic controller (FLC), a general method for constructing an FLC and assessment of its performance is described and the problems which need further research are pointed out. Solatian et al. [14] proposed basic concepts, mathematical parameters and design aspect of Neuro-fuzzy controller for non-linear process to control flow rate of a plant. The proposed controller is more
versatile in comparison to conventional PID and other fuzzy controllers for non-linear process plants. The organization of this paper is as follows: Section 2 has basic concept and mathematical model of a binary distillation process, Section 3 presents the PID controller tuning of the process. In section 4 basics of ANFIS are presented whereas section 5 presents the comparative study of the designed controllers. Finally section 6 concludes the work.

II. DISTILLATION PROCESS

The distillation process is probably the most known and important process studied in the chemical engineering literature. Distillation is used in many chemical processes for separating feed stream into its component fractions and for purification of final and intermediate product streams [15]. The distillation process utilizes the relative volatility of component fractions for separation.

An ideal binary distillation column is shown in figure 1. The column has N stages on which the vapour-liquid equilibriums occur. The feed is a mixture of two components and enters the column on the stage Nf. A reboiler is used for vaporization of mixture and it is near the bottom of column. The lighter vapour rises to the top of the column which further goes to condenser and is converted into liquid. The condensed liquid is the distillate product. The part of the condensed liquid is sent back to the top tray which is called as reflux flow. The reflux flow rate is controlled to enhance the purity of the product. The heavier component is drawn from the bottom and serves as the bottom product.

\[
\frac{dM_D}{dt} = V - R - D
\]

\[
\frac{d(M_Dx_D)}{dt} = V y_{NT} - (R + D) x_D
\]

Top Tray:

\[
\frac{dM_{NT}}{dt} = R - L_{NT}
\]

\[
\frac{d(M_{NT}x_{NT})}{dt} = RX_D - L_{NT}x_{NT} + Vy_{NT-1} - Vy_{NT}
\]

\[
\frac{dM_n}{dt} = L_{n+1} - L_n
\]

\[
\frac{d(M_nx_n)}{dt} = L_{n+1}x_{n+1} - L_nx_n + Vy_{n-1} - Vy_n
\]

Feed Tray:

\[
\frac{dM_{NF}}{dt} = L_{NF+1} - L_{NF} + F
\]

\[
\frac{d(M_{NF}x_{NF})}{dt} = L_{NF+1}x_{NF+1} - L_{NF}x_{NF} + Vy_{NF-1} - Vy_{NF} + Fz
\]

Reboiler and column base:

\[
\frac{dM_B}{dt} = L_1 - V - B
\]

\[
\frac{d(M_Bx_B)}{dt} = L_1x_1 - Vy_B - Bx
\]

A liquid-hydraulic relationship is given by:

\[
L_n = \overline{L}_n + \frac{M_n - \overline{M}_n}{\beta}
\]

where \(\beta\) = hydraulic time constant.

\(M_n\) = liquid molar holdup on the tray, lb-mol.

\(L_n\) = liquid flow rate leaving the tray, lb-mol/h.

The simulation algorithm of binary distillation process is as follows:

a) Vapor composition is calculated on all trays from equation

\[
y_n = \frac{ax_n}{1 + (a-1)x_n}
\]

b) All liquid flow rates are calculated from equation (11).

c) Evaluation of all derivatives using equations (1 to 10).

d) Integrate all ODEs and repeat step a.
III. PID CONTROLLER TUNING OF THE PROCESS

PID controller involves three terms i.e., proportional, integral and derivative. A PID controller calculates an "error" value as the difference between a measured process variable and a desired set point. The controller attempts to minimize the error by adjusting the process control inputs. The PID controller produces the control signal as follows:

\[ u(t) = u(t-1) + K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt} \]  

(13)

where \( u(t) \) is the plant input, \( e(t) \) is the difference between the set point \( r(t) \) and measured value \( y(t) \) at time instant \( t \). \( K_p \), \( K_i \) and \( K_d \) are the proportional gain, integral gain and derivative gain respectively. There are various methods available in literature to determine these parameters. Zeigler-Nichols and Tyreus-Luyben tuning methods are described below.

Ziegler-Nichols (Z-N) Method and Tyreus-Luyben (T-L) tuning parameters:

a. Turn on the controller to proportional mode by setting \( T_0 = 0 \) and \( T_1 = \infty \).

b. Using proportional control action only, increase \( K_p \) from 0 to critical value \( K_c \). And observe the output response of the system until it reaches to the sustained oscillation. Mark the value of \( K_p \) as \( K_o \), the ultimate gain. The period of oscillation, \( P_o \) is also measured.

c. Using the values of \( K_o \) and \( P_o \), the values of \( K_p \), \( T_1 \) and \( T_2 \) are calculated with the help of Table 1.

The controller-1 used for bottom product composition control by manipulating vapor flow rate is tuned with the help of Z-N method. The controller-2 controls the distillate composition by manipulating the reflux flow rate and is tuned with the help of Tyreus-Luyben method. The tuning parameters for the two controllers are given in table 2.

Table 1: Ziegler-Nichols and Tyreus-Luyben tuning parameters

<table>
<thead>
<tr>
<th>PID</th>
<th>Controller-1(Z-N)</th>
<th>Controller-2(L-L)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( K_p )</td>
<td>( T_1 )</td>
</tr>
<tr>
<td></td>
<td>1.7</td>
<td>2.2</td>
</tr>
</tbody>
</table>

Table 2: Ziegler-Nichols and Tyreus-Luyben tuning parameters

<table>
<thead>
<tr>
<th>PID</th>
<th>Controller-1(Z-N)</th>
<th>Controller-2(T-L)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( K_p )</td>
<td>( T_1 )</td>
</tr>
<tr>
<td></td>
<td>23529.4</td>
<td>22.5</td>
</tr>
</tbody>
</table>

IV. ANFIS CONTROLLER

A adaptive network can be defined as feed-forward multi-layer Artificial Neural Network (ANN) with partially or completely adaptive nodes, where the outputs are estimated on the parameters of the adaptive nodes and the adjustment of parameters due to error term is given by the learning rules. ANFIS is a kind of neural network that is based on Takagi-Sugeno fuzzy inference system. Since it integrates both neural networks and fuzzy logic principles, it has potential to capture both in a single framework. Its inference system corresponds to a set of fuzzy IF-THEN rules that have learning capability to approximate non-linear functions. Hence, ANFIS is considered to be Universal Approximator. For developing fuzzy rules with suitable membership functions, ANFIS is the implementation of fuzzy inference system (FIS) to adaptive networks, to have required inputs and outputs. FIS consists of five subcomponents: a rule base (covers fuzzy rules), a database (portrays the membership function of the selected fuzzy rules), fuzzification, inference and defuzzification. The first two subcomponents make knowledge base and last three makes reasoning mechanism.

![Fig. 2 FNN Structure](image)

**ANFIS modeling:**

The fuzzy inference system under consideration has two inputs \( x \) and \( z \) and one output \( y \). Assuming rule base containing two fuzzy if-then rules of Takagi-Sugeno type.

Rule 1: If \( x \) is \( A_1 \) and \( z \) is \( B_1 \), then \( f_1 = p_x x + q_x z + r_1 \).

Rule 2: If \( x \) is \( A_2 \) and \( z \) is \( B_2 \), then \( f_2 = p_x x + q_x z + r_2 \).

The node functions are described as:

Layer 1: Every node \( i \) in this layer is a square node with a node function

\[ O^1_i = \mu_{A_i}(x) \]  

(14)

Where \( x \) is the input to node \( i \), \( A_i \) is the linguistic label associated with node function, \( O^1_i \) is the membership function of \( A_i \).

Layer 2: Every node in this layer is a circle node labeled as \( \pi \) which multiplies the incoming signals and sends the product out. Each node output represents the firing strength of the rule.

\[ \omega_i = \mu_{A_i}(x) \times \mu_{B_i}(z) \]  

(15)
Layer 3: Every node in this layer is a circle node labeled N. The i th node labeled calculates the ratio of the i th rules firing strength called as normalized firing strengths.

\[ \tilde{a}_i = \frac{a_i}{w_1 + w_2} \quad i=1,2. \]  

Layer 4: Every node i in this layer is a square node with a node function

\[ O_i^L = \tilde{a}_i f_i = \tilde{a}_i (p_i + q_i + r_i) \]  

Where \( \tilde{a}_i f_i \) is the output of the layer 3. \( \{p_i, q_i, r_i\} \) are the parameter sets. These layer parameters are called consequent parameters.

Layer 5: The single node in this layer is a circle node labeled \( \sum \) that computes the overall the overall output as the summation of all incoming signal, i.e.

\[ y=O_5^L = overall \ output = \sum_i \tilde{a}_i f_i \]  

The ANFIS controller is designed with the help of generated fuzzy inference system structure from data using grid partition. The controller is designed to minimize the error between set point and the actual output by adjusting the adaptive parameters. An ANFIS controller is designed to control a binary distillation process. Results and Discussion. The PID controllers are designed with the help of Ziegler-Nichols and Tyreus–Luyben tuning method to control the vapor flow rate and reflux flow rate respectively. ANFIS controllers are also designed for the same purpose. The data required for training the ANFIS controllers is developed by simulating the process. A set of values of the manipulating variables are provided to the simulation model and the corresponding controlled variables are obtained. The input data consists of error (difference between the set point and the actual output) and change in error whereas the output data is the change in manipulating variable. The data sets so generated are then used to train the ANFIS controllers. The performance of the designed controllers is analyzed for composition control, set point changes and disturbance rejection as given in the following sections.

A) Composition Control:

Fig. 3 and Fig. 4 show composition control of bottom product \((x_B)\) and distillate \((x_D)\) respectively. It is observed from the results that ANFIS controller controls bottom composition as well as distillate composition much earlier as compared to the PID controller. It is also observed that the ANFIS has less oscillation as compared to PID controllers.

B) Set Point Tracking:

The set point tracking of bottom product composition is changed from 0.02 to 0.023 whereas in case of distillate composition the set point is changed from 0.98 to 0.977. Fig. 5 and Fig. 6 show the set point tracking for the bottom and distillate composition respectively. It is observed from the results that the ANFIS controller controls the process in a smoother manner as it has fewer transients and tracks the desired set point earlier as compared to PID controllers.

c) Disturbance Rejection:

The disturbance is introduced in the feed composition from 0.55 % mole fraction to 0.50 % mole fraction. The disturbance is introduced in the feed composition from 0.02 to 0.023 whereas in case of distillate composition the set point is changed from 0.98 to 0.977. Fig. 5 and Fig. 6 show the set point tracking for the bottom and distillate composition respectively. It is observed from the results that the ANFIS controller controls the process in a smoother manner as it has fewer transients and tracks the desired set point earlier as compared to PID controllers.
% mole fraction at 600th iteration. The bottom composition and distillate composition control results of binary distillation process are shown in Fig. 7 & Fig. 8, respectively. It is observed from the results that disturbance is equally being rejected by both the controllers.

**Fig. 7 Disturbance rejection in bottom composition**

**Fig. 8 Disturbance rejection in distillate composition**

**CONCLUSION**

In the present work an adaptive-neuro fuzzy inference controller is designed for composition control of binary distillation process. A PID controller is also designed for comparative study. The designed controllers are tested for composition control, set point tracking and disturbance rejection in feed composition. It is observed from the results that the proposed ANFIS controller performs better than the conventional PID controllers in all respects of the performance of the controllers.

**REFERENCES**


