

# Simulation and Control of an Aromatic Distillation Column

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**ABSTRACT:** *In general, the objective of distillation control is to maintain the desired products quality. In this paper, the performances of different one point control strategies for an aromatic distillation column have been compared through dynamic simulation. These methods are: a) Composition control using measured composition directly. This method suffers from large sampling delay of measuring devices. b) Composition control by controlling the temperature of a specific tray. In this strategy, the composition-temperature relationship is used to find the temperature setpoint corresponding to the desired composition. Since composition-temperature relation depends on feed condition, an artificial neural network has been proposed which receives the feed specifications and provides the setpoint of the temperature control loop. c) Using temperature measurements for predicting the composition and controlling the composition based on predicted values of composition (inferential control). Simulation results indicate that controlling the 8th tray temperature and using an artificial neural network for calculating corresponding tray temperature setpoint, has the best performance. Due to negligible pressure drop along the column, controlling the tray temperature difference does not improve the control loop performance.*

**KEY WORDS:** *Distillation column, Inferential control, Multirate sampling, Identification, Artificial neural network, Dynamic simulation.*

## INTRODUCTION

Distillation columns are the major part of most chemical processing plants. The purpose of a distillation column is to split the feed into two or more products with compositions different from the feed. The desired composition of the products may be fixed by products requirements or may be obtained from some plantwide optimization. An important objective of the control system is to keep these product compositions at their desired levels. There are a lot of different methods for distillation control. Using tray temperature control loop

for distillation control is one of the most popular strategies. Tray temperature control loops for distillation control have been used for many decades in industry. Theoretically, the best place to locate a temperature sensor to control the overhead distillation composition would be the top tray for constant-pressure binary system. The tray temperature would represent the true distillate composition and the lag between the manipulated and controlled variables would be minimized. However the practical considerations of sensor sensitivity and variable

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pressure, usually requires the temperature sensor to be moved down into the rectifying section. The ratio of the tray temperature change to the distillate composition change ( $\Delta T/\Delta X_D$ ) decreases as the sensor is moved up the column. A point will be reached where the sensor can no longer detect small changes to control the distillate satisfactorily. On the other hand, the lower in the column the sensor is located the more steady state deviation in  $X_D$  will be experienced. This occurs because the manipulated variable change required to hold the control tray temperature constant will not, in general, be the correct change to hold the distillate composition constant. The selection of most appropriate location for temperature sensor is done according to the sensitivity of tray temperature to the changes in feed conditions and changes in manipulated variables.

If changes occur in feed specifications (composition, flow rate and temperature), it is quite difficult to keep product composition at its setpoint by using tray temperature control loop because the tray temperature and overhead composition relation depends on feed specification. In addition, pressure changes also cause temperature variations. In order to cope with this problem, many approaches have been proposed. The influence of non-key components can be reduced by locating a temperature measurement in the region of the column where their compositions are nearly constant [1]. Yu and Luyben used the differential temperature for non-key component compensation [2]. One of the temperature sensors is located on the most sensitive trays in the rectifying section and the other is located on the most insensitive trays in the column. Using this configuration for temperature sensors compensates tray temperature changes due to the changes of pressure through the distillation column. Whitehead and Parnis used a weighted average of several temperature difference for pressure disturbance compensation [3].

Another strategy for controlling the distillation product is direct control of composition. The limitation of this technique is the composition measurement lag. The accurate composition measuring devices like G.C. have considerable lags which deteriorates the performance of feedback loops. On the other hand, fast measuring devices do not have enough accuracy.

Using measurements of product composition with measurements of secondary process outputs, such as tray

temperature, leads to the control strategy called inferential control. This control strategy was proposed by Brosilow *et al.*, and discussed very briefly below [4].

An inferential control system uses measurements of secondary process output, such as temperature with high frequency sampling, to infer the effect of unmeasurable disturbances on primary process output, such as product quality with low frequency sampling. A linear estimator which minimizes an objective function is used to infer the product quality. An appropriate estimate of product quality can be obtained when the measurement of secondary output is available. This estimated values can be used for process control purposes. The proposed estimator is a static estimator and does not take into account the changes in operating conditions. Since then, a lot of studies and researches have been done to improve the performance of the estimator [5-10]. One of these schemes is the adaptive inferential estimator. In adaptive strategy the model parameters are updated when the process characteristics are changed.

Recently the application of artificial neural network for estimating and controlling the quality of distillation column has received extensive attention [11-13]. Willis *et al.*, discuss a neural network based estimation procedure for composition control of an industrial distillation tower using measured quantities such as overhead temperature [12].

In this article composition control of an aromatic distillation column is studied. Different approaches are considered and their performances are compared through simulation. The paper is organized as follows: First, an aromatic distillation column is modeled. Tray temperature measurement selection and design of composition estimator are studied next. Finally, the performances of different control strategies for setpoint tracking and load rejection are compared through simulation studies.

## AROMATIC DISTILLATION COLUMN MODELING

In this part the static and dynamic behaviors of a multicomponent distillation column are studied. The schematic diagram of the column is shown in Fig. 1. The column has 60 sieve trays and operates under total condensation and full reflux. Column diameter is 1.68 m and tray spacing is 0.6 m. The liquid holdups of the reflux drum and the reboiler are 7.5 m<sup>3</sup> and 9.5 m<sup>3</sup>, respectively. The feed stream enters the column at the

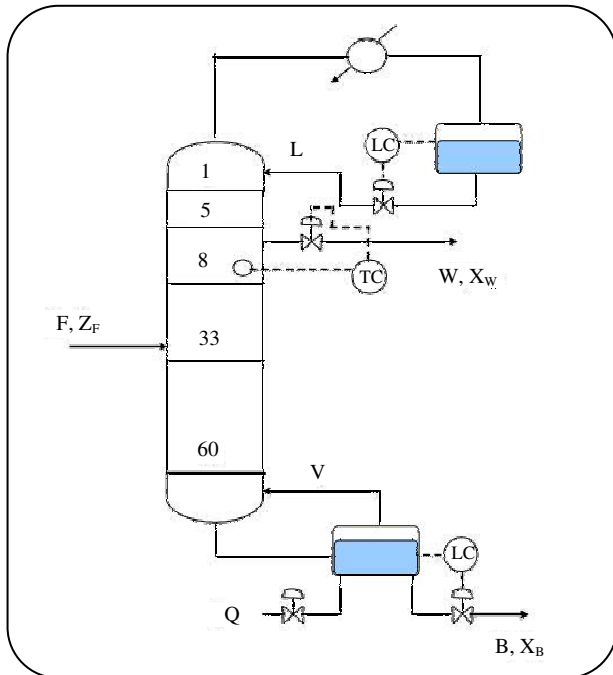


Fig. 1: The schematic diagram of studied distillation column.

33th tray. The specifications of different streams are given in table 1. Side product stream is taken from tray 5. The desired concentration of benzene in the side stream is 99 %.

### STEADY STATE MODELING

For steady-state modeling of the distillation column the following equations has been used:

#### Material Balance

$$V_{j+1}Y_{j+1,i} = L_jX_{j,i} + DX_{D,i} \quad (j=1,2,3,5) \quad (1)$$

$$V_{j+1}Y_{j+1,i} = L_jX_{j,i} + DX_{D,i} + WX_{W,i} \quad (j=6,7,\dots,f-2)$$

$$V_f Y_{f,i} + V_F Y_{F,i} = L_{f-1} X_{f-1,i} + DX_{D,i} + WX_{W,i}$$

$$V_{j+1}Y_{j+1,i} = L_jX_{j,i} - BX_{B,i} \quad (j=f, f+1, \dots, N-1)$$

$$FX_i = DX_{D,i} + BX_{B,i} + WX_{W,i}$$

#### Enthalpy Balance

$$V_{j+1}H_{j+1} = L_jh_j + DH_D + Q_C \quad ; \quad (j=1,2,3,5) \quad (2)$$

$$V_{j+1}H_{j+1} = L_jh_j + DH_D + Q_C + WH_w \quad ; \quad (j=6,7,\dots,f-2)$$

$$V_f H_f + V_F H_F = L_{f-1} h_{f-1} + DH_D + Q_C + WH_w$$

$$V_{j+1}H_{j+1} = L_jh_j - Bh_B + Q_R \quad ; \quad (j=f, f+1, \dots, N-1)$$

$$FH_F = Bh_B + DH_D + WH_w + Q_C - Q_R$$

#### Equilibrium relationships

$$y_{ji} = K_{ji} X_{ji} \quad ; \quad (j=1,2,\dots,N) \quad (3)$$

$$\sum_{i=1}^C y_{ji} = 1 \quad ; \quad (j=1,2,\dots,N)$$

$$\sum_{i=1}^C X_{ji} = 1 \quad ; \quad (j=1,2,\dots,N)$$

It is assumed that liquid and vapor streams leaving each tray are ideal solutions so, as a result, the following equations have been used for calculating liquid and vapor enthalpy.

#### Vapor enthalpy

$$H_j = \sum_{i=1}^C H_{ji} y_{ji} \quad (4)$$

#### Liquid enthalpy

$$h_j = \sum_{i=1}^C h_{ji} X_{ji} \quad (5)$$

For calculating top product enthalpy, total condenser is assumed for column so the top product leaving the column at the bubble point condition:

$$H_D = \sum_{i=1}^C h_{li} X_{D,i} = \sum_{i=1}^C h_{li} X_{li} = h_1 \quad (6)$$

For reboiler also we have:

$$h_B = \sum_{i=1}^C h_{Bi} X_{B,i} = \sum_{i=1}^C h_{Ni} X_{N,i} = h_N \quad (7)$$

For solving the above equations, the "θ method of convergence" has been used. The static simulation results of the developed software and the corresponding industrial data are given in table 2. As can be seen, the results of the prepared software have an acceptable agreement with the industrial data.

### DYNAMIC MODELING

For dynamic modeling of the distillation column, the governing equations describing the system are given below:

#### Component molar balances

For column trays except feed and sidestream trays:

Table 1: Studied distillation column characteristics.

Stream Spec.	Temp. (°C)	Benzene (wt %)	Toluene (wt %)	Mxylene (wt %)	Oxylene (wt %)	Pxylene (wt %)	E-benzene (wt %)
Feed	123	13.15	44.91	17.84	8.78	8.16	7.16
Sidestream	89	99	1	0	0	0	0
Bottom	142	0	51.69	20.57	1	9.39	8.24

Table 2: Simulation results and industrial data.

	Temp. (°C)	Benzene (wt %)	Toluene (wt %)	Mxylene (wt %)	Oxylene (wt %)	Pxylene (wt %)	E-benzene (wt %)
Industrial side stream data	89	100	0	0	0	0	0
Simulated sidestream	92.65	100	0	0	0	0	0
Industrial bottom product data	142	0	51.69	20.57	10	9.39	8.24
Simulated Bottom	146.9	0	51.62	20.66	10.25	9.47	8.34

$$\frac{dM_{i,K}}{dt} = L_{K+1}x_{i,K+1} + V_{K-1}y_{i,K-1} - L_K x_{i,K} - V_K y_{i,K} \quad ; \quad i=1,\dots,NC \quad ; \quad K=1,\dots,N \quad (8)$$

For feed tray:

$$\frac{dM_{i,f}}{dt} = L_{f+1}x_{i,f+1} + V_{f-1}y_{i,f-1} + F_f z_{i,f} - L_f x_{i,f} - V_f y_{i,f} \quad (9)$$

For sidestream tray:

$$\frac{dM_{i,w}}{dt} = L_{w+1}x_{i,w+1} + V_{w-1}y_{i,w-1} - w_w y_{i,w} - L_w x_{i,w} - V_w y_{i,w} \quad (10)$$

**Energy balances**

For column trays except feed and sidestream trays:

$$\frac{dU_K}{dt} = L_{K+1}h_{K+1} + V_{K-1}H_{K-1} - L_K h_K - V_K H_K \quad ; \quad K=1,\dots,N \quad (11)$$

For feed tray:

$$\frac{dU_f}{dt} = L_{f+1}h_{f+1} + V_{f-1}H_{f-1} + F_f h_f - L_f h_f - V_f H_f \quad (12)$$

For sidestream tray:

$$\frac{dU_w}{dt} = L_{w+1}h_{w+1} + V_{w-1}H_{w-1} - w_w h_w - L_w h_w - V_w H_w \quad (13)$$

where for column trays [14]:

$$U_K = M_K^L h_K + M_K^V H_K - 0.1 P_K \text{Vol}_{\text{tray}} \quad ; \quad K=1,\dots,N \quad (14)$$

$$\frac{M_k^L}{\rho_k^L} + \frac{M_k^V}{\rho_k^V} = \text{Vol}_{\text{tray}} \quad ; \quad k=1,\dots,N \quad (15)$$

**Equilibrium relationships**

$$y_{i,k} = k_{i,k} x_{i,k} \quad ; \quad i=1,\dots,NC \quad ; \quad K=1,\dots,N \quad (16)$$

$$k_{i,k} = \frac{P_{i,k}^{\text{sat}}}{P_K} \quad ; \quad i=1,\dots,N \quad ; \quad K=1,\dots,N \quad (17)$$

$$\sum_{i=1}^{NC} y_{i,k} = 1 \quad ; \quad K=1,\dots,N \quad (18)$$

$$\sum_{i=1}^{NC} x_{i,k} = 1 \quad ; \quad K=1,\dots,N$$

Component molar hold-ups:

$$M_{i,K} = M_K^L x_{i,K} + M_K^V y_{i,K} \quad ; \quad i=1,\dots,NC \quad ; \quad K=1,\dots,N \quad (19)$$

**For column reboiler**

Component molar balances:

$$\frac{dM_{i,R}}{dt} = L_1 X_{i,1} + V_R y_{i,R} - B X_{i,R} ; i = 1, \dots, NC \quad (20)$$

Energy balances

$$\frac{dU_R}{dt} = L_1 h_1 - V_R H_R - B h_R + Q_R \quad (21)$$

**For column condenser and reflux drum**

Component molar balances:

$$\frac{dM_{i,c}}{dt} = V_N y_{i,N} - L_c X_{i,c} ; i = 1, \dots, NC \quad (22)$$

$$\frac{dM_{i,d}}{dt} = L_c X_{i,c} - (R + D) X_{i,d} ; i = 1, \dots, NC \quad (23)$$

Energy balances:

$$\frac{dU_c}{dt} = V_N H_N - L_c h_c - Q_c \quad (24)$$

$$\frac{dU_d}{dt} = L_c h_c^1 - (R + D) h_d^1 \quad (25)$$

The liquid flow rate leaving each tray is given by the following correlation [15]:

$$L_k = \begin{cases} 0, & \text{if } \text{Level}_k \leq \text{height}_{\text{weir}} \\ 1.84 \rho_k^1 \text{length}_{\text{weir}} (\text{Level}_k - \text{height}_{\text{weir}})^{1.5} \times 60 & \\ k = 1, \dots, N & \text{otherwise} \end{cases} \quad (26)$$

where:

$$\text{Level}_k = \frac{M_k^1}{\rho_k^1 A_{\text{tray}}} ; k = 1, \dots, N \quad (27)$$

Using the above equations and *Matlab* software, the column has been simulated under dynamic conditions. *Runge-Kutta* Method has been used for solving algebraic differential equations.

In this study one point control strategy has been considered. Sidestream flow rate is used as manipulated variable for product composition control. Liquid level in the reflux drum is controlled by reflux stream flow rate and the reboiler liquid level is controlled by manipulating the bottom product flowrate. Column reboiler heat duty is fixed. Digital PI controllers are used for all control loops.

For liquid level low gain controllers are used in order to reduce the interaction between liquid level and composition control loops. For dynamic simulation it has been assumed that secondary measurement, tray temperature, is available every 30 sec and side product composition is available every 2.5 min.

**TRAY TEMPERATURE SELECTION**

Open loop testing uses the steady state model to identify the appropriate temperature sensor location for inferring product composition. This is accomplished by changing the manipulated variable (side stream flowrate)  $\pm 5\%$  from the base case value and obtaining the steady state temperature profile along the column. The results are shown in Fig. 2.

Fig. 3 shows tray temperature changes for three different steady state conditions when  $\pm 7\%$  and  $\pm 10\%$  changes are applied to feed temperature and flow rate, respectively. In Fig. 3 curve 1 is the base case condition, curve 2 corresponds to  $-7\%$  and  $-10\%$  changes in feed temperature and flow rate, respectively, and curve 3 is for  $+7\%$  and  $+10\%$  changes in feed temperature and flow rate, respectively.

It can be concluded from Figs. 2 and 3 that tray 8 is a good location for temperature sensor because this tray is the most sensitive one to changes in feed conditions and manipulated variable. As a result the 8th tray temperature control loop is one of the control strategies that will be considered later.

As can be seen from Figs. 2 and 3, trays 23 to 27 have the lowest sensitivity to the aforementioned changes and therefore temperature differences of trays 8 & 23 and trays 8 & 27 can be used for temperature difference control strategy.

**COMPOSITION ESTIMATION**

We assume that composition ( $y$ ) and temperature ( $\theta$ ) are related to sidestream ( $u$ ) by the following linear models:

$$y_0(t) = G_1(q^{-1})u(t - m_1) \quad (28)$$

$$\theta_0(t) = G_2(q^{-1})u(t - m_2) \quad (29)$$

$$y(t) = y_0(t - d_1) \quad (30)$$

$$\theta(t) = \theta_0(t - d_2) \quad (31)$$

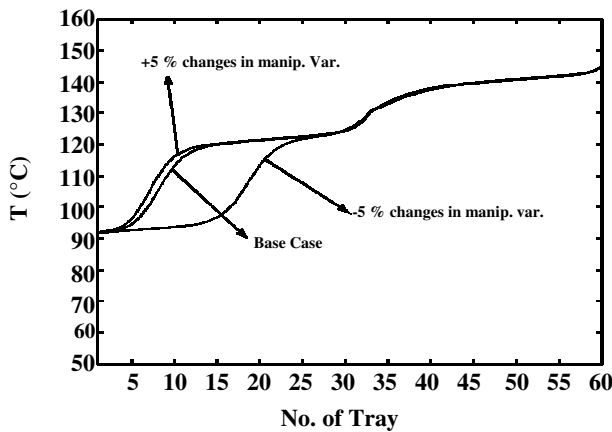


Fig. 2: Column tray temperature variation due to changes in manipulated variable.

where  $y_0(t)$  and  $\theta_0(t)$  are the primary (composition) and secondary (temperature) outputs at time  $t$  and  $y(t)$  and  $\theta(t)$  are their corresponding measurements.  $d_1$  and  $d_2$  are measurement delays associated with  $y(t)$  and  $\theta(t)$  and are assumed to be multiple of the sample time.  $m_1$  and  $m_2$  are process transportation lags.

The relation between composition estimate ( $\hat{y}(t)$ ), temperature ( $\theta(t)$ ) and manipulated variable ( $u(t)$ ) can be expressed as follows[11]:

$$\hat{y}(t+d_1) = \frac{B_1(q^{-1})}{A_1(q^{-1})}u(t-m) + \frac{C_1(q^{-1})}{A_1(q^{-1})}\theta(t+d_2) \quad (32)$$

where:

$$m = \min(m_1, m_2)$$

$$A_1(q^{-1}) = 1 + a_1q^{-1} + a_2q^{-2} + \dots + a_nq^{-n}$$

$$B_1(q^{-1}) = b_1q^{-1} + b_2q^{-2} + \dots + b_nq^{-n}$$

$$C_1(q^{-1}) = c_0 + c_1q^{-1} + c_2q^{-2} + \dots + c_nq^{-n}$$

Estimated composition can be calculated whenever the measured values of the temperature  $\theta(t)$  and sidestream flow rate  $u(t)$  are available.

Since the sample rate of composition is slower than temperature, the parameters of equation (32) in the present form can not be estimated by using recursive identification methods and some modification should be done. If both sides of equation (32) are multiplied by the following polynomial [6]:

$$\prod_{i=1}^n [1 - \lambda_i q^{-1} + \dots + (-\lambda_i)^{d_1-1} q^{-d_1+1}] \quad (33)$$

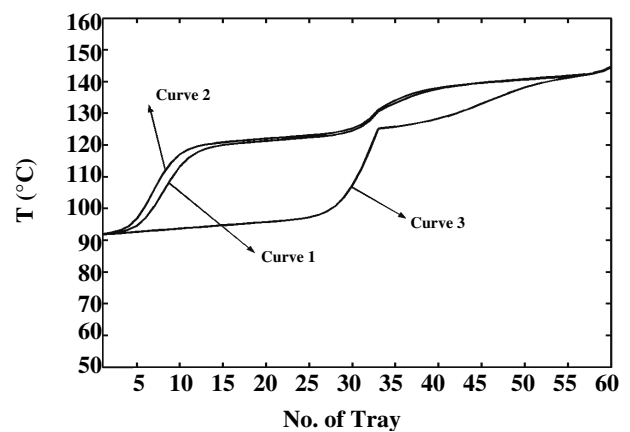


Fig. 3: Column tray temperature variation due to changes in feed conditions.

then we have:

$$\hat{y}(t) = \phi(t-d_1)^T \Theta(t) \quad (34)$$

$$\phi(t-d_1)^T = [-\hat{y}(t-d_1) - \hat{y}(t-2d_1), \dots, -\hat{y}(t-nd_1)] \quad (35)$$

$$u(t-m-d_1-1), \dots, u(t-m-(n+1)d_1), \theta(t-d_1+d_2), \theta(t-d_1+d_2-1), \dots, \theta(t-(n+1)d_1+d_2)]$$

$$\Theta(t) = [\alpha_d, \dots, \alpha_{nd}, \beta_1, \dots, \beta_{nd}, \gamma_0, \dots, \gamma_{nd}] \quad (36)$$

Equation (34) can be used in adaptive framework. Whenever composition measurement becomes available, the model parameters ( $\Theta(t)$  vector) are updated using any recursive identification method. Between two consecutive composition measurements, composition is estimated by using equation (34). In the present work, we have used recursive least squares identification and the corresponding updating equations are given below:

$$\Theta(t) = \Theta(t-1) + \quad (37)$$

$$\frac{P(t-1)\phi(t-d_1)}{[1 + \phi(t-d_1)^T P(t-1)\phi(t-d_1)]} e(t)$$

$$P(t) = P(t-1) - \quad (38)$$

$$\frac{P(t-1)\phi(t-d_1)\phi(t-d_1)^T P(t-1)}{[1 + \phi(t-d_1)^T P(t-1)\phi(t-d_1)]}$$

where:

$$e(t) = y(t) - \hat{y}(t) \quad (39)$$

The covariance resetting has been used to avoid vanishing the identifier gain and initial value of matrix P is set to 1000I.

### TEMPERATURE SETPOINT ESTIMATION USING ARTIFICIAL NEURAL NETWORK

As it was mentioned before, in multicomponent distillation column, variation in feed conditions affect the tray temperature-composition relationship and therefore for maintaining the column product quality unchanged the setpoint of temperature loop should be changed accordingly. The static relation which specify steady state condition are not valid if some loads are introduced into the system. In this work in order to solve this problem, artificial neural network have been used to correlate temperature and composition and provide setpoint for temperature control loop. Designed artificial neural network have three layers, input, hidden and output layers. Input layer has three perceptrons that receive feed conditions (temperature, flow rate and composition) as input data. Hidden layer also has three perceptrons which receive weighted signals from input layer perceptrons. Output layer has one perceptron which receives weighted signal from hidden layer and provides tray temperature setpoint as the network output. Schematic diagram of the proposed neural network is shown in Fig. 4.

Note: It is assumed that the feed concentration changes have a very low frequency. This is true because feed is supplied from large tanks and the composition is fixed as long as it is supplied from a specific reservoir. On the other hand, feed temperature and flow rate can change with a higher frequency. Since composition, temperature and feed flowrate are the network inputs, composition is needed when feed temperature and flow measurements become available. But it should be noted that the composition can not be measured at the same frequency of feed flow and temperature. To solve the problem, composition is assumed to be constant until the new measurement becomes available. Off-line sampling and measurement of feed composition is carried out and the result is fed to the network.

For training and validation tests of each designed neural network a series of 100 static data obtained from 100 steady state conditions of studied distillation column have been used. This static data is given in table 3. Half of the data has been used for training purposes and the rest has been used for validation test. Since three

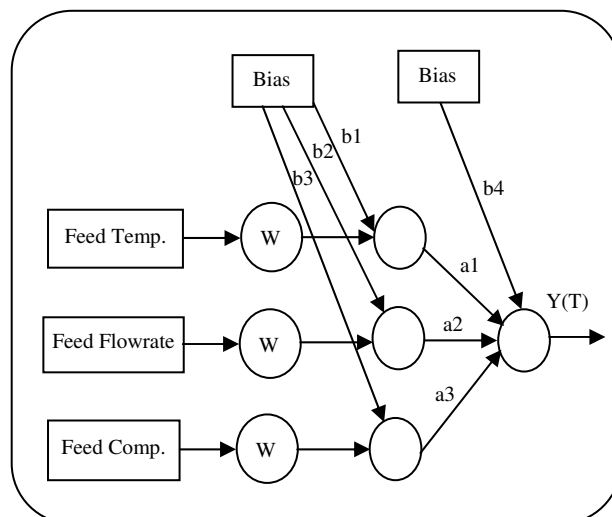


Fig. 4: Proposed artificial neural network structure.

temperature loops will be considered later, three networks have been trained. Figs. 5a, 5b and 5c show the output errors of these networks.

### CONTROL STRATEGIES AND SIMULATION RESULTS

As mentioned before, the composition in a distillation column can be controlled by several control strategies:

- Using composition-temperature relation and controlling the temperature of a specific tray or the temperature difference of two trays.
- Composition control by using composition measurements.
- Using temperature measurements for predicting the composition and controlling composition using the predicted values of composition (inferential control). The compared different control strategies are listed as given in table 4.

### INFERENCE CONTROL LOOP

In this work the 8th tray temperature was chosen as secondary measurement to infer the product composition. It is assumed that temperature measurements are available every 30 sec and the product composition every 2.5 min. Real composition values are used for updating the model parameters.

In order to test the ability of adaptive inferential estimator in predicting the composition, the flowrate of sidestream was changed according to Fig. 6 and the estimated composition was calculated and shown in

Table 3: Static data used for training and validation of neural network.

FT (° C)	FF (K mole/h)	FCB (mole %)	FT (° C)	FF (K mole/h)	FCB (mole %)	FT (° C)	FF (K mole/h)	FCB (mole %)
123	245.1	0.16014	121.6	207	0.157	128.5	260	0.171
124	245.1	0.16014	122.8	214	0.138	128.5	266	0.168
125	250	0.16014	123.6	223	0.169	129.2	266	0.16
125	240	0.16014	125.8	253	0.158	130	250	0.16
125	235	0.14	126.3	236	0.125	130	230	0.15
123	235	0.14	123	245.1	0.16014	130	240	0.143
121	240	0.16	125.3	200	0.155	127.5	270	0.143
120	250	0.18	121.6	208	0.164	126.3	270	0.153
122	270	0.15	122.4	216	0.133	125.3	228	0.153
125	265	0.14	123.3	223	0.143	125.3	240	0.147
127	255	0.13	124.7	241	0.153	124.4	240	0.147
129	230	0.11	125.9	256	0.166	122.2	272	0.163
130	220	0.14	126.4	268	0.181	122.2	266	0.175
128	200	0.13	126.4	274	0.185	123.6	254	0.172
127	210	0.15	123.9	284	0.177	120.6	230	0.172
120	230	0.17	123.9	256	0.177	120.6	240	0.168
119	210	0.15	124.9	256	0.177	118	260	0.15
121	235	0.16	124.9	256	0.166	118	230	0.15
123	265	0.18	127	256	0.166	120	220	0.13
120	275	0.13	127	220	0.166	120	210	0.145
124	260	0.14	126	220	0.144	124.2	210	0.168
125	268	0.17	126	220	0.188	127.3	215	0.185
125	258	0.17	126	220	0.158	125.5	225	0.185
124.5	240	0.16	126	220	0.133	124.5	225	0.185
123.5	230	0.12	126	220	0.122	123.5	225	0.18
122.5	220	0.13	125	264	0.126	122.5	215	0.18
121.5	235	0.145	125	264	0.136	121.5	215	0.17
120.5	265	0.155	122	264	0.136	120.5	235	0.17
119.5	255	0.165	120	264	0.136	125.7	273	0.16
118.5	220	0.12	123	257	0.148	126.7	273	0.15
117.5	210	0.15	123	268	0.148	128	280	0.18
116.5	230	0.14	124.8	254	0.158			
120	210	0.17	126.6	264	0.171			
120.8	202	0.166	127.4	268	0.171			

Note: FT: Feed Temperature, FF: Feed Flowrate and FCB: Feed Composition of Benzen.



Table 4: Different control algorithms.

Control loop	Algorithm
Controlling T8 tray temperature	Algorithm 1
Controlling T8 and T23 temperature difference	Algorithm 2
Controlling T8 and T27 temperature difference	Algorithm 3
control of side stream composition using composition measurements	Algorithm 4
Inferential control	Algorithm 5

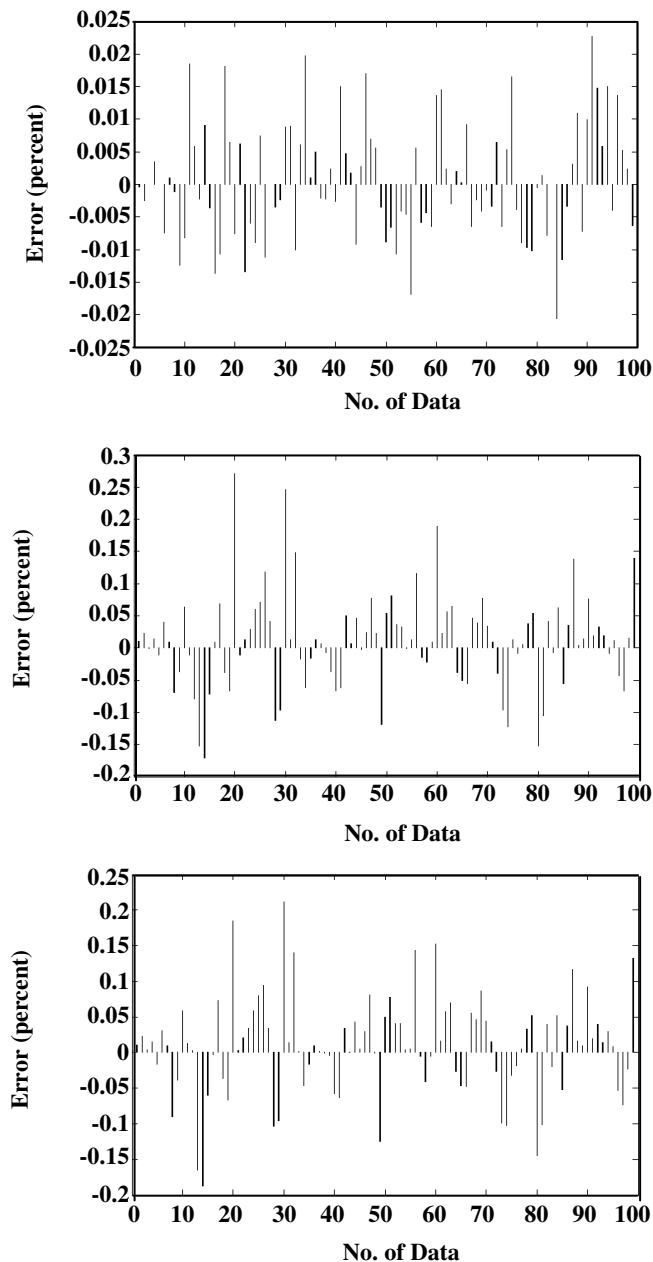


Fig. 5: Network error a) T8 setpoint as the network output, b) T23-T8 setpoint as the network output, c) T27-T8 setpoint as the network output.

Fig. 7. Initial large deviation between real and estimated composition is due to off initial guess of the model parameters. As can be seen from Fig. 7 the estimation converges to real composition after 50 min.

For control purposes, the estimated values obtained for model parameters are used as initial values in applying inferential control strategy.

### SETPOINT TRACKING

For temperature loops it is necessary to have the setpoints corresponding to the desired product composition. Using steady state data, three algebraic equations have been developed for obtaining the temperature setpoints (for three different temperature loops) from the desired product composition. As it was discussed earlier these equations are valid if the feed conditions are fixed. These equations are as follows:

#### Algorithm 1

$$T8 = \frac{(129.54593 - 118.51838C)}{(1 - 0.80011865C - 0.083287772C^2)} \quad (40)$$

#### Algorithm 2

$$T23 - T8 = \frac{10300.046 - 45822.451C + 76640.262C^2}{-57118.983C^3 + 16029.924C^4} \quad (41)$$

#### Algorithm 3

$$T27 - T8 = \frac{1}{(0.29197893 - 0.26833978C - 0.0098688234C^2)} \quad (42)$$

The above equations are obtained using the CurveExpert software. In these equations, C is the product composition and T is the tray temperature. Optimal parameters of the digital PI controllers have been calculated by minimization of ISE (Integral of square of error) index. Initial guess for these parameters have been obtained by using approximated first order model and the Ziegler - Nichols technique. These models are obtained from system step responses and are given in table 5.

In order to investigate the performances of discussed control strategies for setpoint tracking, the product composition is changed from 0.91 to 0.99 and the results

Table 5: First order plus lag models.

Input - Output	First Order Model
T8-sidestream	$G(s) = \frac{0.214e^{-8s}}{32S+1}$
T23-T8 -sidestream	$G(s) = \frac{-0.201e^{-6s}}{29S+1}$
T27-T8 -sidestream	$G(s) = \frac{-0.175e^{-5s}}{28S+1}$
Composition-sidestream	$G(s) = \frac{-0.00145e^{-8s}}{23S+1}$

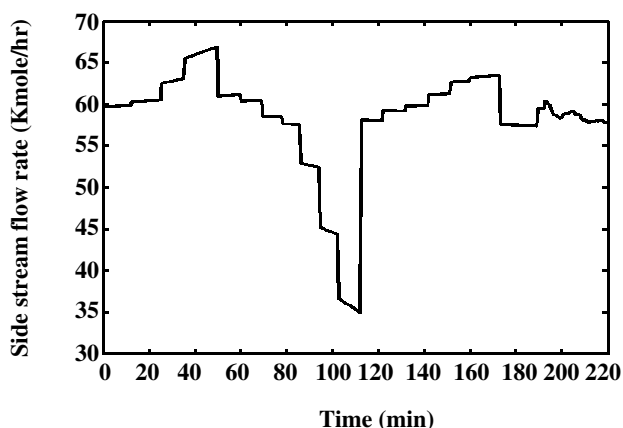


Fig. 6: Sidestream flowrate vs time.

for different algorithms are shown in Figs. a, 8b and 8c.

The corresponding ISE values are given in table 6. As can be seen from the results, algorithm 1 and algorithm 2 have better performances than other algorithms.

### LOAD REJECTION

In order to study the performances of proposed control algorithms for load rejection, feed temperature and composition are increased 7 % and 20 %, respectively. The results are shown in Figs. 9a and 9b. The corresponding ISE values are given in table 7.

As it was mentioned earlier, new tray temperature setpoints for temperature control loops should be calculated for new feed condition. The new temperature setpoints have been obtained by using the trained artificial neural networks.

It is evident from the simulation results that the best performance belongs to algorithm 1, considering both setpoint tracking and load rejection. Also, using inferential control strategy has better performance compare to the direct composition control.

Table 6: ISE values for set point tracking.

Algorithm	(ISE)
Algorithm 1	1.461
Algorithm 2	1.467
Algorithm 3	1.543
Algorithm 4	1.552
Algorithm 5	1.488

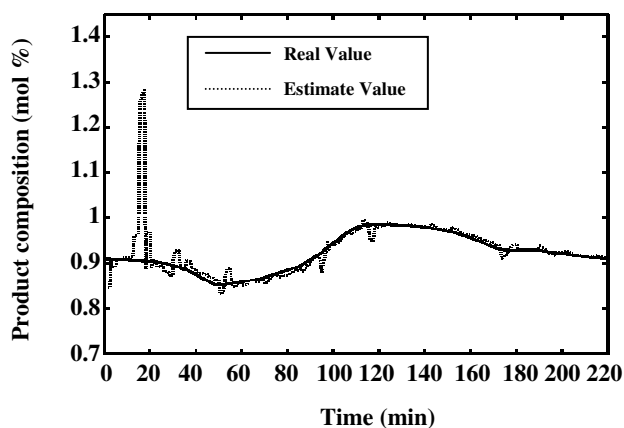


Fig. 7: Composition estimation: real value (solid line), estimated value (dotted line).

### CONCLUSIONS

In the present paper, different one point control strategies for an aromatic distillation column have been considered. Using the conservation laws, the system has been modeled under steady state conditions. The accuracy of the model has been tested by comparing the simulation results with industrial data and an acceptable agreement has been observed.

For temperature control loops two static and one adaptive dynamic estimators have been developed. The first static estimator is in the form of an algebraic equation while the second one is a multilayer artificial neural network. Simulation results indicate that controlling the 8th tray temperature has the best performance for both setpoint tracking and load rejection. Also, using inferential control strategy, compared to direct composition control, improves the performance of the control loop.

Due to negligible pressure drop along the column, controlling the temperature difference of two trays has no advantage over the single tray temperature control loop.

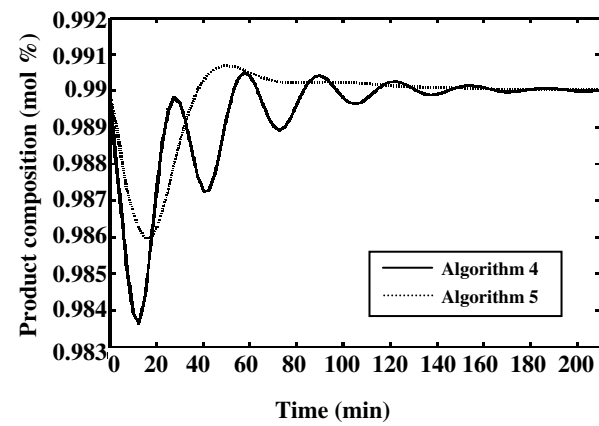
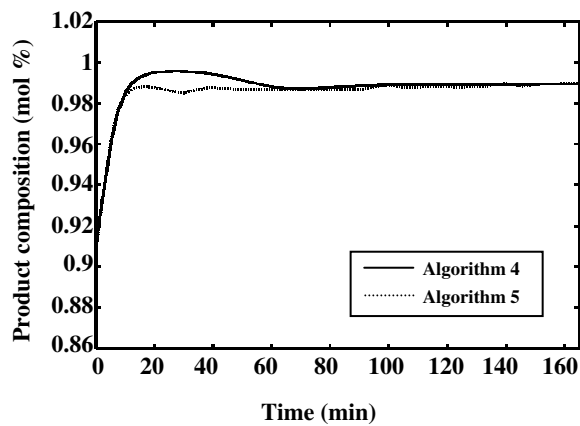
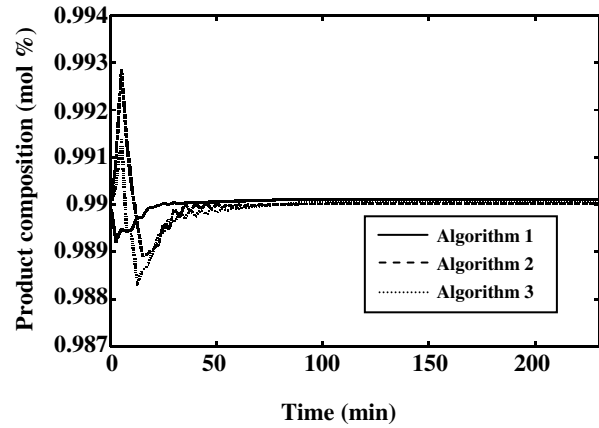
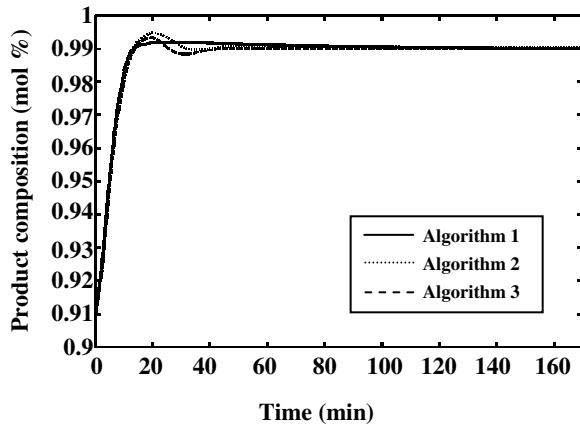


Fig. 8: Setpoint tracking results a) algorithm 1 (solid line), algorithm 2 (dotted line) and algorithm 3 (dash line) b) algorithm 4 (solid line) and algorithm 5 (dotted line).

Fig. 9: Load rejection results a) algorithm 1 (solid line), algorithm 2 (dash line) and algorithm 3 (dotted line) b) algorithm 4 (solid line) and algorithm 5 (dotted line).

### Nomenclatures

$A_1, B_1, C_1$	Polynomials of $z^{-1}$
$A_{tray}$	Active area of the tray, ( $m^2$ )
$B$	Bottom product flowrate, (kmole/min)
$C$	Product composition
$D$	Distillate flowrate (top product), (kmole/min)
$d$	Measurement delay
$e$	Estimation error
$eff_{i,k}$	Murphree efficiency for component (i) on tray k
$f$	Feed tray number
$F$	Feed rate, (kmole/min)
$G$	Polynomial of $q^{-1}$
$H$	Molar vapor enthalpy, (MJ/kmole)
$h$	Molar liquid enthalpy, (MJ/kmole)
$height_{tray}$	Total height of the tray, (ft)
$i$	Component index
$j$	Tray number

$K$	Vapor liquid equilibrium coefficient
$L$	Liquid flowrate leaving each tray, (kmole/min)
$Level_k$	Liquid level of tray k
$length_{weir}$	Tray weir length, (m)
$M_{i,k}$	Molar hold-up of component (i)
$N$	Number of trays
$N_c$	Number of component
$P_{i,k}^{sat}$	Saturated pressure of component 'i' in the temperature of plate 'k'
$P_k$	Total pressure of tray 'k'
$P$	Covariance matrix in least squares method
$Q_C$	Condenser external cooling rate, (MW)
$Q_R$	Reboiler external heating rate, (MW)
$R$	Recycle molar flow rate
$T$	Temperature, (k)
$V$	Vapor flowrate leaving each tray, (kmole/min)
$vol_{tray}$	Tray volume

Table 7: ISE values for load rejection.

Algorithm	Load 1
Algorithm 1	2.81e-4
Algorithm 2	2.54e-3
Algorithm 3	1.81e-3
Algorithm 4	3.26e-2
Algorithm 5	2.85e-3

w	Sidestream tray number
W	Side stream flowrate, (kmole/min)
X	Liquid mole fraction of component
y	Vapor mole fraction of component
$y_i^*$	Equilibrium vapor mole fraction of component (i)
$Z_{i,f}$	Mole fraction of component (i) in feed
$z^{-1}$	Backward shift operator
U	Energy hold-up
$\rho_k^v$	Vapor density
$\rho_{lk}$	Liquid density
$\theta$	Secondary process output
$\emptyset$	Vector of input-output
$\Theta$	Vector of parameter estimates

Received : 19<sup>th</sup> September 2005 ; Accepted : 20<sup>th</sup> November 2006

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