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Artificial Intelligent-Based Predictive Control of Divided Wall Column

Rajeev Kumar Dohare

Abstract

Distillation is the most popular thermal separation technique used in the chemical and petrochemical process industry for the liquid mixture separation. Certainly, the distillation has a plenty of advantages, yet it has a drawback such as more energy requirement. In order to reduce the energy consumption of the conventional distillation column, energy integration is applied within the distillation column. The most important thermally coupled distillation column sequence is the Petlyuk column, which uses two recycle streams. Petlyuk column is a novel design that integrates two distillation columns into one shell, which is known as a dividing wall column. A dividing wall column (DWC) offers the possibility to separate a multicomponent mixture into high-purity products or sharp splits. Artificial neural network predictive controller (ANNPC) has been implemented to control the DWC. The performance of the ANNPC control strategies and the dynamic response of the DWC are investigated in terms of the product composition in the different sections of the dividing wall column for the different persistent disturbances such as feed flow rate, feed compositions, and liquid split factor.

Keywords: artificial intelligent, DWC, BTX, distillation, simulation, MATLAB

1. Introduction

Divided wall column is the combination of four thermally coupled distillation columns. The schematic diagram of the DWC is shown in **Figure 1**.

Benzene-toluene-o-xylene (BTX) system as feed is the dividing wall column for separation purpose. Feed introduced into the prefractionator side of the wall. A side stream is removed from the other side. The side stream is mostly the intermediate boiling component of the ternary mixture. The lightest component (benzene) goes overhead in the distillate product, and the heaviest component (o-xylene) goes out in the bottom product. Therefore, a single dividing wall column can separate a ternary mixture into three pure product streams. Due to high interactions among the process variables and due to restricted experiences, it is very difficult to control by the conventional controller.

In many chemical processes, artificial neural network has been implemented successfully in the process identification and control of the nonlinear dynamic systems. This is the main reason to switch over to the recent control strategies such as artificial neural network, fuzzy logic, etc. All such control technique-based

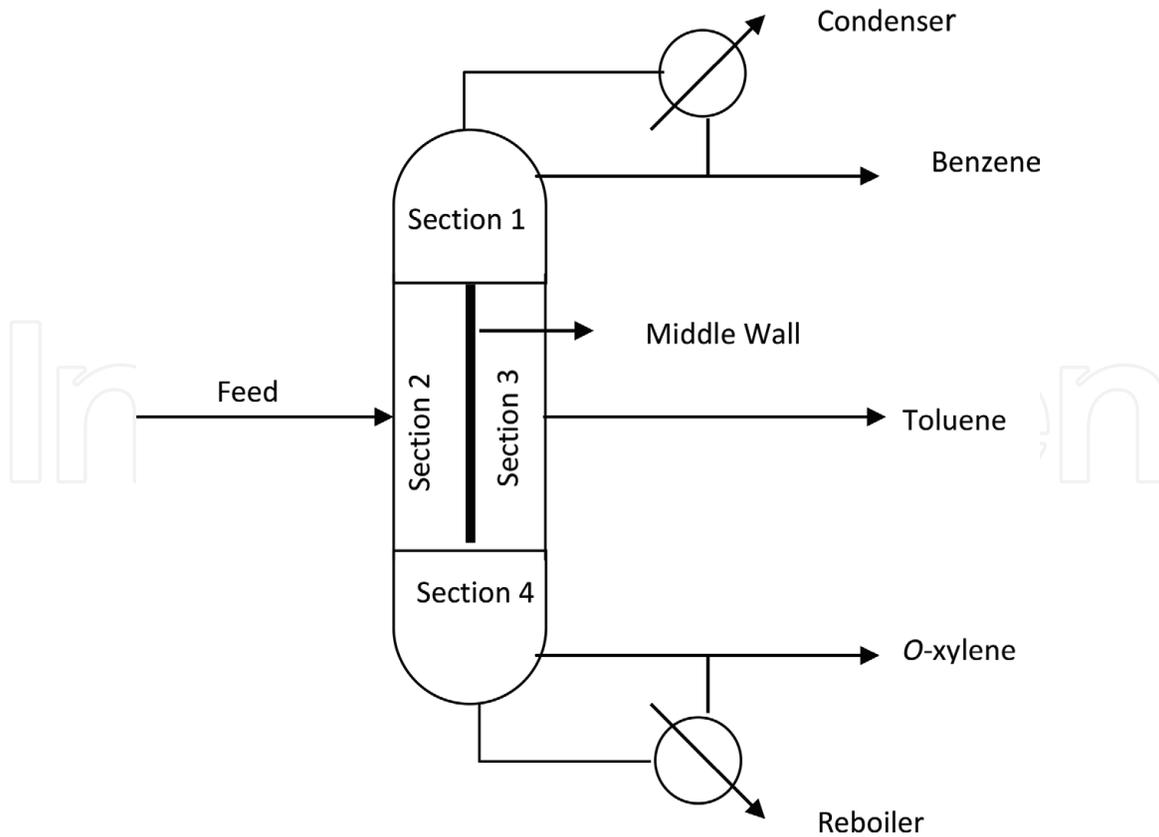


Figure 1.
Schematic diagram of divided wall distillation column.

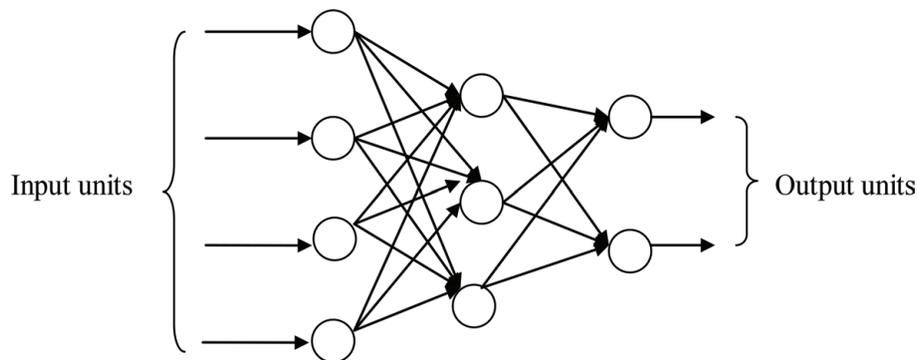


Figure 2.
ANN structure.

controllers are known as intelligent controllers. Settling time in the model-based controller is less in comparison to the conventional controller without compromising the product purities. To further improve the control performance, the artificial intelligence techniques were also attempted.

Artificial neural networks (ANN) have been designed on the complexities of the brain functions in an effort to capture the amazing learning capabilities of the brain as shown in the **Figure 2**. ANN is a parallel computer or processor designed to imitate the way the brain accomplishes a certain task [1]. The smallest processing element of ANN is a neuron or node, which helps to do sample calculations. Using the neurons collectively with massive connections among them results in a network that is able to process and store relative information for mapping the network inputs to its outputs. With this feasibility and its capability, there are most widespread

interests in solving complicate problems particularly in the fields of pattern recognition, control, forecasting, classification, system identification, and optimization.

Authors already discussed, about the desired product purity at the optimized operating parameters viz. feed tray location, reflux ratio, liquid reflux rate, vapor split ratio, etc. [2]. To control the dividing wall column is the big challenge for the control engineers due to its high dynamics. Conventional controller like PID is not performed well in comparison to the advanced controller which was shown by the authors in their research [3]. Artificial neural network has been applied on dividing wall column for controlling the tray temperatures that is based on predictive technique. Composition of the product in the dividing wall column is the main controlled variable but due to the measurement delay in the online analyzer, it is rarely used. For successful operation, monitoring, and controlling chemical process, an accurate online analyzer of important quality variables is essential. However, the measurement of all these variables online is a big task due to the limitations such as the high cost, time delay, and reliability, therefore they cannot be directly close-loop controlled. Composition is controlled indirectly by controlling the temperature of the different sections in DWC. To enhance the controllability, artificial neural network-based predictive controller (ANNPC) can be used to control the temperature of the different sections in the dividing wall column.

In actual industrial circumstances, it would be ensured that the equipment should be run safely and efficiently with the important process variables that relate mostly with system stabilizations and product qualities have to be controlled in real time. However, it is very difficult to measure these variables by online physical sensors and its economic issue [4]. Due to the importance of the control problem, many methods have been adopted in the past: the first method is a quality open-loop control, in which to get the quality of the products, the undue purification is required; the second method is useful indirectly to control the quality of close-loop, such as controlling the temperature at each plate in the column at different sections. But sometimes, this method cannot control the quality of the product; third method is online process gas chromatography. Due to its limitations like cost, reliability, and the time delay, it cannot satisfy the online control requirement of quality.

2. MIMO neural network generation

The artificial neural network predictive control was trained using Levenberg-Marquardt optimization algorithm. Hidden neurons use the sigmoid activation function, whereas output layer neurons use the linear activation function. The selection of the different layer neurons depends on the complexity of the problem. On a trial-and-error basis, a number of neurons were selected in this present study. The general structure of the neural network is shown in **Figure 1**. For the normalization, all the inputs and outputs should be dealt up with different magnitudes. The total number of data is divided into different parts for neural network model building: (1) training data, (2) validation data, and (3) testing data. First part of the data is used for training purpose, the second part for validation of the network structure, and third part of the data is useful to evaluate the selected model.

3. Artificial neural network predictive controller

Artificial neural network predictive control (ANNPC) is a combination of artificial neural network- and model-based controller. The multilayer

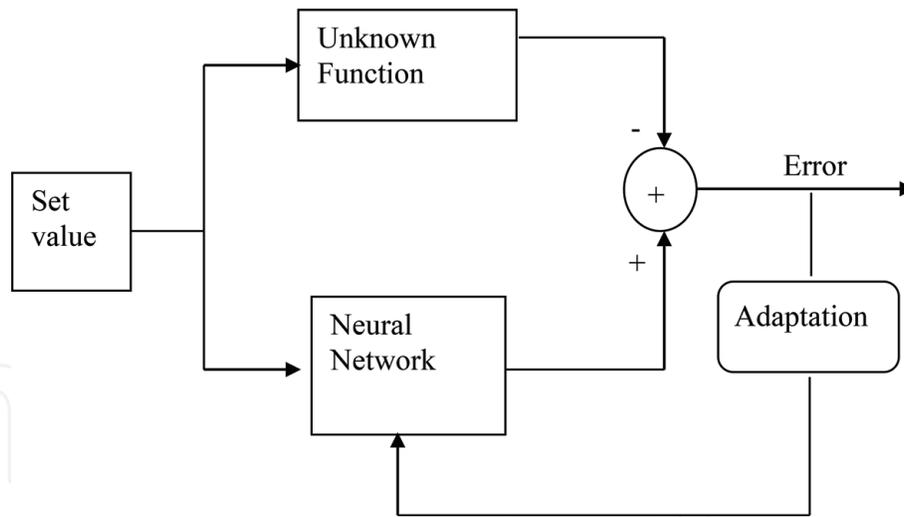


Figure 3.
Line diagram of neural network predictive control.

perceptron makes it a good choice for modeling nonlinear systems and for implementing nonlinear controller. The line diagram for the use of a neural network implemented on a process is shown in **Figure 3**. The unknown function may correspond to a controlled system, and the neural network is the identified plant model. Two-layer networks, with sigmoid transfer functions in the hidden layer and linear transfer functions in the output layer, are universal approximations. Artificial neural network is considered here as a predictive model for controlling the BTX system. The ultimate achievement of the model-based predictive controller is to generate a sequence of control signals minimizing a cost index that is the function of difference between the future process outputs from the desired set points and control moves. The ANN control structure was designed in “nntool” box, which was exported in Simulink environment to control DWC. An S-function was written in MATLAB for representing the DWC model. This DWC model was integrated with neural network control structure in MATLAB.

4. Data generation for training, testing, and validation of the network

To generate training data for the neural network training, a uniform random number generator for all the three input variables has been taken in the Simulink model as shown in **Figure 4**. The random number was kept constant at least for 1000 s. About 700 samples of each variable were generated with a sampling period of 100 s. These entire sample data were divided into three segments, viz.: training data, validation data, and testing data, in the ratio of 70:15:15, respectively.

The output performance of neural network depends on the number of neurons in input layer, number of hidden layer and optimizing algorithms. For the better output performance of the neural network, 90 neurons have been chosen in the input layer. The 90-input neurons correspond to 15 past values of each input and output variables. The numbers of neurons in hidden layer were found by the performance index such as R2. The performance analysis of the neural network is shown in **Table 1**.

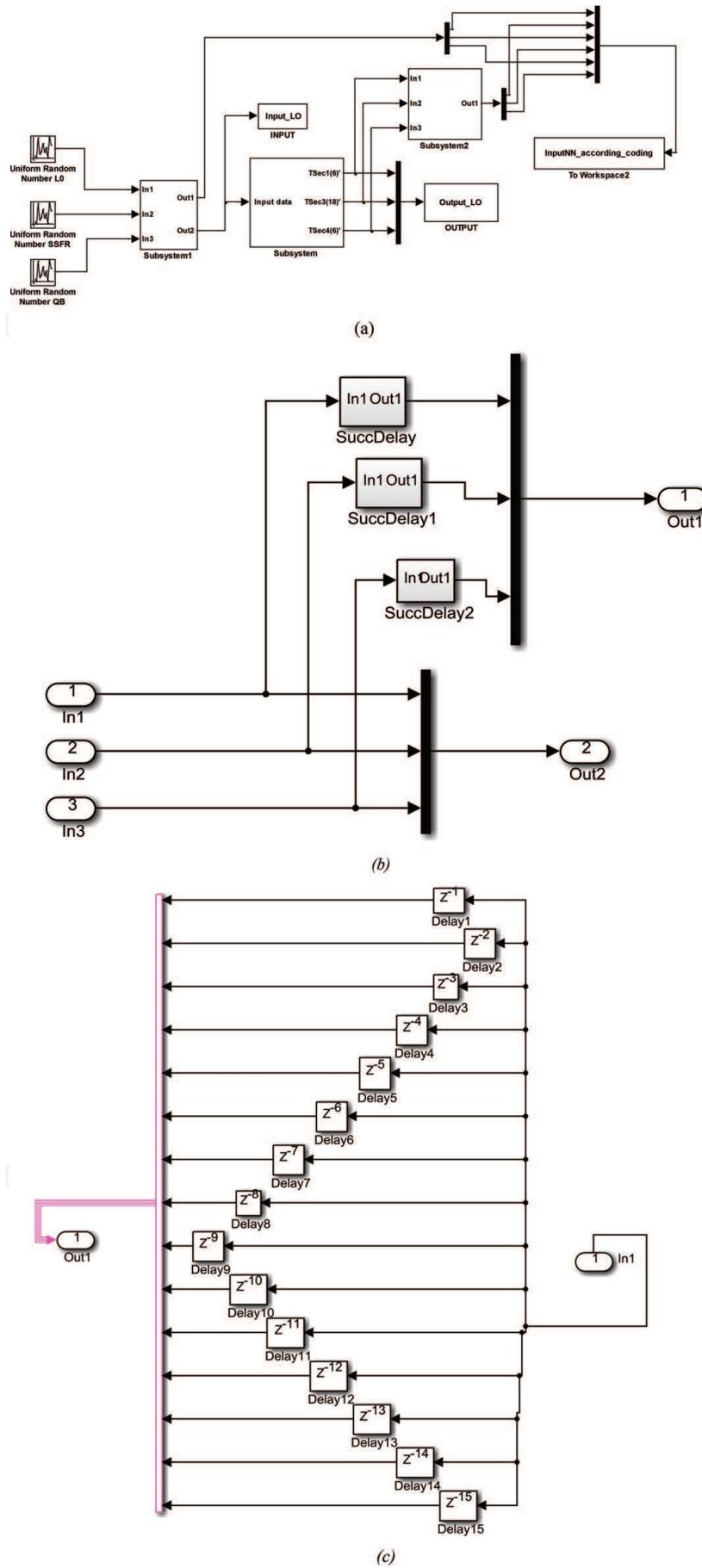


Figure 4. Systematic Simulink model of the dynamic DWC for data generation. (a) Main figure, (b) subsystem1, and (c) subsystem of subsystem1 "SuccDelay."

Training algorithm	Performance function	Neurons in hidden layer	Epoch	Max validation check	Tolerance	Training	Validation	Testing
Levenberg-Marquardt backpropagation	Mean squared normalized error	10	200	100	1e-7	0.93	0.95	0.96
		10	150	100	1e-7	0.96	0.88	0.93
		10	100	100	1e-7	0.94	0.92	0.95
		10	100	100	1e-6	0.95	0.91	0.94
		10	50	25	1e-6	0.95	0.94	0.93
		10	50	25	1e-7	0.93	0.97	0.98
		10	20	10	1e-7	0.94	0.96	0.97

Table 1.
Performance parameters of neural network.

5. Neural network training and its algorithm

Delgado et al. [5] suggested controlling the process online by the neural network; it requires accurate network training data to design some network frames, so that the model has better extrapolation and suaveness ability [5].

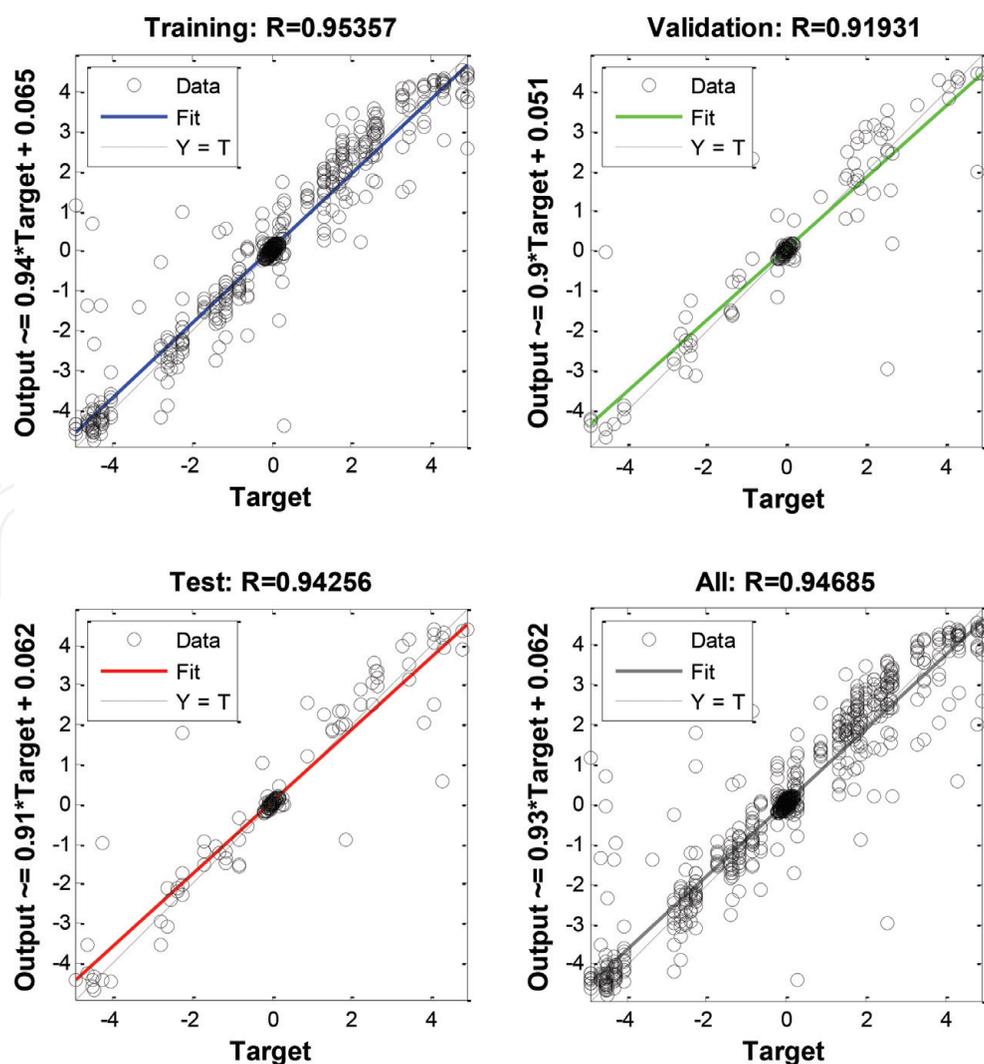


Figure 5.
Training, testing, and validation of the generated data of DWC.

When artificial neural network technique is applied on any process model, the common method is to collect the data for training either directly from the process plant or from the simulation. The training datasets for the network generation in the neural network have been obtained by the open-loop process under dynamic operating conditions because all the steady-state variables are in nonoscillatory motion. Due to nonavailability of the experimental BTX data of dividing wall distillation column, a mathematical model has been developed and then simulated in real time to find out the training data for network generation. Backpropagation algorithm has been used as a training algorithm to tune the connection weights for the function of each neuron.

For the offline training of the neural network, different types of training algorithms such as Levenberg-Marquardt, gradient-descent, and conjugate gradient can be used. But Levenberg-Marquardt algorithm is a fast-converging optimization technique among all. For DWC, the training, testing, and validation results are shown in **Figure 5**. The results show that there is a good fit between actual data and predicted data.

This algorithm works on the gradient and Hessian matrix of the objective function. In the Levenberg-Marquardt algorithm, Hessian matrix is approximated by Jacobian matrix and it is calculated by second-order derivative of objective function [6]. It is an easy way to improve the calculation up to the desired precision.

6. Simulink model of artificial neural network predictive controller

A Simulink model was designed to analyze the control performance of the artificial neural network predictive controller on the various load disturbance parameters. A systematic block diagram of the artificial neural network predictive controller is given in **Figure 6**.

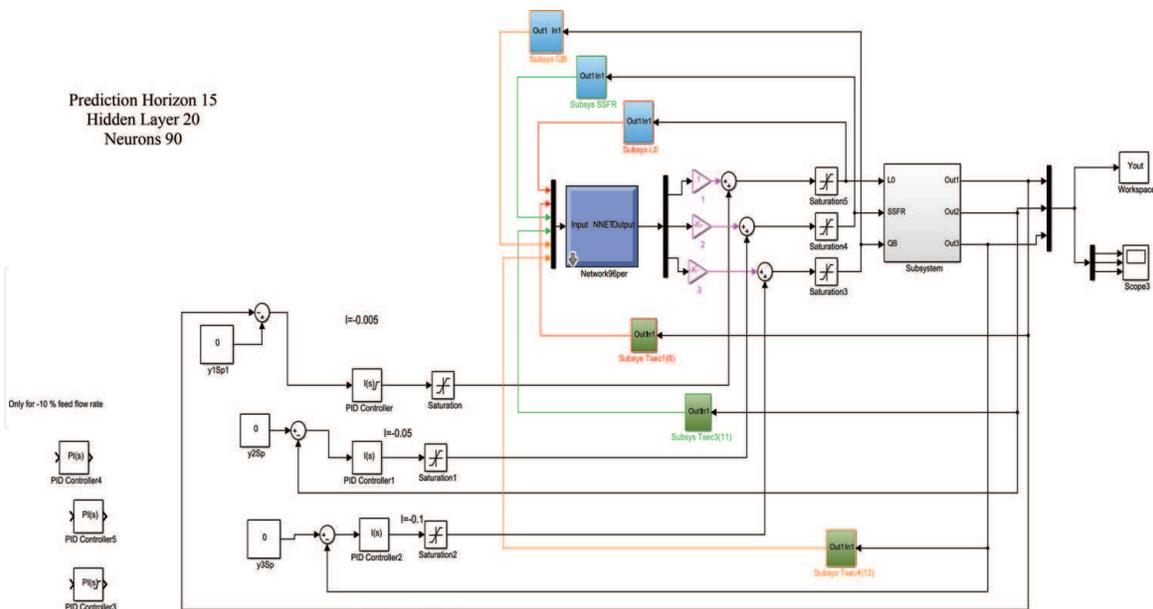


Figure 6.
 Systematic block diagram of artificial neural network predictive control.

7. Results and discussions

7.1 Effect of benzene composition change in feed

Load change of $\pm 10\%$ in benzene composition of the feed was given to check the performance of ANNPC as shown in **Figure 7**. The controller was able to bring

the temperatures in all the sections to the desired set points without any offset. The settling time in section 1 and section 4 for $\pm 10\%$ change in benzene composition is nearly 0.6 and 0.45 h, respectively. Although main column has 0.32 and 0.42 h settling time for -10% change and $+10\%$ change in benzene composition, respectively. The maximum peak of temperature in the section one (T_{sec1}) is 0.4 and 0.28°C at -10% change and $+10\%$ change, respectively. Section 3 temperature (T_{sec3}) and section 4 temperature (T_{sec4}) have very small peak value in the range of 10^{-3} and 10^{-10}°C for the $\pm 10\%$ change. With respect to the temperature change of the section 1, benzene composition reaches to the desired set point without any offset in 0.6 and 0.7 h for -10% and $+10\%$ change. Moreover, toluene and xylene composition acquires the desired value in 0.5 and 0.4 h, respectively without showing moderate offset and small peaks (i.e., in the range of 10^{-4} and 10^{-5}). Meanwhile, the entire manipulated variable varies independently to control the composition indirectly.

Load change of $\pm 20\%$ in benzene composition of the feed was also given to check the robustness of ANNPC as shown in **Figure 8**. In this case also, the controller was able to bring the temperatures in all the sections to the desired set points without any offset.

7.2 Effect of toluene composition change in feed

Figure 9 shows the effect of $\pm 10\%$ change in toluene composition of the feed as a load change in the system. Temperature overshoot in the section 1 at $+10\%$ change is 0.81°C and at -10% change is 0.41°C . The rest two sections have overshoot of 0.01 and 0.05°C , respectively. The temperatures acquire the desired set point without showing any offset in sections 1, 3, and 4 up to 0.8, 0.7 and 0.5 h, respectively. Corresponding to temperature variation in the individual section, composition also varies. At $\pm 10\%$ change in toluene composition, benzene composition shows the maximum peak in comparison to the toluene and xylene compositions. Due to high peak in the benzene composition, the settling time is also more (i.e., 0.66 h) with respect to the other two composition settling times. All the compositions in the different sections are also controlled with marginal offset. Load change of $\pm 20\%$ in

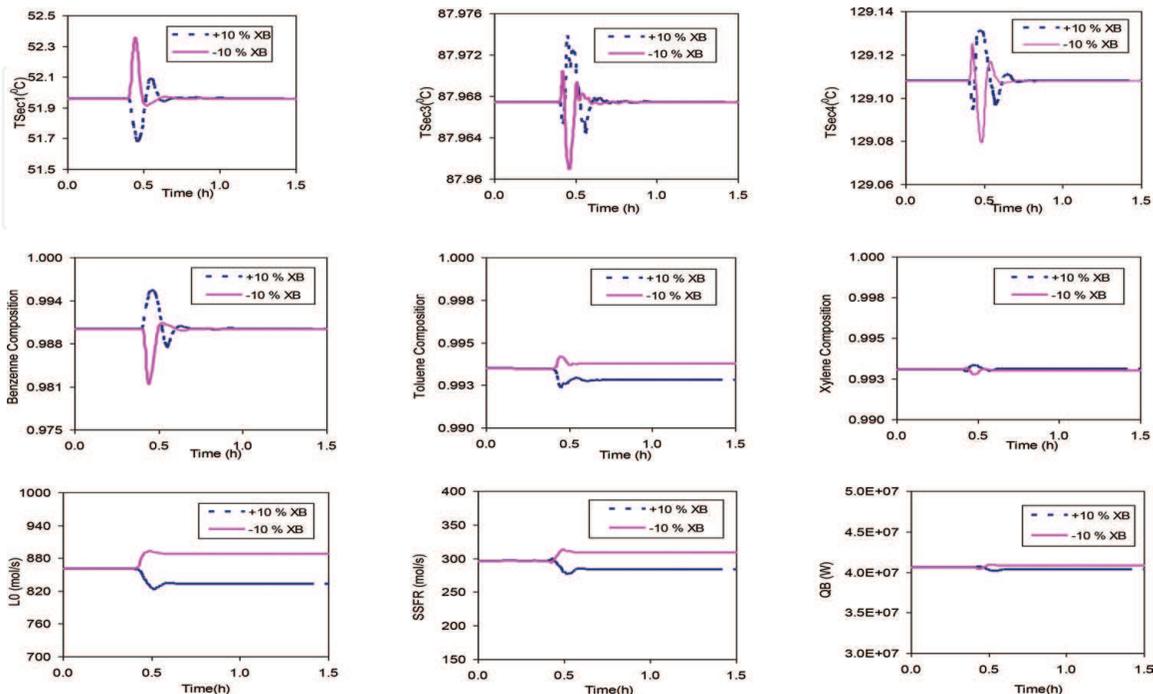


Figure 7.
 $\pm 10\%$ change in benzene composition in feed.

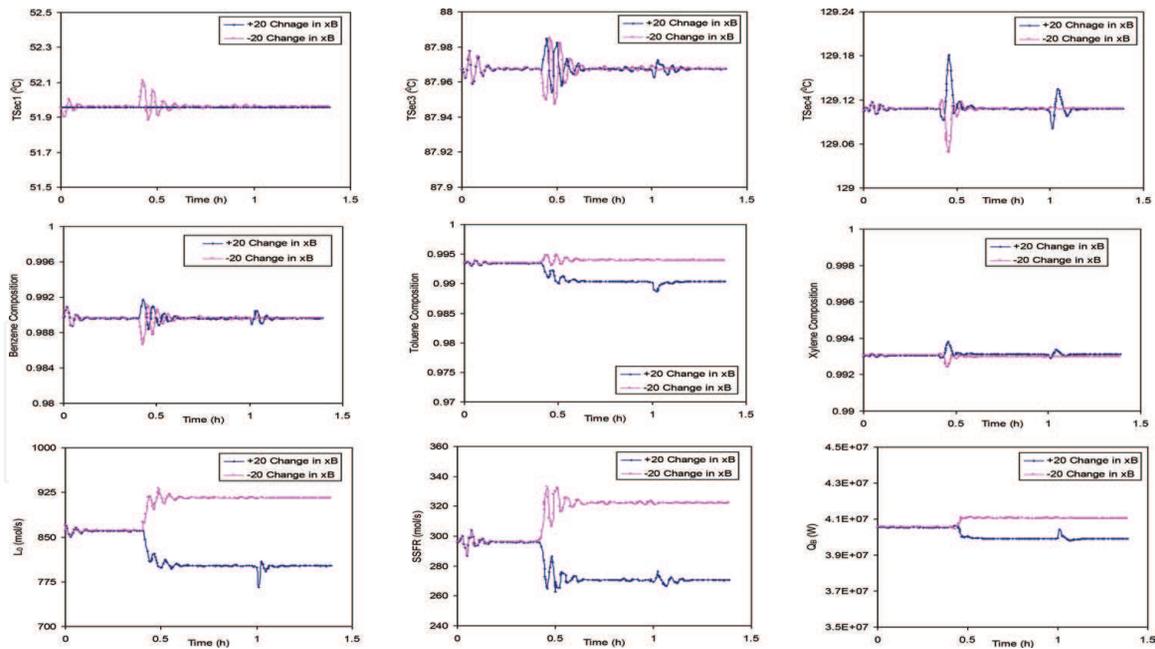


Figure 8.
 $\pm 20\%$ change in benzene composition in feed.

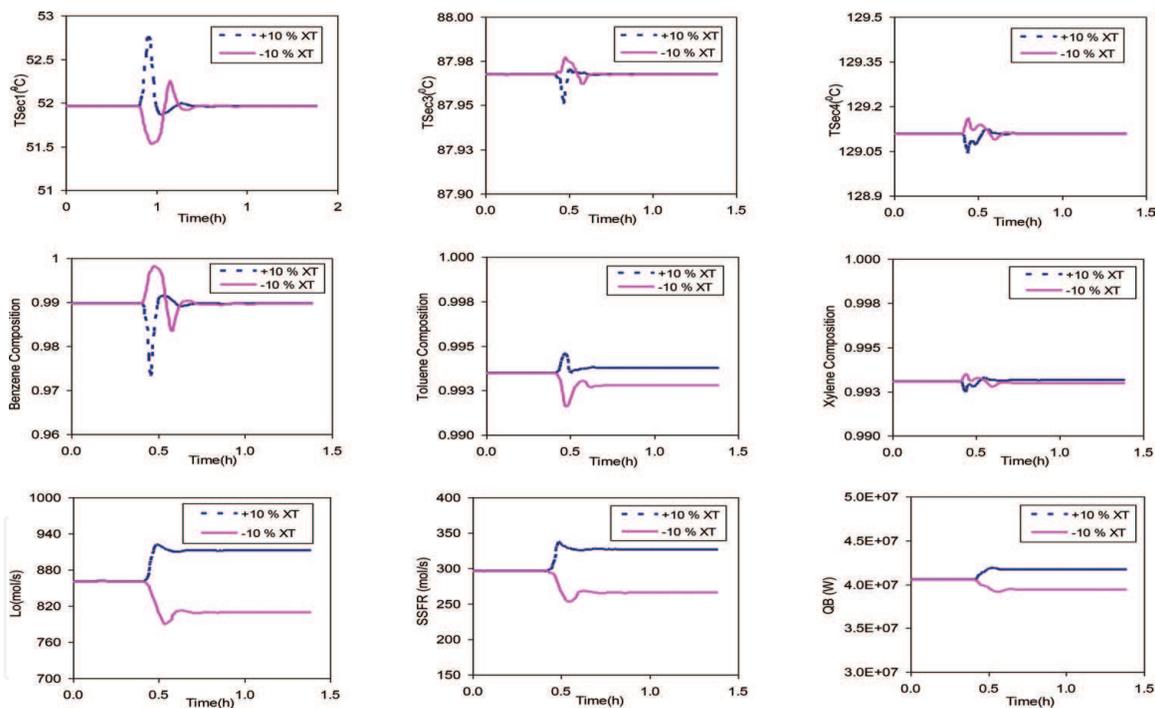


Figure 9.
 $\pm 10\%$ change in toluene composition in feed.

toluene composition of the feed was also given to check the robustness of ANNPC as shown in **Figure 10**. In this case also, the controller was able to bring the temperatures in all the sections to the desired set points without any offset.

7.3 Effect of o-xylene composition change in feed

A load change of $\pm 10\%$ in o-xylene composition was also imposed to check the performance of the controller as shown in **Figure 11**. As a $\pm 10\%$ change in o-xylene composition, temperature overshoot in the last section is near to 0.06°C . In comparison to the stripping section, rectifying section shows the maximum peak and

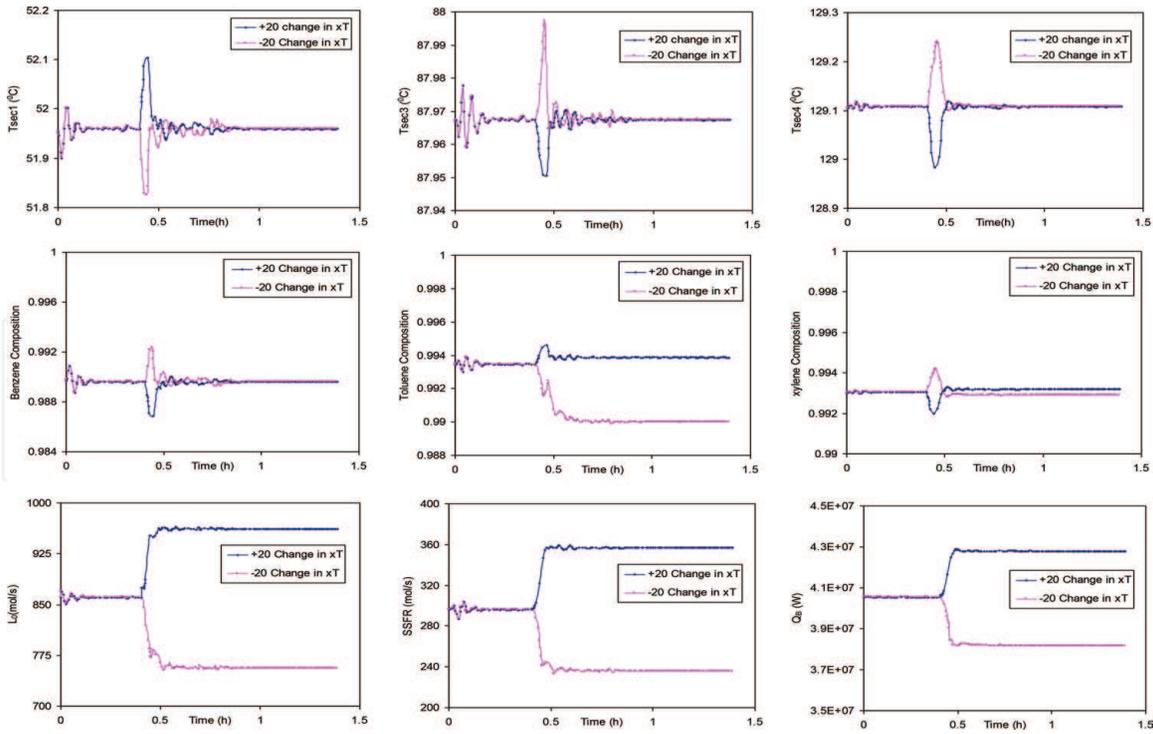


Figure 10.
±20% change in toluene composition in feed.

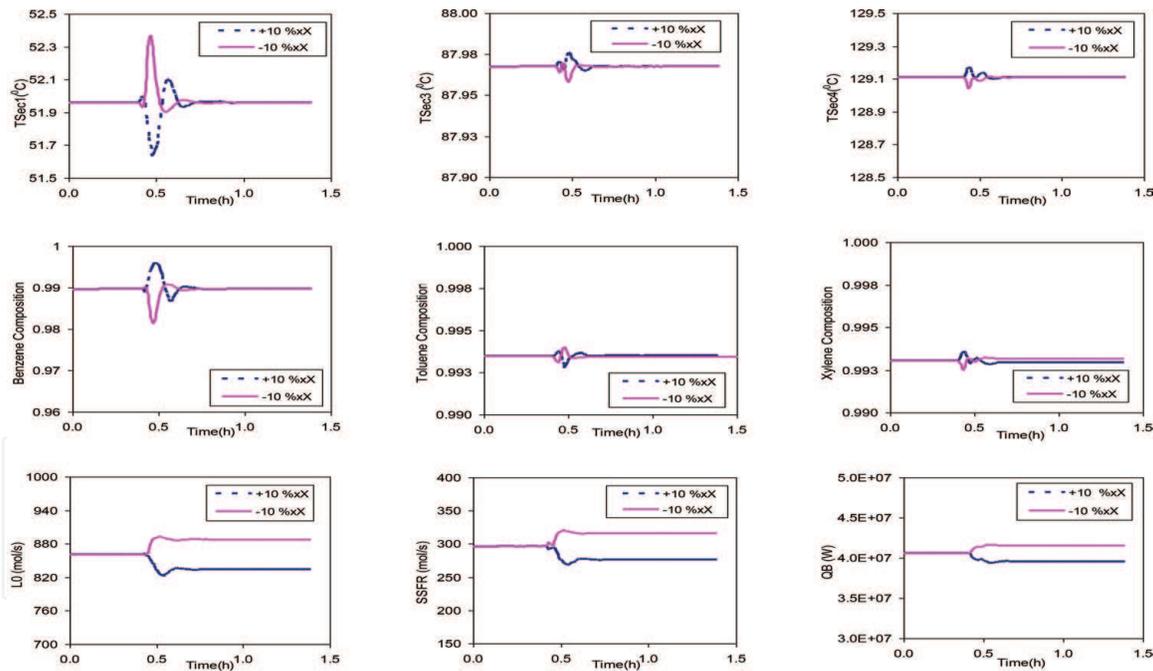


Figure 11.
±10% change in xylene composition in feed.

the main column shows minimum peak. After giving a load change of ±10% in o-xylene composition, benzene composition gets settled in 0.32 h, while toluene and o-xylene compositions take only 0.22 h to achieve the steady-state condition. Moreover, all the composition peaks are in the range of 1×10^{-3} (mole fraction), which is very small. Settling time of the temperature profile is 0.5 h in the rectifying section; 0.3 h in the main column and stripping section. Composition profiles of the sections 3 and 4 show very small offset and section 1 does not have any offset. The controller also showed the robustness for ±20% change in xylene composition in the feed as shown in **Figure 12**.

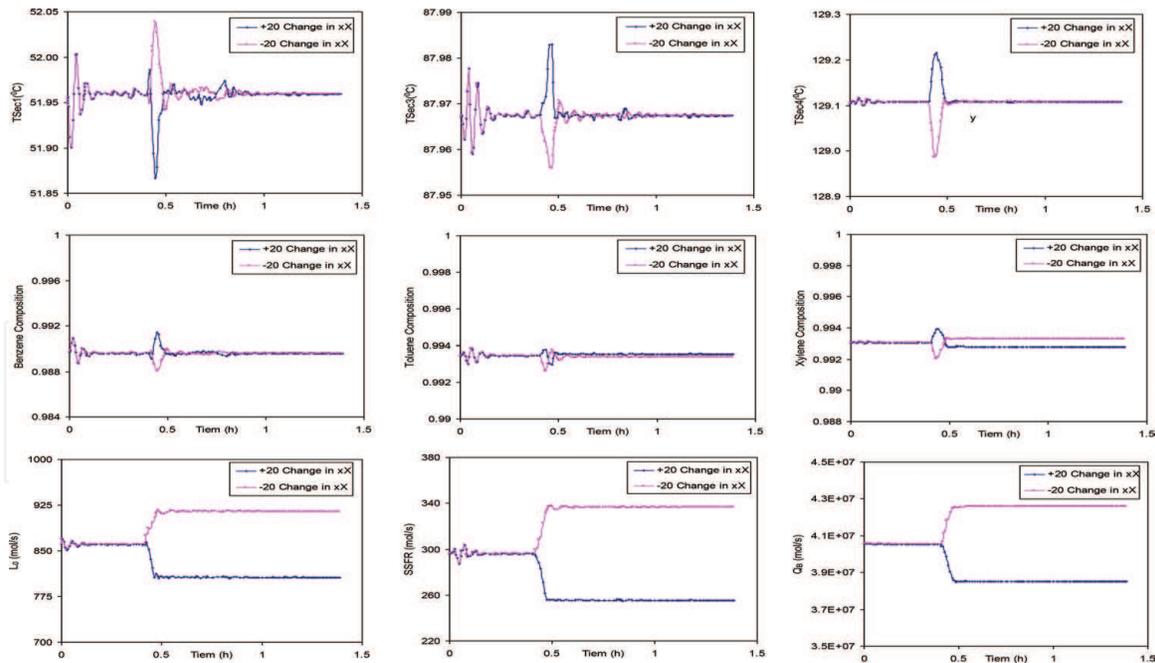


Figure 12.
 $\pm 20\%$ change in xylene composition in feed.

7.4 Load change in feed low rate

About $\pm 10\%$ load change was given in the feed flow rate to see the performance of ANNPC as given in **Figure 13**. The temperatures in all the three sections are brought back to the set point without significant offset. The temperature overshoot is very high in section 1 at $+10\%$ change in feed flow rate in comparison to -10% change. Moreover, sections 3 and four have similar peaks in both sides. Due to the high temperature peak in section 1 at $+10\%$ change, the settling time is twice of that in -10% change.

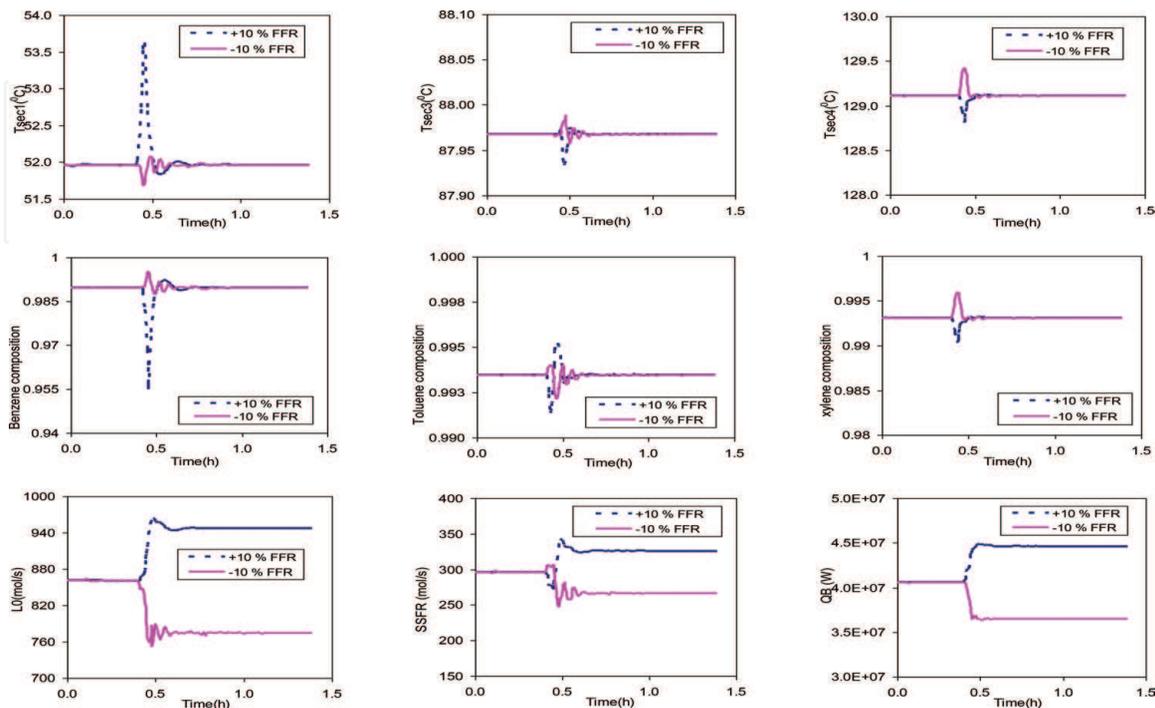


Figure 13.
 $\pm 10\%$ change in feed flow rate.

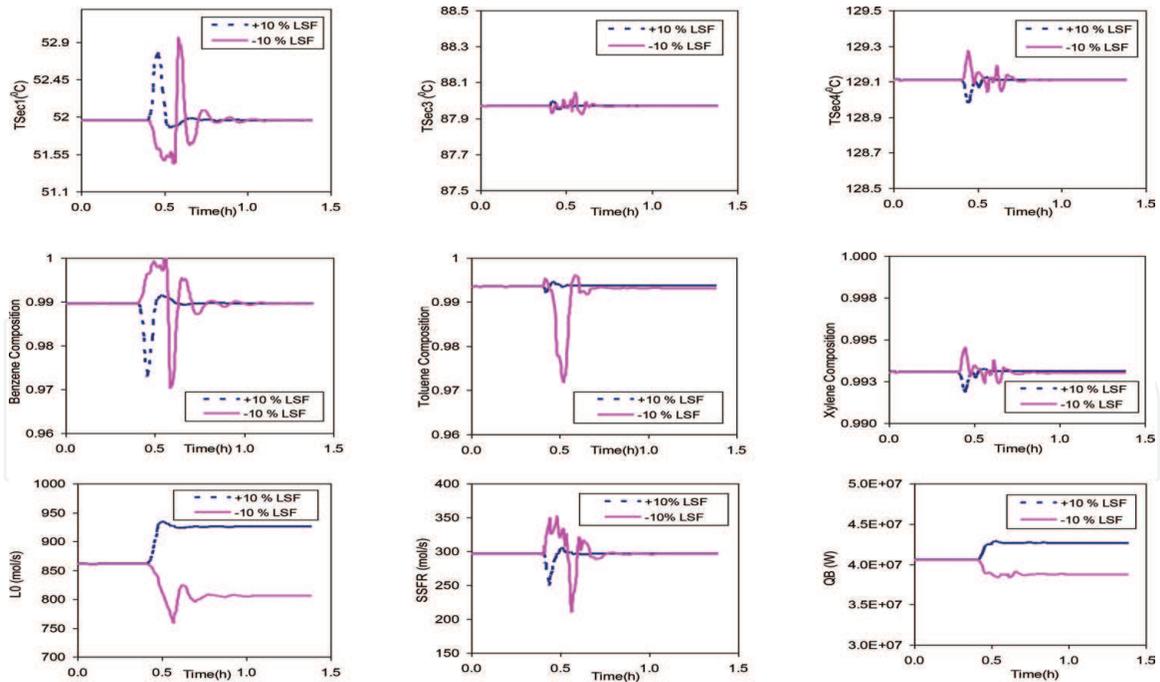


Figure 14.
±10% change in liquid split faction.

Change in feed flow rate creates more disturbances in the main column of the DWC, and therefore, the settling time in this section is more in comparison to the others. The peak of benzene composition at +10% change is 0.0346°C and -10% change is $5.4 \times 10^{-3}\text{C}$, which is too low as compared to +10% change in feed flow rate.

7.5 Load change in liquid split factor

To analyze the performance of the ANNPC, liquid split factor was also considered as load disturbance as shown in **Figure 14**. Due to liquid distribution in the main column and the prefractionator column, variation in temperature profile is more. Settling time in section 1 is more in comparison to the other load changes. The overshoot in this section is 0.017 (mole fraction) at +10% change and 0.019 (mole fraction) at -10% change. Overshoot in the section 3 is 0.016 (mole fraction) only at -10% change. Moreover, o-xylene composition overshoot in section 4 is in the range of 1×10^{-3} (mole fraction).

8. Conclusion

To analyze the control performance of artificial neural network, random training data were generated. In total, 700 data were generated on the time interval of 100 s. Generated data were divided into the ratio of 70:15:15 for training, testing, and validation, respectively. Architecture of the neural network was assumed to consist of 90 input and 3 output neurons, which showed R2 of 96% for validation. The load changes in feed flow rate, feed composition, and liquid split factor were also induced to find the control performance in all the three sections by manipulating variables, viz. reflux rate, side stream flow rate, and reboiler heat duty. Settling time in the ANNPC controller was found to be very low in comparison to conventional controller. The ANNPC was also tested for $\pm 20\%$ change in feed composition of benzene, toluene, and xylene, which confirmed the robustness of this controller with respect to change in feed composition.

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