Chapter 8

Advanced Process Control

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Additional information is available at the end of the chapter

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Abstract

The debutanizer column is an important unit operation in petroleum refining industries. The top product is liquefied petroleum gas and the bottom product is light naphtha. This system is difficult to handle. This is because due to its non-linear behavior, multivariable interaction and existence of numerous constraints on its manipulated variable. Neural network techniques have been increasingly used for a wide variety of applications. In this book, equation-based multi-input multi-output (MIMO) neural network has been proposed for multivariable control strategy to control the top and bottom temperatures of the column. The manipulated variables for column are reflux and reboiler flow rates, respectively. This neural network model are based on multivariable equation, instead of the normal black box structure. It has the advantage of being robust in nature while being easier to interpret in terms of its input-output variables. It has been employed for set point changes and disturbance changes. The results show that the neural network equation-based model for direct inverse and internal model approach performs better than the conventional proportional, integral and derivative (PID) controller.

Keywords: distillation column, artificial neural network, equation-based method, multivariable process control

1. Introduction

Controlling two compositions require more complex instrumentation. The top and bottom composition loops interact and dynamic stability problems can arise. Holding heat input or reflux constant simplifies the control system and avoid interaction problem. Composition of the column are based on online measurement performance variable directly related to composition. The common measurement is temperature. However, temperature-composition relationship is influenced by column pressure control. If temperature is used as a control variable, the sensing element is usually not placed directly in the product stream. Often, product streams are relatively pure so that boiling point is relatively insensitive to small changes in concentration. Instead of investigating the steady state column temperature profile, the sensing element should be located at the tray from the end, at a point where the gradient is large. At this point, a fixed change in product composition causes a larger temperature change. Controlling the temperature gives tight control on product composition despite wide variations in other factors such as internal reflux ratio [1]. The variables that need to be controlled are the top and bottom temperatures and the variables that need to be estimated is top and bottom compositions. Application of composition control to both ends of a debutanizer column has been considered with generally little success. The difficulty results because two individual control loops interact. The top loop controls the heavy key in the overhead stream and the bottom loop controls the light key in the bottom stream. Some disturbances cause the light key concentration in the bottom stream to increase. The lower loop acts to reduce the concentration by adding heat. This action lowers the light key concentration sends more heavy key up the column. If both loops are tuned tightly, the column becomes unstable, and the system can be stable by detuning one loop. Processes with only one output being controlled by a single manipulated variable are classified as single-input single-output (SISO) system. Many processes do not conform to such a simple control configuration. In the process industries, any unit operation cannot do so with only a single loop. In fact each unit operation requires control over at least two variables, product rate and product quality. Systems with more than one control loop are known as multi-input multi-output (MIMO) or multivariable control system. There will therefore be a composition control loop and temperature control loop. Minimization of energy usage is achievable if the compositions of both the top and bottom product streams are controlled to their design values, which are called dual composition control [1]. A common scheme to overcome this problem is to use reflux flow to control top product composition while the heat input is used to control bottom product composition. Loop interaction may also arise as a consequence of process design, typically the use of recycle streams for heat recovery purposes. Changes in the feed temperature will in turn influence bottom product composition. It is clear that interaction exists between the composition and pre heat control loops. The simple approach in dealing with loop interactions is by the design of multivariable control strategies. This is to eliminate interactions between control loops [1]. The outline in the book for this chapter is the multivariable controller used consists of neural network equation based for the forward model and inverse model. The multivariable control system is to control the top and bottom temperature and estimating the top and bottom composition. The use of the neural network-based controller compared to conventional PID controllers is because all the process variables surrounding the debutanizer column are non-linear in nature and PID could not handle non-linearities.

The use of neural network models and controllers from available literature involve the use of black box models. This method is non-versatile and non-robust in nature and difficult to handle due to the relationship between the inputs and outputs of the system, which are important for industry. In this book, the main contribution and novelty, the proposed is to use an equation based inverse neural network models in a multi-input multi-output (MIMO) system to control the top and bottom temperature of the column simultaneously. The control structure is by using the direct inverse control (DIC) and internal model control (IMC) approach. Neural network equation-based models have also been used for the column to estimate the compositions as estimator. The other contribution of this book is that it utilizes a

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mixture of online close loop and open loop data that are available from industry for training the neural network models.

2. Application of artificial neural network

Artificial neural network (ANN) is a reliable and popular tool when dealing with problems involving prediction of variables in engineering at the present age. Details of the ANN application can be found in literature [2–7]. The main advantage of ANN is in its ability to estimate an arbitrary function mechanism that learns from data that is input to the network. However, it is not an easy step to apply neural network for control purposes. Good understanding of the underlying theory is essential and important. The first important criteria are the model selection which depends on the data representation and its application. A significant number of experiments are required for selecting and tuning an algorithm for training. The other criteria that are involve for training is robustness analysis. For the model, cost function and learning algorithm are important to be selected appropriately, so that the ANN final result can be robust. Neural network has been extensively used for a wide of chemical engineering applications which involve identification, control and prediction. Work has been done of various applications using neural network for control simulation and online implementation for chemical processes can be seen in literature [2].

As for today feed forward neural network (FANN) architecture is the widely used neural network architecture. It has a global approximation model for a multi-input multi-output function for fitting a low-order polynomial through a set of data. Various collection of different learning and network algorithms are available [8, 9] but the network is important to be selected as the basic building block. The formula describing the networks in mathematical form takes the following equation

$$y = F_i\left[\sum_{j=1}^{n_k} W_{i,j}.f_j\left(\sum_{l=1}^{n_\varphi} w_{j,l}\varphi_l + w_{j.0}\right) + W_{i.0}\right] \tag{1}$$

where φ is the external input, n_φ is the number of input in an input layer, n_k is the number of hidden neurons in a hidden layer, W and w are the weights. The activation functions for hidden layer and output layer are f and F, respectively.

In order to model the system dynamically using recurrent neural network (ELMAN) or neural network with ARX, in this book neural network with non-linear autoregressive network with exogenous inputs (NARX) structure which are used to model the dynamic system based on time-series data gives optimum result. The equations describing the NARX structure can be expressed as follows

$$Y = f(Y_1, Y_2, \ldots, Y_n,\ \ U_1, U_2, \ldots, U_m) \tag{2}$$

where $Y = [y_1(k+1)\ \ y_2(k+1)]^T$; $Y_1 = [y_1(k), y_1(k-1), \ldots, y_1(k-ny_1)]$, …, $Y_n = [y_n(k), y_n(k-1), \ldots, y_n(k-ny_n)]$; $U_1 = [u_1(k), u_1(k-1), \ldots, u_1(k-nu_1)]$, …, $U_m = [u_m(k), u_m(k-1), \ldots, u_m(k-nu_m)]$ and

m is number of input variables n is number of output variables and n_y and n_u are the history length for output variables and input variables, respectively. The model was trained, validated and test for different number of neurons together with the n_y and n_u values. The time lags in the input and manipulated variables, that is, n_y and n_u are chosen based on trial and error and the values are give to be n_y = 3 and n_u = 2, respectively, on the combination that gives the lowest RMSE values with the least lag time. It is observed that the lowest RMSE for the top and bottom temperature during training, validation and test occurs at same configuration. This is also based on experience from various literatures on dynamic modeling using NN-based models for non-linear chemical processes [10, 11].

However, the applications used previously have neural network utilized as a black box model, which has its own disadvantages. This limitation using black box model is due to robustness. In this book, the proper choice of the activation function and the neural network model can be represented by equation in form of algebraic. The equation used to approximate the output from the neural network model can estimate for a two layer network as follows

$$y = f^2\left(LW^{2,1}f^1\left(IW^{1,1}p + b^1\right) + b^2\right) \tag{3}$$

where $IW^{1,1}$ = weight at layer 1; b^1 = bias value at layer 1; $LW^{2,1}$ = weight at layer 2 (hidden layer); b^2 = bias value at layer 2; p = inputs to the neural network; y = outputs from the neural network; f = activation function at layer i.

By multiplying the matrix input layer and the biases value with the matrix hidden layer, the f^1 and f^2 are simplified. By choosing the activation function to be linear, the equation can be simplified in the form of

$$y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \left[LW^{2,1}\left[IW^{1,1}p + b^1\right] + b^2\right] \tag{4}$$

where the matrix definition $LW^{2,1}$, $IW^{1,1}$, b^1 and $b^2$are given as

$IW^{1,1}$ = weight at layer 1 (input layer); b^1 = bias value at layer 1; $LW^{2,1}$ = weight at layer 2 (hidden layer); b^2 = layer 2 bias value.

These representations can also be used in this book to estimate the top and bottom compositions. While the multivariable controllers are used to control the top and bottom temperatures simultaneously that will be shown in the next sections.

3. Control strategies neural network

There are two types of control strategies which are direct inverse control (DIC) and internal model control (IMC) methods are to be implemented for neural networks, which is the inverse model-based control schemes. These methods are described briefly in **Figures 1** and **2**.

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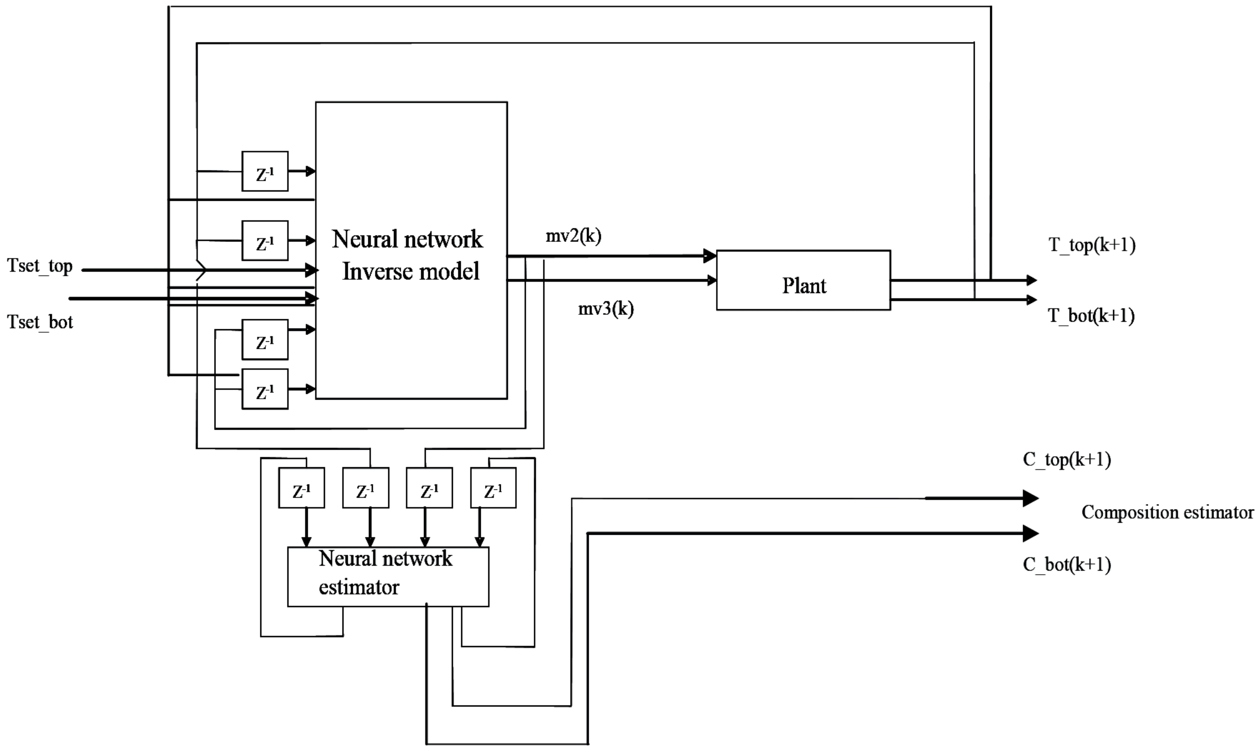

Figure 1. Control loop of neural network-based direct inverse model control (DIC).

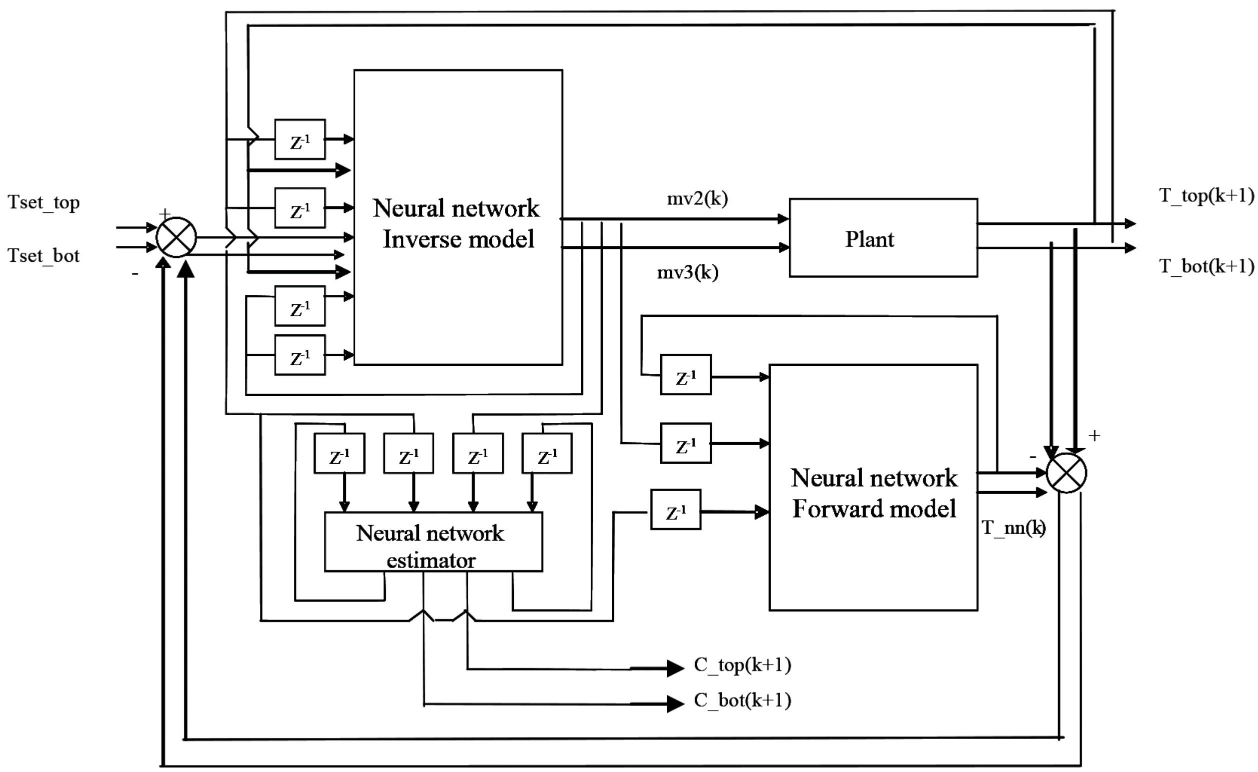

Figure 2. Control loop of neural network-based internal model controller (IMC).

3.1. Method 1: direct inverse control (DIC)

This control strategy which is placed in series with neural network inverse models acts as a controllers. In this scheme, the outputs will predict the system input, while the desired set point acts as the output which is then fed to the network with the past plant inputs. In this case, the appropriate control parameter for the desired target will be predicted based on its input. Neural networks acting as the controller has to learn to supply at its input. As shown in **Figure 1**, the inverse model is then utilized in the control strategy by cascading it with the controlled system or plant. This method depends on the accuracy of the inverse model. The controlled variables used in this method are the top and bottom temperatures. The manipulated variables are the reflux and reboiler flow rate for the DIC method.

3.2. Method 2: internal model control (IMC)

Neural network-based IMC method highlighted in this book are presented in both inverse and forward model control scheme. The dynamic forward model of the process represents it is placed in parallel within the system. This is important to cater for mismatches of the model during implementation [12]. On the other hand, the inverse model could also be used as a controller. In this scheme, the error between the plant output and the neural network forward model is then subtracted from the set point before being fed into the inverse model, as shown in **Figure 2**. With this detection feature, the internal model-based controller can be used to move forward the controlled parameter to the desired set point even when disturbances and noise are present. The optimum performance for controller performance is the IMC method. The error produced by the process model could be minimized and compensated by the error produced by the neural network forward process model [12]. The controlled and manipulated variables used in the IMC method are similar to the DIC method.

3.3. Neural networks models

Before applying the inverse model neural network control strategies for the debutanizer column, it is crucial to discuss the development and configuration of the forward and inverse models. Using neural network architecture and equation-based neural network are important fundamentals to these model-based control strategies as necessary.

3.3.1. Forward models

The procedure of training a neural network to represent the forward dynamics of a column is by predicting the outputs using the required inputs. This method is called forward modeling. The straightforward and good approach is to augment the network inputs data in real forms, from the model and system being identified [13, 14]. Other fundamental variables under state can also be fed into the network and considered as inputs. In this method, the network is fed with the present input, past inputs as well as the past outputs to predict the desired output. The neural network model is placed in parallel with the system. The error between the system output and network output are the prediction error which is used as the training signal for the network. The forward models that have been mentioned previously are used to determine the inverse model. The forward model which is inversed to get the inverse model is then changed to the equation based. The equation-based method has been used to replace the black box model neural network for IMC and DIC method. The inverse models as controllers are used in the IMC and DIC methods. The composition forward models are used as a neural network estimator to predict the top and bottom compositions.

The forward model for temperature is as follows

In this case, p is the input to the neural network temperature given by the vector

$$\begin{bmatrix} mv1(k)\ \ mv1(k-1)\ \ mv2(k)\ \ mv2(k-1)\ \ mv3(k) \\ mv3(k-1)\ \ f(k)\ \ f(k-1)\ \ T_{top}(k)\ \ T_{top}(k-1)\ \ T_{bot}(k)\ \ T_{bot}(k-1) \end{bmatrix}^T \tag{5}$$

After pruning the neural network structure (simplifying the weights and biases values), p is given as matrix vector are defined in Eq. (6)

$$y = \begin{bmatrix} T_1 \\ T_2 \end{bmatrix} = \begin{bmatrix} -0.16 & -0.14 & 0.04 & -0.002 & -0.094 & -0.95 & 1.03 & -0.61 & -0.71 & 0.81 & 0.16 & -0.049 \\ 0.42 & 0.07 & 0.04 & 0.20 & -0.30 & -0.19 & 0.12 & -0.28 & 0.35 & -0.29 & -0.48 & 0.168 \end{bmatrix} p + \begin{bmatrix} -0.28 \\ -0.22 \end{bmatrix} \tag{6}$$

T_1 and T_2 is the output neural network top and bottom temperature prediction.

3.3.2. Neural network estimator

The forward model for neural network for composition is composition n-butane used for control system IMC method is as follows

In this case, p is the input to the neural network composition given by the vector

$$\left[mv2(k)\ \ mv2(k-1)\ \ mv3(k)\ \ mv3(k-1)\ \ f(k)\ \ f(k-1)\ \ p_{top}(k)\ \ p_{top}(k-1)\ \ p_{bot}(k)\ \ p_{bot}(k-1)\right]^T \tag{7}$$

After pruning the neural network structure (simplifying the weights and biases values), Eq. (7) can further be simplified to give the composition Eq. (8)

$$\begin{bmatrix} y1 \\ y2 \end{bmatrix} = \begin{bmatrix} -0.26 & 0.15 & 0.37 & 0.23 & 0.38 & 0.40 & -0.50 & 0.97 & 0.12 & -0.31 \\ -0.09 & 0.006 & 0.31 & -0.10 & 0.02 & 0.02 & -0.42 & -0.12 & 0.36 & -0.085 \end{bmatrix} p + \begin{bmatrix} -0.28 \\ -0.21 \end{bmatrix} \tag{8}$$

y_1 and y_2 is the output neural network bottom and top composition predictions.

3.3.3. Models for inverse

Inverse models are basically the structure by representing the inverse of the network dynamics after the completion of training. The methods for inverse models are achieved by switching the required outputs and inputs. The important manipulated variable that is used for switching the inputs of the neural net is the manipulated variable reboiler and reflux. The outputs predicted are the future predictions of top and bottom temperatures are switched with the manipulated variables. The sequence of the inputs of the network needs to be maintained. The training procedure outlined in this book is called inversed modeling. $y(k+1)$ is the required set point. The network representation of the inverse is finally given below

$$u(k) = f^{-1}\left[y_p(k+1), y_p(k), y_p(k-1), u(k), u(k-1)\right] \tag{9}$$

where f^{-1} represents the inverse map of the forward model.

In this case the manipulated variable reboiler and reflux flow rate are the output variable which are used in inverse model. The one-step ahead prediction of the control output, $mv2$ (k) and $mv3$ (k) is performed inconformity with that of the forward model. The one-step ahead control action application in the control strategies involving the neural network-based strategies.

The training and validation data set are predicted for inverse model for the networks are similar to that used for forward modeling. Nevertheless, inverse model will have different input and output configuration.

The inverse model for temperature is as follows

In this case, p is the input to the neural network inverse temperature given by the vector

$$\begin{gathered}[mv1(k)\ \ mv1(k-1)\ \ mv2(k-1)\ \ mv3(k-1)\ \ f(k)\ \ f(k-1)\ \ T_{top}(k+1)\ \ T_{top}(k)T_{top}(k-1)\\ T_{bot}(k+1)\ \ T_{bot}(k)\ \ T_{bot}(k-1)]^T\end{gathered} \tag{10}$$

After simplifying the weights and biases values by pruning the neural network structure Eq. (10) can further be simplified in order to give the inverse temperature below in a form of equation

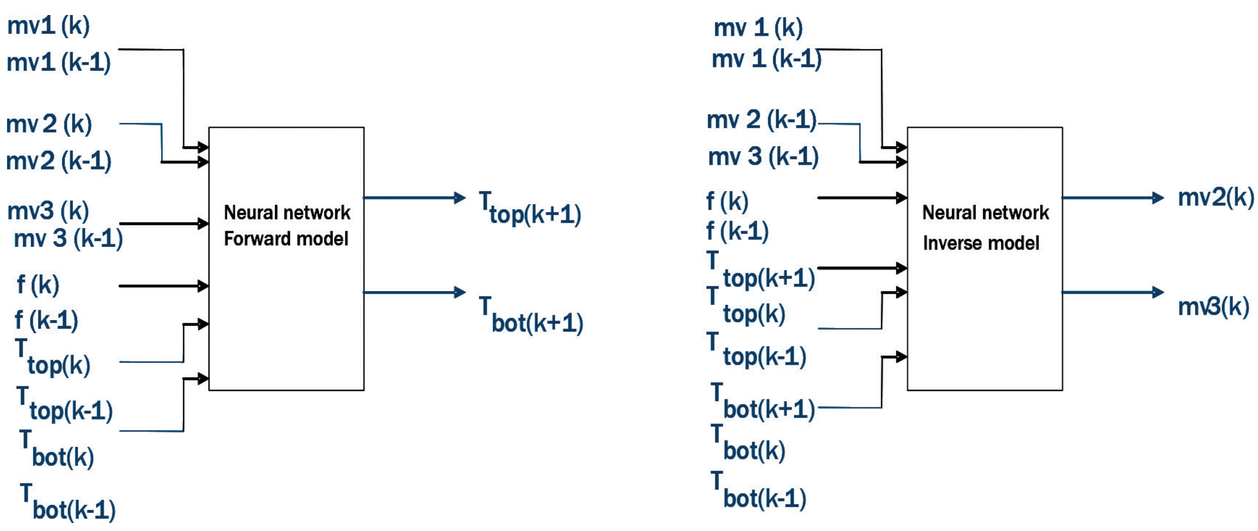

Figure 3. Forward and inverse models to control temperature.

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$$\begin{bmatrix} mv2(k) \\ mv3(k) \end{bmatrix} = \begin{bmatrix} -0.16 & 0.14 & 0.039 & -0.004 & -0.09 & -0.95 & 1.03 & -0.61 & -0.72 & 0.81 & 0.17 & -0.05 \\ 0.42 & 0.077 & 0.039 & 0.20 & -0.30 & -0.19 & 0.13 & -0.27 & 0.34 & -0.28 & -0.47 & 0.16 \end{bmatrix} p + \begin{bmatrix} -0.79 \\ -0.008 \end{bmatrix} \tag{11}$$

$mv2(k)$ and $mv3(k)$ is the manipulated variable reflux and reboiler flow rate, respectively. The equation is implemented in SIMULINK in MATLAB by having the system with more than one control loop which are multi-input and multi-output (MIMO) or multivariable control. **Figure 3** shows the forward and inverse model to control temperature.

4. Neural network development

The control strategies used in this work are DIC and IMC method. In order to develop and analyze the controller performance for the debutanizer column, there are two criteria for advanced process control which are the set point changes and disturbances changes applied to the column. The set point changes is the step increases for the temperature and the disturbances changes is by introducing a disturbance of the column feed temperature. The performance of the composition are used based on using a neural network estimator.

4.1. Set point changes

First the top temperature is increased from 30 to 58°C. The bottom temperature is increased from 60 to 137°C. The starting point for the top temperature is 30°C and for bottom temperature is 60°C. This is because the starting point temperature mentioned here is based on the experience of the engineers to maintain and control that particular temperature. **Figures 4** and **5** show the fluctuation of the top and bottom temperature due to set point changes. There are three types of control strategies implemented for the control strategies which are the IMC, DIC and PID controller. It can be seen that IMC and DIC show similar trends with small error, no overshoot and fast settling time and straight goes to the set point. The settling time for top and bottom temperatures fluctuation is at 200 min. The IMC and DIC method gives the least fluctuations for the set point changes. The fluctuations during step point changes for the PID controller does not give good results because it has large overshoot and small decay ratio. The settling time for PID also shows large value compared to the IMC and DIC methods. The PID controller also produces some offset when there are changes made for set point changes. This applies to the top and bottom temperatures, respectively. **Table 1** shows the PID tuning for the column. **Table 2** shows the performance of the controller to control the top and bottom temperature. The results indicate that IMC equation gives the optimum performance as the Integral absolute error (IAE), Integral square error (ISE) and Integral time weighted error (ITAE) values is the smallest compared to the result of the controller. **Figures 6** and **7** show the fluctuation of the manipulated variables to control temperature. The neural network would be able to predict the manipulated variable for reboiler and reflux accurately compared to PID

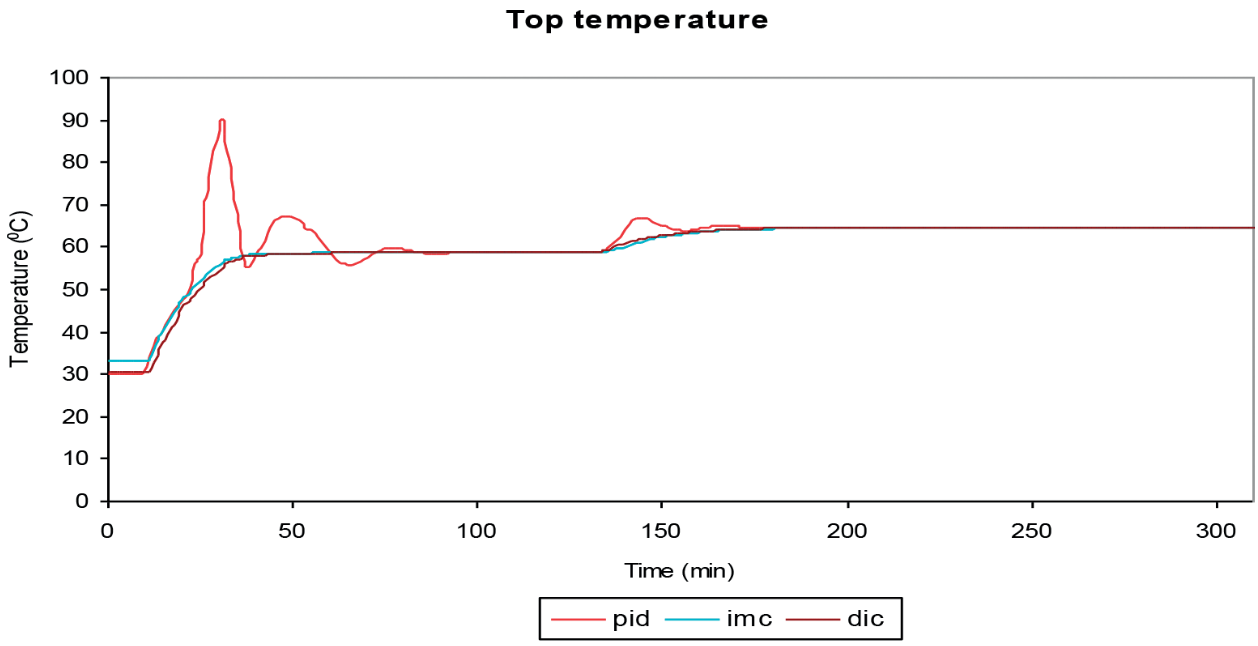

Figure 4. Set point top temperature.

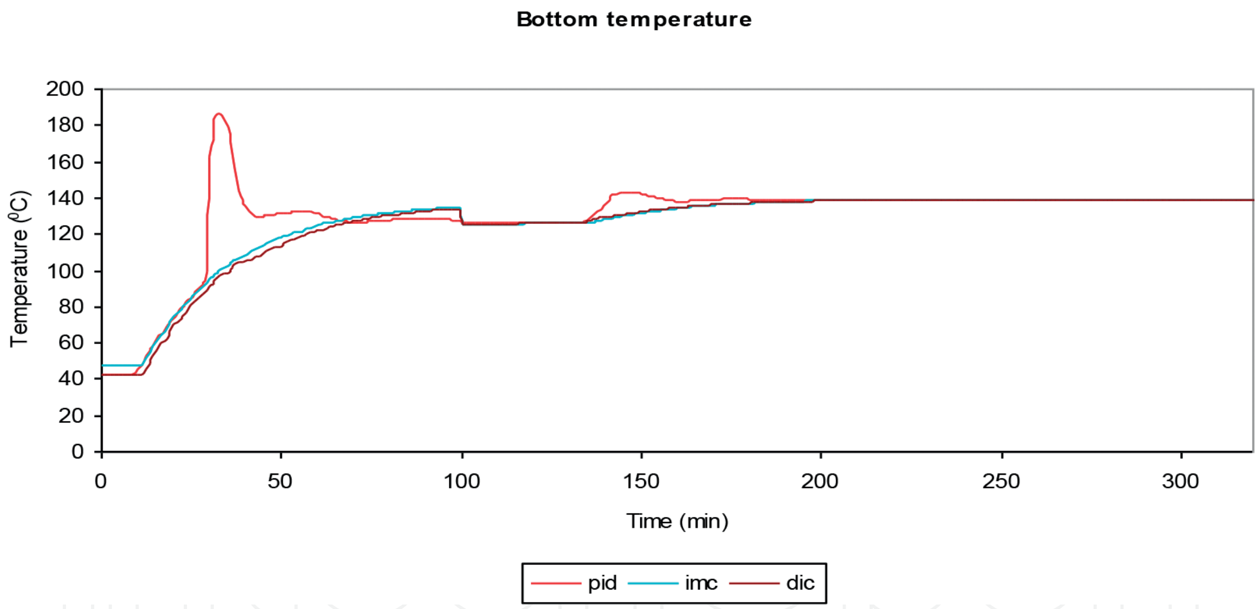

Figure 5. Set point bottom temperature.

Parameter	K_c	T_i	T_d
Top temperature	0.71	1.41	20
Bottom temperature	1.76	3.25	15
Top composition	137.32	3.26	10
Bottom compositon	87.36	3.26	5

Table 1. PID tuning.

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	IMC eq	DIC eq	PID
IAE top	830.76	912.78	1219.70
IAE bottom	3809	4289	4666
ISE top	2.10E+02	2.23E+02	2.69E+02
ISE bottom	1.21E+02	2.67E+02	3.06E+02
ITAE top	4.25E+02	4.48E+02	1.44E+03
ITAE bottom	1.92E+02	2.16E+02	4.45E+02

Table 2. Controller performance during set point changes.

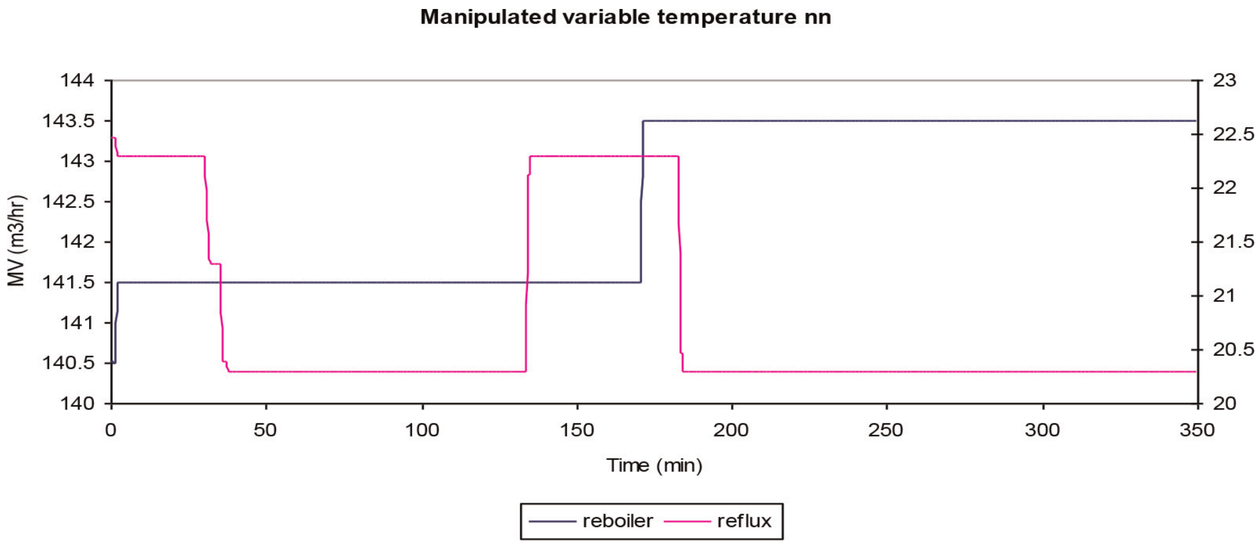

Figure 6. Manipulated variable temperature neural network.

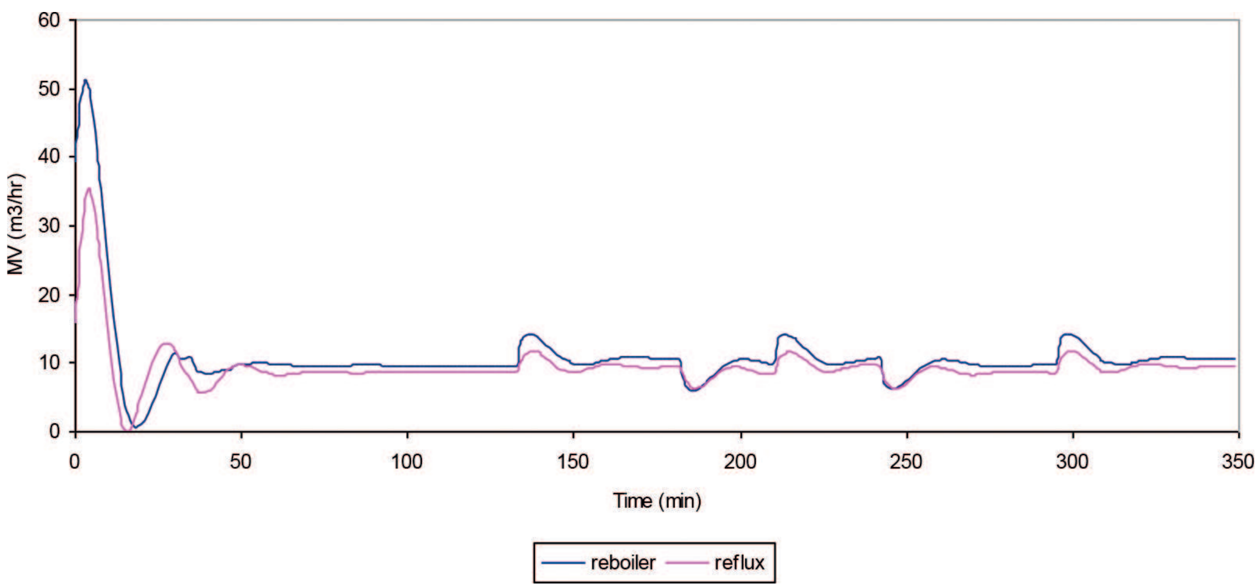

Figure 7. Manipulated variable temperature PID.

controller. Therefore the performance of neural network is better. The fluctuations of the manipulated variable for the reboiler and reflux are very important to see how the controller calculates the error for a control system. The fluctuations for reboiler and reflux flow rate for temperature based on PID show similar trends as time progresses. The units for the calculated IA, ISE and ITAE are dimensionless.

4.2. Disturbances test

Figures 8 and **9** show the fluctuations for the top and bottom temperatures due to disturbances. The disturbances introduced to the debutanizer column are the feed temperature. Similar trends are observed for DIC and IMC methods for the top and bottom temperatures because of disturbances. The neural network control performs well compared to PID controller because there is no overshoot, fast settling time and small error. The PID controller gives unacceptable results as they perform with high overshoot, some offset and large error. This also applies to the top and bottom temperatures. **Table 3** shows the performance of the controller to control the top and bottom temperatures. Results indicate that IMC equation gives the optimum performance as the values of IAE, ISE and ITAE are the smallest compared to other controller. **Figures 10** and **11** show the fluctuation of the manipulated variable to control temperature. The neural network would be able to predict the manipulated variable for reboiler and reflux accurately compared to PID controller. Therefore the performance of neural network is better. The fluctuation of the manipulated variable for the reboiler and reflux flow rate is very important in order to see how the controller calculates the error for a given control system. The fluctuations for reboiler and reflux flow rate for temperature based on PID shows similar trends as time progresses.

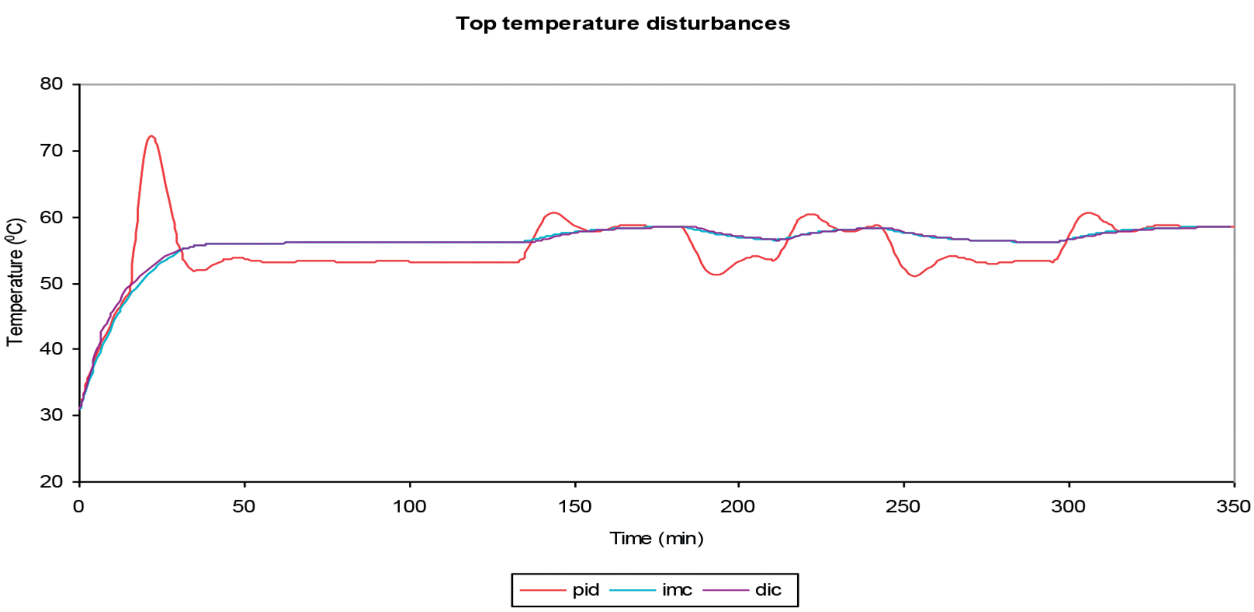

Figure 8. Disturbances top temperature.

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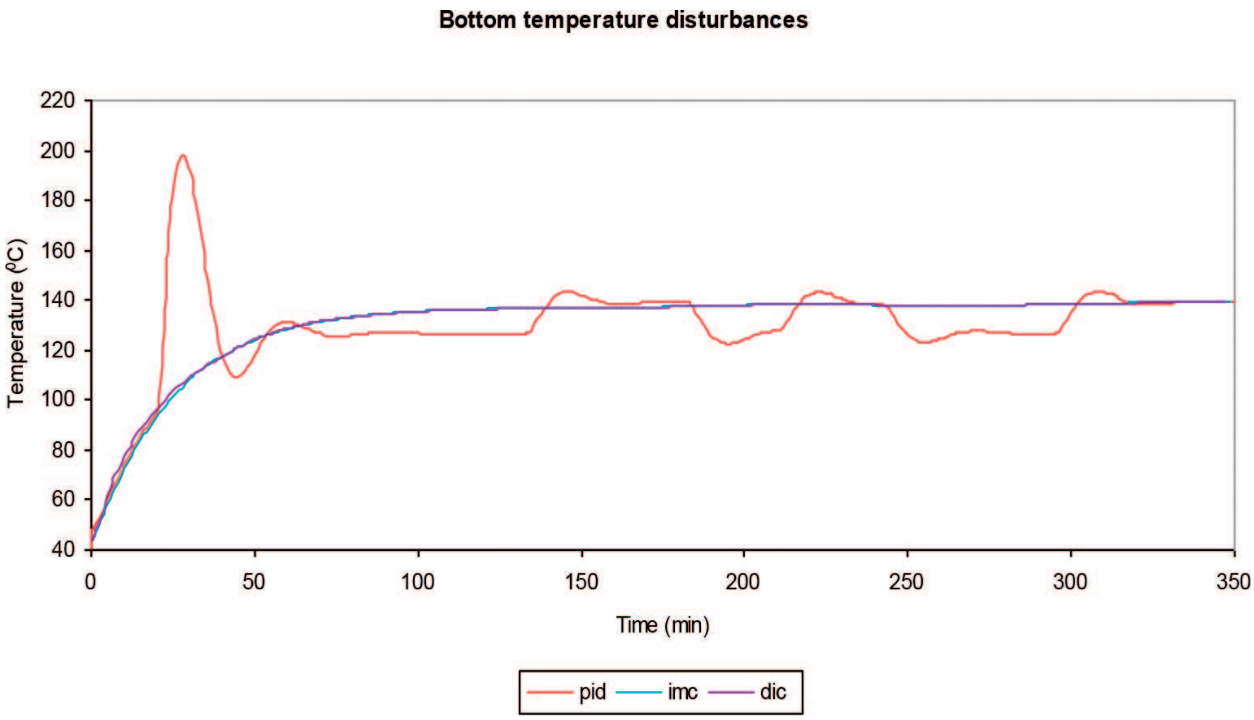

Figure 9. Disturbances bottom temperature.

	IMC eq	DIC eq	PID
IAE top	817.21	836.95	1736.30
IAE bottom	2811.80	2876.00	7891.20
ISE top	6.02E+02	6.63E+02	3.37E+03
ISE bottom	1.14E+02	1.23E+02	1.75E+03
ITAE top	7.78E+02	7.90E+02	1.78E+03
ITAE bottom	1.28E+02	1.30E+02	4.64E+02

Table 3. Controller performance during disturbance changes.

4.3. Estimator neural network

The neural network estimator used in the IMC and DIC method is to estimate and monitor the top and bottom compositions. **Figures 12** and **13** show the fluctuations for the top and bottom compositions which are due to set point changes. For the neural network estimator for IMC for top composition are favorable than DIC method. This is due to the settling time to settle to the required set point for the composition is fastest. This could conclude that both IMC and DIC method perform better compared to the conventional PID controller. This is because the error is small with no overshoot. The results for PID controller are unacceptable because of large overshoot, large error and longer settling time. For the bottom composition fluctuations, the IMC and DIC methods show similar trends. Both methods show better fluctuations compared to PID controller. **Figure 14** shows the fluctuation of the manipulated variable for composition.

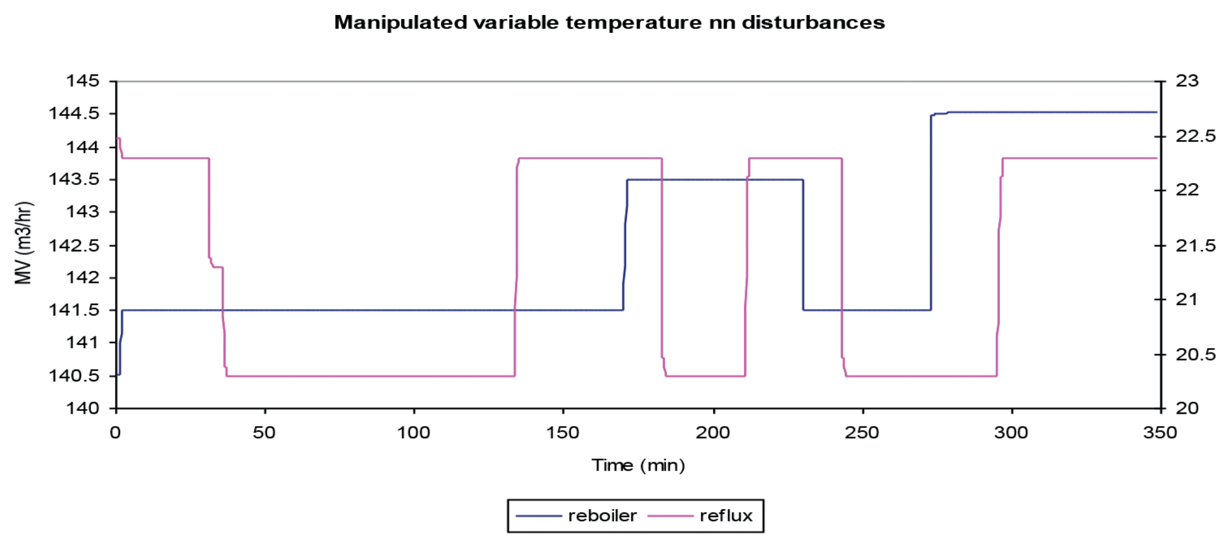

Figure 10. Manipulated variable temperature neural network disturbances.

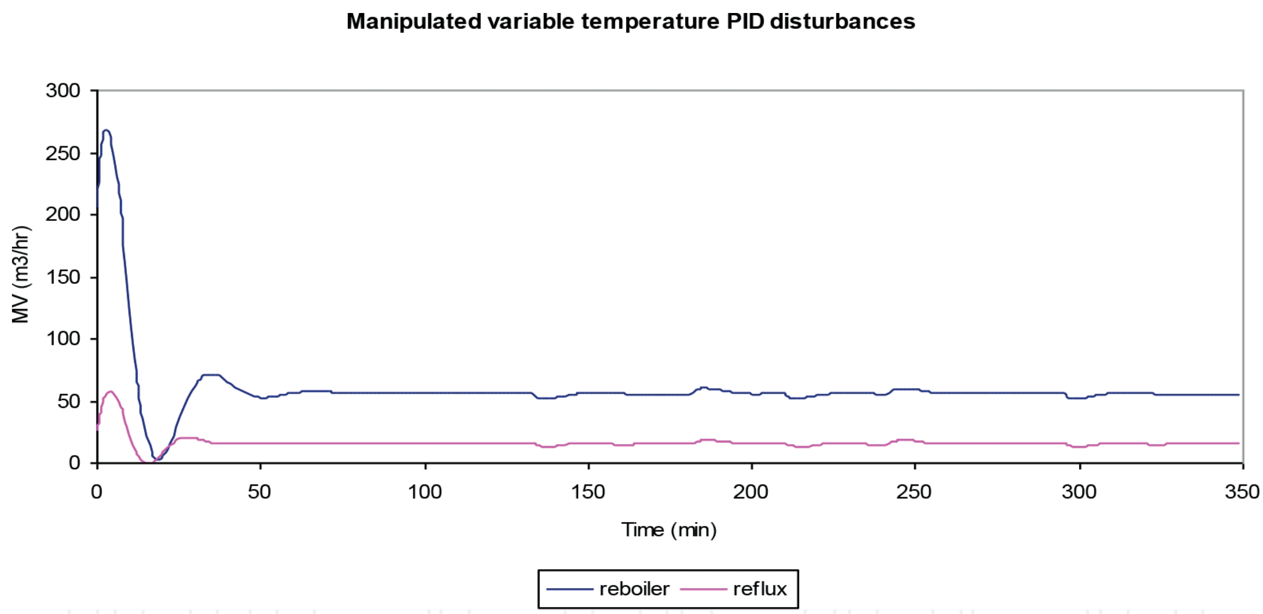

Figure 11. Manipulated variable temperature PID disturbances.

Figures 15 and **16** show the fluctuations for the top and bottom compositions due to disturbances. For the top composition for neural network controller for IMC and DIC methods, it could be concluded that the IMC trend shows similar results to the DIC method. The settling time for the required set point for the composition is similar. Both IMC and DIC methods are superior in comparison to the conventional PID controller. This is because the error is small with no overshoot. The results for PID controller are unacceptable that are due to large overshoot, large error and longer time to settle. For the bottom composition fluctuations, the

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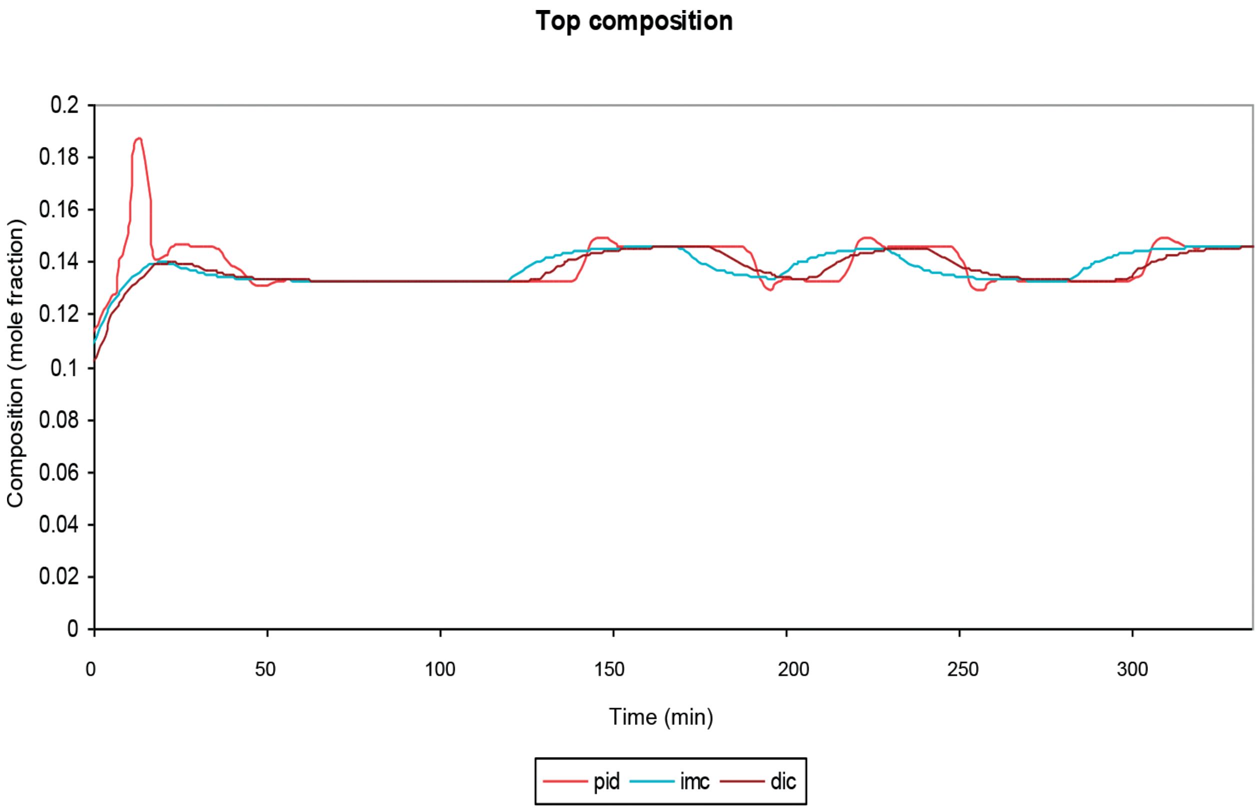

Figure 12. Neural network estimator for the top composition.

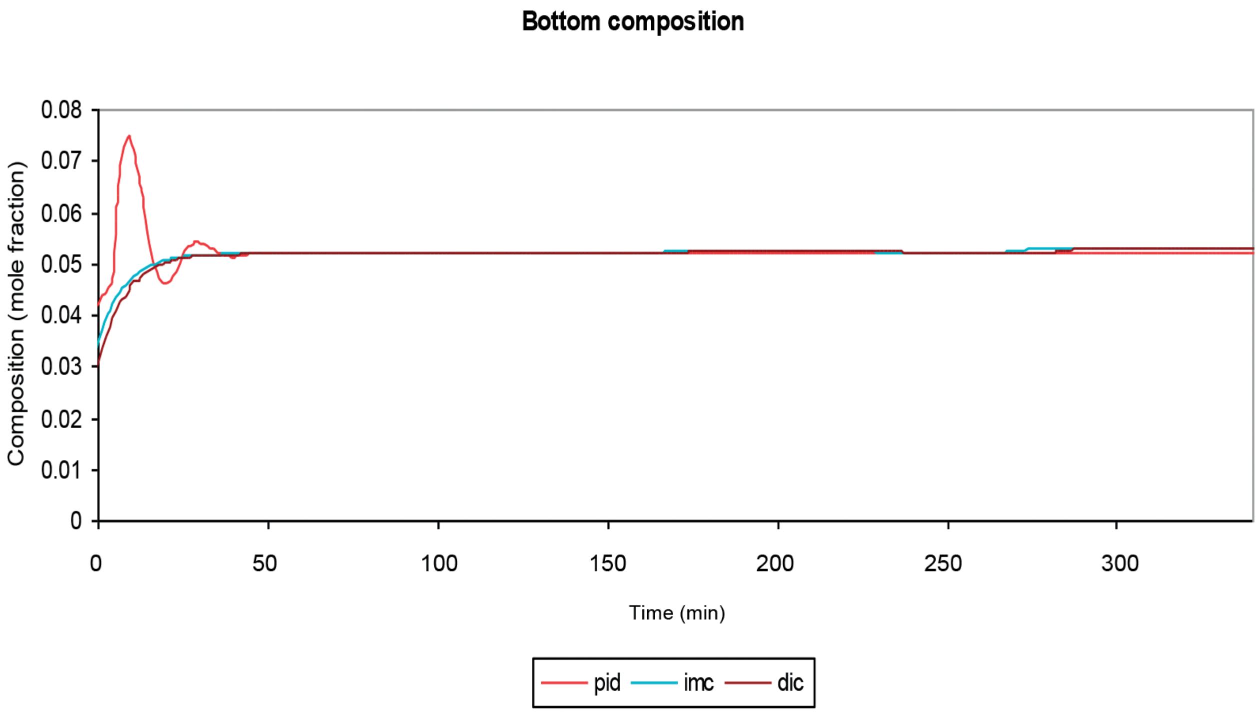

Figure 13. Neural network estimator for the bottom composition.

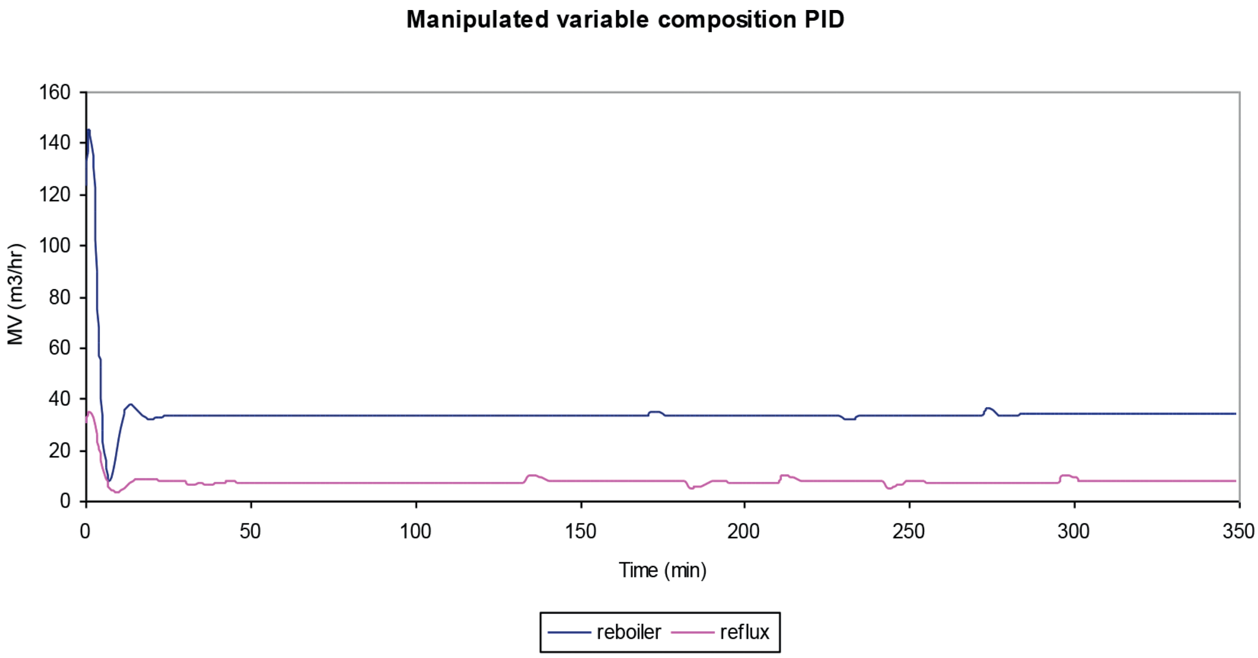

Figure 14. Manipulated variable compositions for PID.

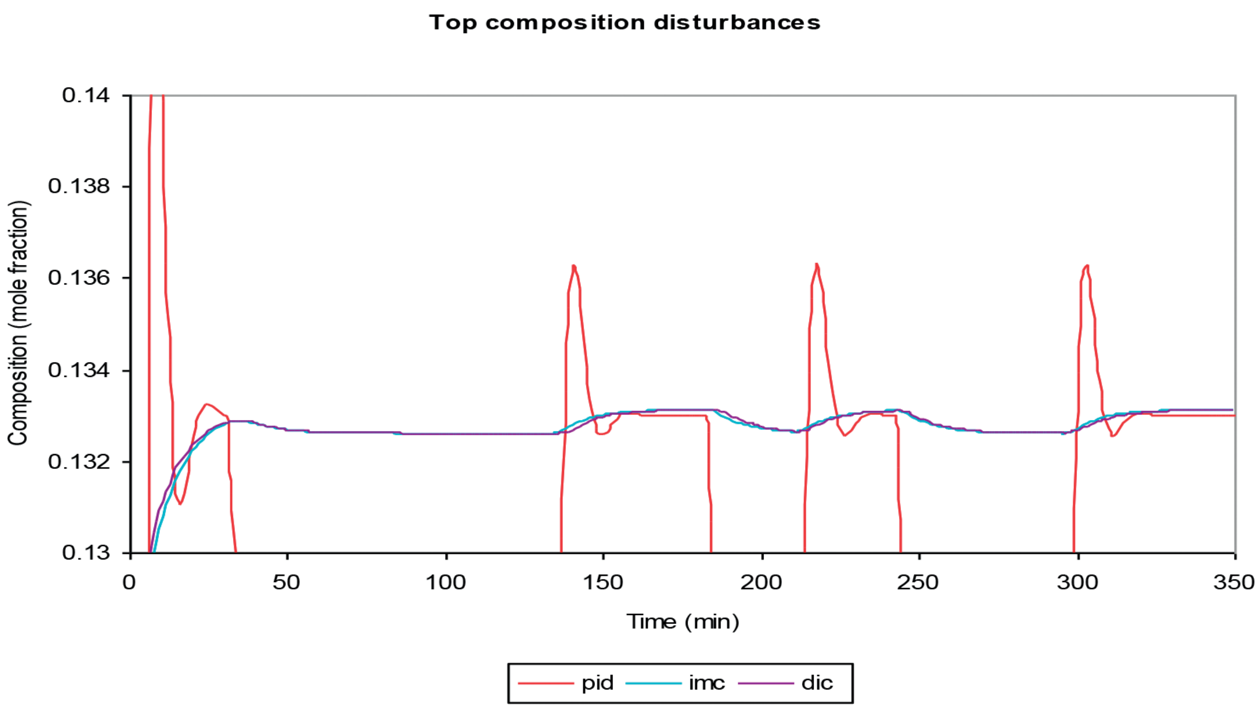

Figure 15. Top composition disturbances.

IMC and DIC methods show similar trends. Both methods show better fluctuations compared to PID controller. **Figure 17** shows the fluctuation of the manipulated variable for composition PID which is due to disturbances.

http://dx.doi.org/10.5772/intechopen.70704

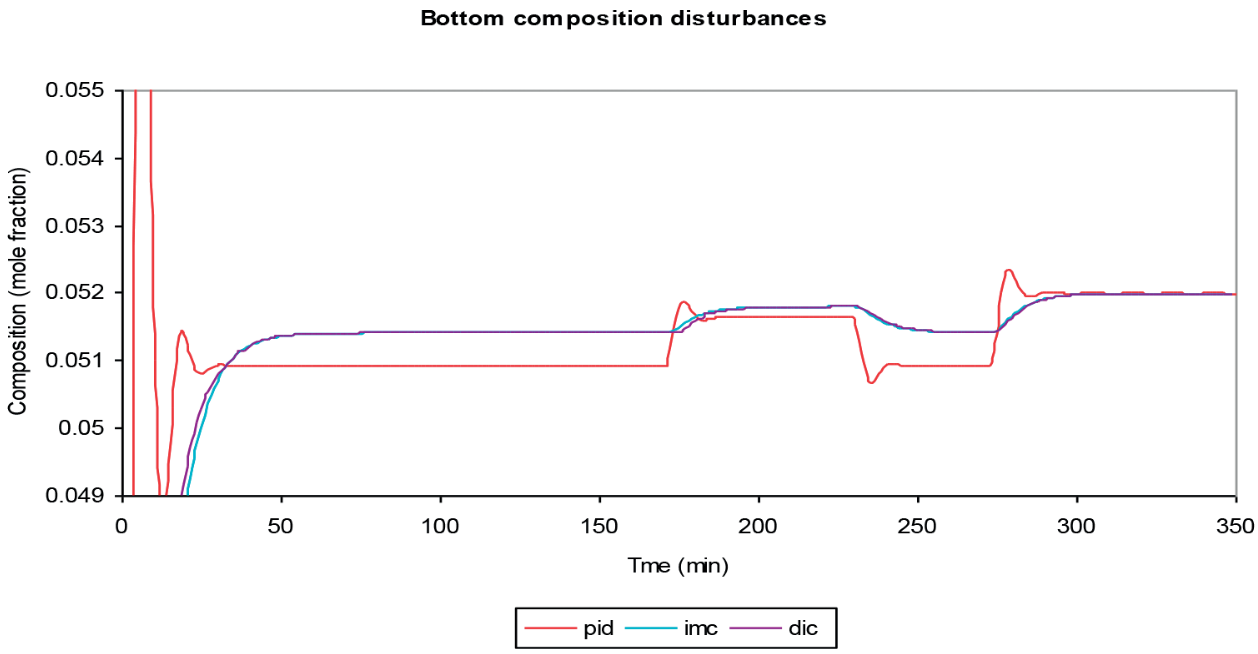

Figure 16. Bottom composition disturbances.

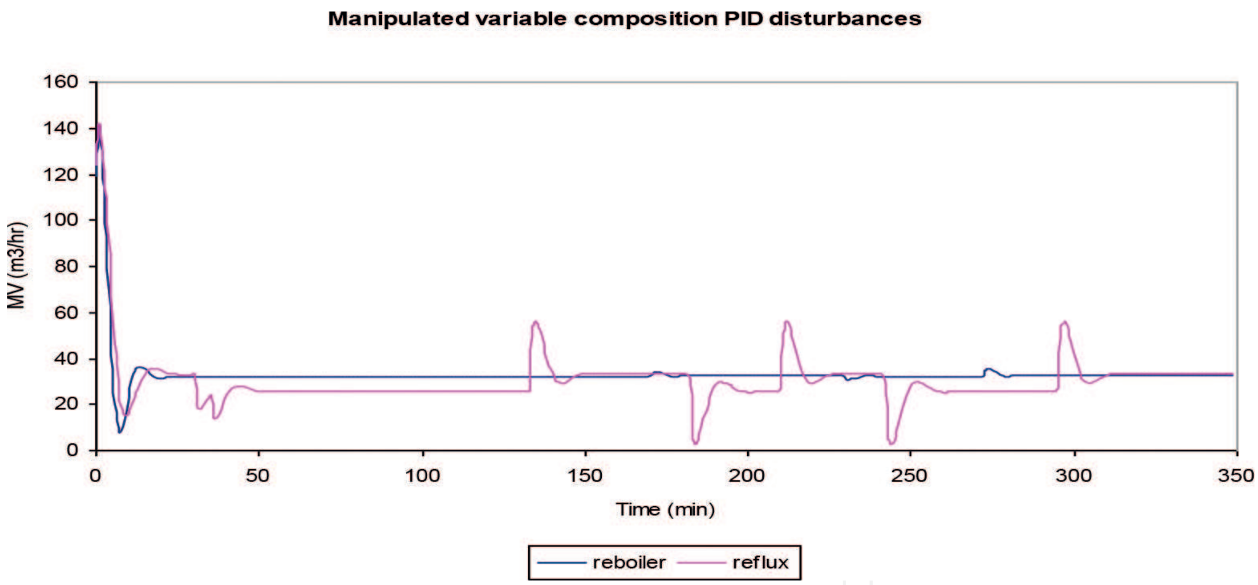

Figure 17. Manipulated variable compositions PID due to disturbances.

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