

Artificial Neural Networks Controller for Crude Oil Distillation Column of Baiji Refinery

Duraïd Fadhil Ahmed* and Ali Hussein Khalaf

Department of Chemical Engineering, University of Tikrit, Iraq

Abstract

A neural networks controller is developed and used to regulate the temperatures in a crude oil distillation unit. Two types of neural networks are used; neural networks predictive and nonlinear autoregressive moving average (NARMA-L2) controllers. The neural networks controller that is implemented in the neural network toolbox software uses a neural network model of a nonlinear plant to predict future plant performance. Artificial neural network in MATLAB simulator is used to model Baiji crude oil distillation unit based on data generated from aspen-HYSYS simulator. A comparison has been made between two methods to test the effectiveness and performance of the responses. The results show that a good improvement is achieved when the NARMA-L2 controller is used with maximum mean square error of 103.1 while the MSE of neural predictive is 182.7 respectively. Also shown priority of neural networks NARMA-L2 controller which gives less offset value and the temperature response reach the steady state value in less time with lower over-shoot compared with neural networks predictive controller.

Keywords: Artificial neural networks model; Neural networks predictive control; NARMA controller; Crude oil distillation unit

Nomenclature

E	Error criteria for network convergence
G(s)	Transfer function
N_u	Horizons over tracking error
t	Time, (min)
T	Temperature, (°C)
u(k)	System input
W _{ij}	Weight value between input and hidden layer
X	Input of neuron
y	Output of neuron
y_r	Desired response
Δ	Difference
α	Momentum rate
η	Learning rate
b	Bias
ρ	Weighting parameter

Introduction

The crude oil distillation unit (CDU) fractionation column separates the feed crude into different cuts suitable for the different refinery processing units. CDU today is facing new challenges in order to meet the requirements with respect to improve fuel properties, product quality and increase the yields of the distillate products with meeting environmental laws. A lot of crude units currently operate with different feed slates to their original feed specifications to satisfying the demands of the market. Most petroleum distillates, especially those from atmospheric distillation tower, have different physical properties depending on the characteristics of the crude oil [1]. The scope of the control systems in process industries has been broadened from the basic regulatory control to advanced control

strategies. The temperature control is based on the assumption that the product composition can satisfy its specification when an appropriate tray temperature is kept constant at its set-point [2]. In the control of crude oil distillation columns is usually difficulty to get accurate and reliable product composition measurements without time delay. Many composition analyzers such as gas chromatography, NIR (Near-Infrared) analyzers, suffer from large measurement delays and high investment and maintenance costs and usually possess significant time lags. The overall time lags in composition measurements are typically between 10 to 20 minutes. Also in inferential control of product composition is used by estimation from other measured variables [3].

Nunzio et al. [4] presented the neural networks controller (NNC) for quality predictions of a crude unit. The Neural networks (NN) implemented compare between predicted and measured quality on the light gasoil stream over a five week. The average % absolute error is about 1.23 with a standard deviation of 1.1. Ali and Khalid [5] implemented intelligent control technology of NN for crude fractionation tower. The simulation results for modeling of the column were used to control the several products property such as naphtha 95% cut point and naphtha Reid vapor pressure. The sum squared error goal of training for control is 0.1 while for in the verification mode is 0.097. Lee et al. [6] used artificial neural network (ANN) controller to identify the feed and product. Two ideas are used to identify the control on feed characteristic as a real time basis. The proposed method can be effectively used for controlling process optimization. Pavel et al. [7] upgraded ANN controller for online inferential property estimation. The neural networks run as function blocks within the automation system's controller. Pasadakis et al. [8] introduced ANN controller.

*Corresponding author: Duraïd Fadhil Ahmed, Department of Chemical Engineering, University of Tikrit, Iraq, E-mail: alihussien853@yahoo.com

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The properties of interest distillation curve with 5% recovery and cold properties of diesel fuel were measured experimentally. Result shows that it can be easily employed in the refinery environment for on-line process control. Omole et al. [9] developed back propagation neural network (BPNN) model for predicting and control crude oil. The data points of ANN models performed better than the existing empirical correlations to control crude oil viscosity.

Henri and Olatunbosun [10] developed NN controller for a crude oil distillation column, field data used from a working unit of crude oil. They estimated the correlation coefficients between the obtained values from NNC and the field values for steam flow and three streams of reflux flow. Lekan et al. [11] presented a simulation of crude oil distillation column and applied the ANN controller. Good results accuracy is obtained and the deviation between NNC from each other of 1.98%. Richalet [2] worked on model based predictive control for crude oil unit. The results showed that the good performance and robustness could be obtained under wide operating condition. Sharad and James [12] proposed inferential measurement to control variable by the systematic approach using neural networks controller. They developed a correlation to predict the ASTM 95% endpoint of kerosene with an error standard deviation of 1.7°C. Abou-jeyab et al. [13] used model predictive control (MPC) of a crude oil distillation column. The results showed that 2.5% increase in production rate and 0.5% increase in product recovery. Kemalolu et al. [14] reviewed the application of a model predictive controller algorithm to a crude oil unit. The system responses for different changing in set-point in the product qualities to be increase 11% in the kerosene yield was achieved as a result of decrease in naphtha yield.

Volk et al. [15] tested the multivariable predictive control of an crude distillation column. This controller keeps the set-points of the distillate and bottom concentration constant. The linear control algorithm is valid in the vicinity of the working point for changes of about 10%. Gabriele et al. [16] introduced simulation model of CDU and controlled by a multivariable predictive controller. The controller tuning is implemented on the actual plant and carry out closed loop identification tests from which the predictive controller implemented. Aliyev et al. [17] tested the crude refinery unit control by using two type of control architecture. The nonlinear model predictive (NMPC) was able to track set points and response of NMPC is better than of response PI control.

Haydary and Tomas [18] investigated two different control methods based on composition of ASTM D86 95% boiling point and temperature for real crude oil distillation plant. Experimental ASTM D86 curves of different products were compared to those obtained by simulations. Sampath [1] used a control layers in the Aspen-HYSYS simulator for crude oil distillation unit, the first control layer is PID and the second control layer is MPC. He concluded that the MPC can handle constraints and presents good robustness features against model mismatch and perturbations. Goncalves et al. [19] applied PID controller for atmospheric distillation unit of crude oil refinery. The dynamic model is developed and combined with a suitable control for several process operating conditions. They study the step responses for quality specifications like ASTM D86 95%, and production flow changes. Rogina et al. [20] worked on light naphtha in CDU control. Experimental and laboratory analyses data was used for neural network based model. The analyses show that conditions at the column top temperature most affect the RVP and NNC are acceptable result for RVP estimation. Mohammadi et al. [21] investigated simulation and control for Kermanshah refinery by applying the PID controller. The

behavior controller was observed after the changing of the crude oil feed flow rate by 3% for five hours. The results show that temperature controllers are faster and more sensitive than the other controllers.

The purpose of this paper builds the artificial neural network model for crude oil distillation unit, and applies neural networks predictive and NARMA-L2 controller to the crude oil distillation column.

Neural Networks Predictive Controller

The neural network predictive controller calculates the control input that will optimize plant performance over a specified future time horizon. The first step of model predictive control is training a neural network to represent the forward dynamics of the plant. The prediction error between the plant output and the neural network output is used as the neural network training signal. The neural network plant model uses previous inputs and previous plant outputs to predict future values of the plant output. The model predictive control method is based on the receding horizon technique. The neural network model predicts the plant response over a specified time horizon. The predictions are used by a numerical optimization program to determine the control signal that minimizes the following performance criterion over the specified horizon.

$$J = \sum_{j=N_1}^{N_2} (y_r(t+j) - y_m(t+j))^2 + \rho \sum_{j=1}^{N_u} (u'(t+j-1) - u'(t+j-2))^2 \quad (1)$$

Where N_1 , N_2 , and N_u are the horizons over which the tracking error and the control increments are evaluated. The u' variable is the tentative control signal, y_r is the desired response, and y_m is the network model response. The ρ value determines the contribution that the sum of the squares of the control increments has on the performance index. The optimization block determines the values of u' that minimize J , and then the optimal u is input to the plant. Figure 1 shows the Block diagram of the neural network predictive control.

Nonlinear Autoregressive-Moving Average NARMA-L2 (Feedback Linearization) Controller

The central idea of this type of control is transforming nonlinear system dynamics into linear dynamics by canceling the nonlinearities. As with model predictive control, the first step in using feedback linearization (or NARMA-L2) control is identifying the system to be controlled and then choose a model structure to use. The nonlinear autoregressive-moving average (NARMA) model is used to represent general discrete-time nonlinear systems as expressed in Eq. 2.

$$y(k+d) = N[y(k), y(k-1), y(k-n+1), u(k), u(k-1), u(k-n+1)] \quad (2)$$

Output Response

Where $u(k)$ is the system input, and $y(k)$ is the system output. For the identification phase, a neural network is trained to approximate the nonlinear function N . This is the identification procedure used for the NN predictive controller. The system output is equal to reference trajectory ($y(k+d) = y_r(k+d)$).

The next step is developing a nonlinear controller as the following form:

$$u(k) = G[y(k), y(k-1), y(k-n+1), y_r(k+d), u(k-1), u(k-n+1)] \quad (3)$$

The resulting controller would have the following form

$$(k) = \frac{y_r(k+d) - f[y(k), y(k-1), y(k-n+1), u(k-1), u(k-n+1)]}{g[y(k), y(k-1), y(k-n+1), u(k-1), u(k-n+1)]} \quad (4)$$

Using Eq. 4 directly can cause realization problems, because the control input $u(k)$ must be determined based on the output at the same time, $y(k)$. Using the NARMA-L2 model, you can obtain the controller

$$u(k+1) = \frac{y_i(k+d) - f[y(k), y(k-1), y(k-n+1), u(k-1), u(k-n+1)]}{g[y(k), y(k-1), y(k-n+1), u(k-1), u(k-n+1)]} \quad (5)$$

which is realizable for $d \geq 2$. Figure 2 shows the Block diagram of the NARMA-L2 control [22].

Simulation Work

The neural network architecture for the design of the crude oil distillation column (CODC) consists of thirteen inputs with one hidden layer which consist of nine nodes and six outputs making a total of 34 nodes distributed over the three layers. The inputs to the network are volumetric flow rates of top pumparounds, intermediate pumparounds, bottom pumparounds, steam, reflux, naphtha, kerosene, and light gas oil (LGO) top-temperature, top-pressure, specific gravity, temperature, and volumetric flowrate of feed. The outputs from the NN architecture are temperatures of naphtha, kerosene, LGO D86 95%, top, intermediate and bottom pumparounds. The back propagation algorithm is used for the ANN of crude oil distillation unit. Figure 3 shows the neural network architecture of the crude oil distillation column, 1487 records set are collected from the designed unit in aspen-HYSYS simulator, these data are collected by making step changed in the manipulated variables for dynamic case and record the response for each input and output mentioned earlier in aspen-HYSYS simulator and converted to Excel spreadsheet, the range of data used in the training is shown in Table 1. These data are used in MATLAB simulator to build NN model for CDU. Nonlinear autoregressive network with exogenous inputs (NARX) are used for the ANN model in MATLAB.

Input Variable	Range of data
Feed specific gravity	0.8807-0.8332
Feed temperature, (°C)	328.22-349
Feed volumetric flowrate, (m³/hr)	800-1030.4
Top pumparounds volumetric flowrate, (m³/hr)	733.2-685.13
Intermediate pumparounds volumetric flowrate, (m³/hr)	533.7-560
Bottom pumparounds volumetric flowrate, (m³/hr)	225.5-320
Top temperature, (°C)	135.3-170
Top pressure, (kN/m²)	127-157
Steam volumetric flowrate, (m³/hr)	4.31-4.97
Reflux volumetric flowrate, (m³/hr)	113.2-302.39
Naphtha volumetric flowrate, (m³/hr)	176.4-180.27
Kerosene volumetric flowrate, (m³/hr)	115-150
LGO volumetric flowrate, (m³/hr)	100-180
Variable name of output	Range of data
Naphtha D86 95%, (°C)	150-183
Kerosene D86 95%, (°C)	224-309
LGO D86 95%, (°C)	325-393
Top pumparounds temperature, (°C)	60-138
Intermediate pumparounds temperature, (°C)	175-214
Bottom pumparounds temperature, (°C)	184-255

Table 1: Input and output training values range.

Since the case is studying the dynamic behavior and control of crude oil distillation unit. Input and output data are loaded to the workspace from excel spreadsheet. 70% of the data are selected for training and 30% are used for validation and testing. The simulator normalized the training data between (-1,1).

After establishing the ANN model that has been developed and converted to simulink, the control system is built for this model using neural network predictive and NARMA-L2 control methods. The neural network controller that is implemented uses a neural network model of a nonlinear plant to predict future plant performance. NN predictive controller and NARMA-L2 controller blocks are installed to the SIMULINK window and connected with NN model and filling the controller's parameters then identified the plant. Controllers are trained by train algorithm. We applied six NN predictive controller and six NN NARMA-L2 controllers to control each one of the six model outlet. The controller architecture for the six controlled variable are shown in the Figures 4-9.

Results and Discussion

Model of crude oil distillation column

Artificial neural network model is established successfully for the crude oil distillation column. Figure 10 shows neural network training performance. This figure shows the architecture of the network build and the value of mean square error (MSE) is 0.25 and the iteration time for the program is 18 iterations. Figure 11 shows the neural network validation performance is equal to 23.34 at epoch 12 (time steps for adaption). Neural network training regression for training and validation are 0.99996 and 0.99844 respectively as shown Table 2. This model has been tested with different step changes in input variables and we get satisfied result for the output but the step changes should be in the training limits. Neural network model for the nonlinear unit of crude distillation unit promise a good performance to handle the complexity and nonlinearity at the same time this is due to the full representation of the nonlinear dynamic of the unit.

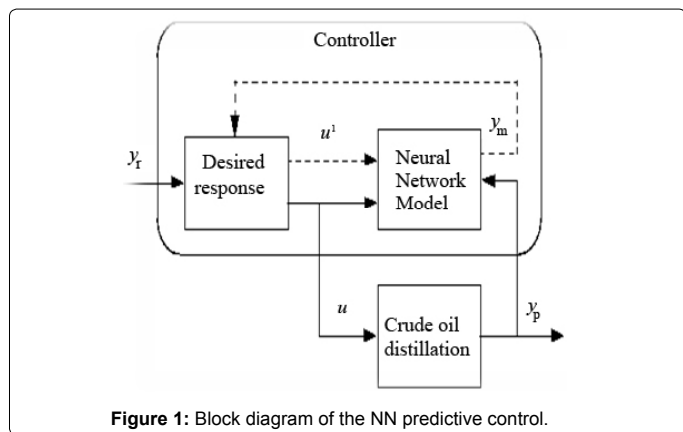


Figure 1: Block diagram of the NN predictive control.

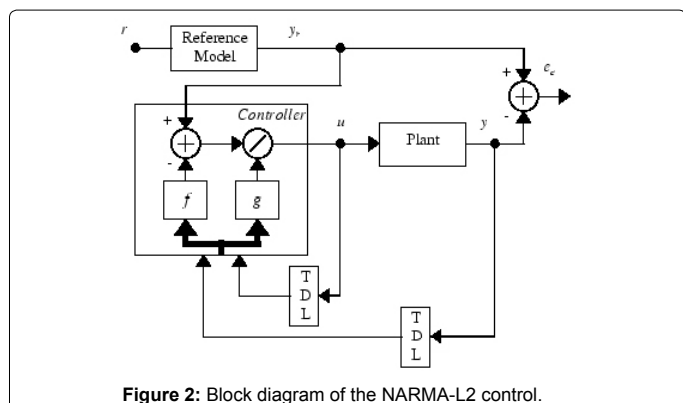


Figure 2: Block diagram of the NARMA-L2 control.

Controlled variable	Disturbance (load) variable	Value of step change	Method	MSE
Naphtha D86 95%	Temperature of feed, (°C)	350-340	Neural predictive	165.7
	Temperature of feed, (°C)	350-340	NARMA-L2	103.1
Kerosene D86 95%	Temperature of feed, (°C)	350-340	Neural predictive	182.7
	Temperature of feed, (°C)	350-340	NARMA-L2	150
Diesel D86 95%	Temperature of feed, (°C)	350-340	Neural predictive	41.12
	Temperature of feed, (°C)	350-340	NARMA-L2	18.61
Top pumparounds temperature controller	Temperature of feed, (°C)	350-340	Neural predictive	0.515
	Temperature of feed, (°C)	350-340	NARMA-L2	0.43
Intermediate pumparounds temperature controller	Temperature of feed, (°C)	350-340	Neural predictive	0.725
	Temperature of feed, (°C)	350-340	NARMA-L2	1.559
Bottom pumparounds temperature controller	Temperature of feed, (°C)	350-340	Neural predictive	14.88
	Temperature of feed, (°C)	350-340	NARMA-L2	7.59

Table 2: The mean square error (MSE) for neural network method.

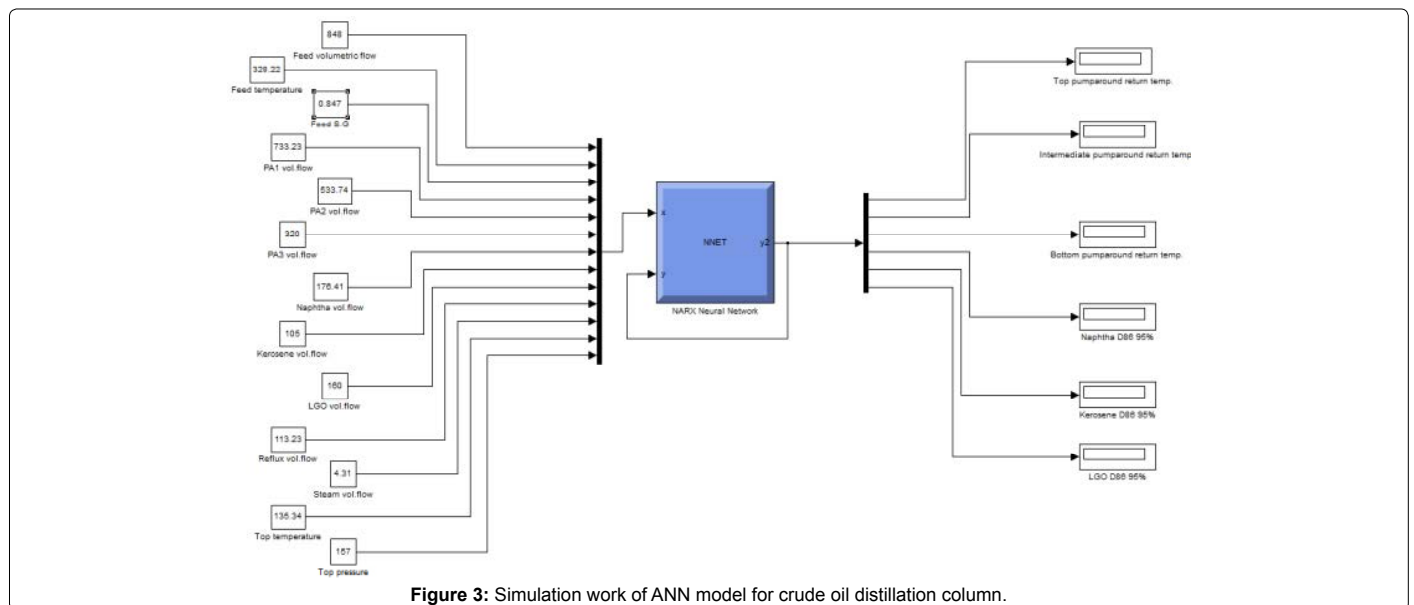


Figure 3: Simulation work of ANN model for crude oil distillation column.

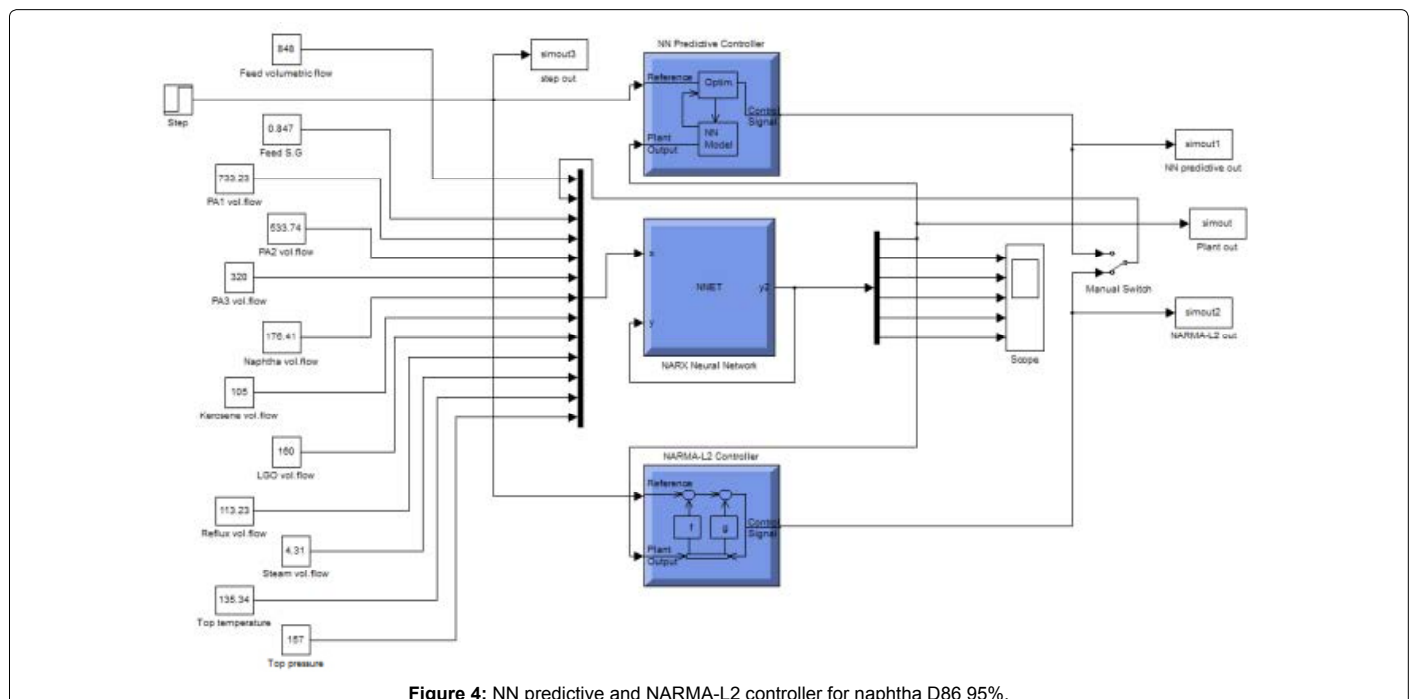
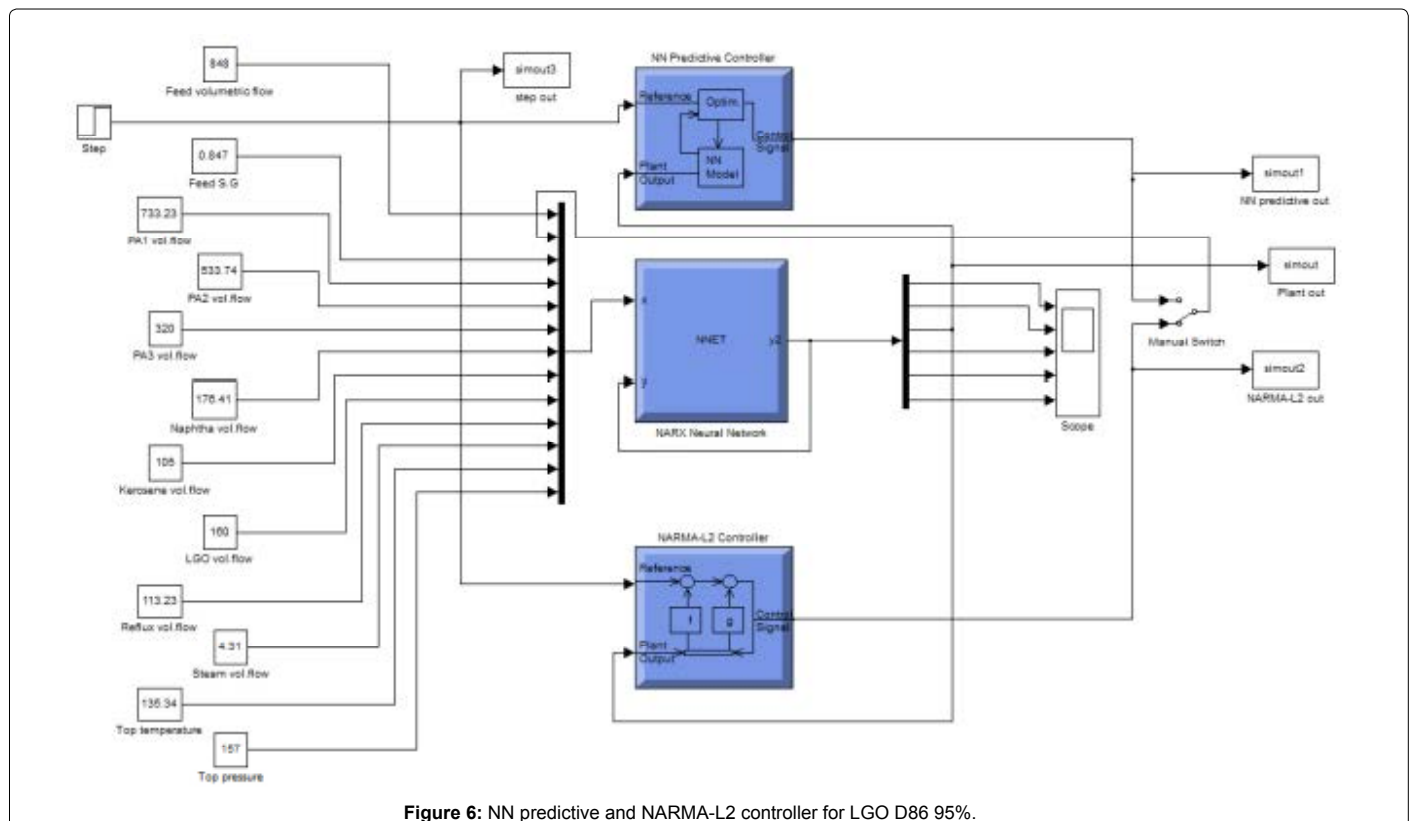
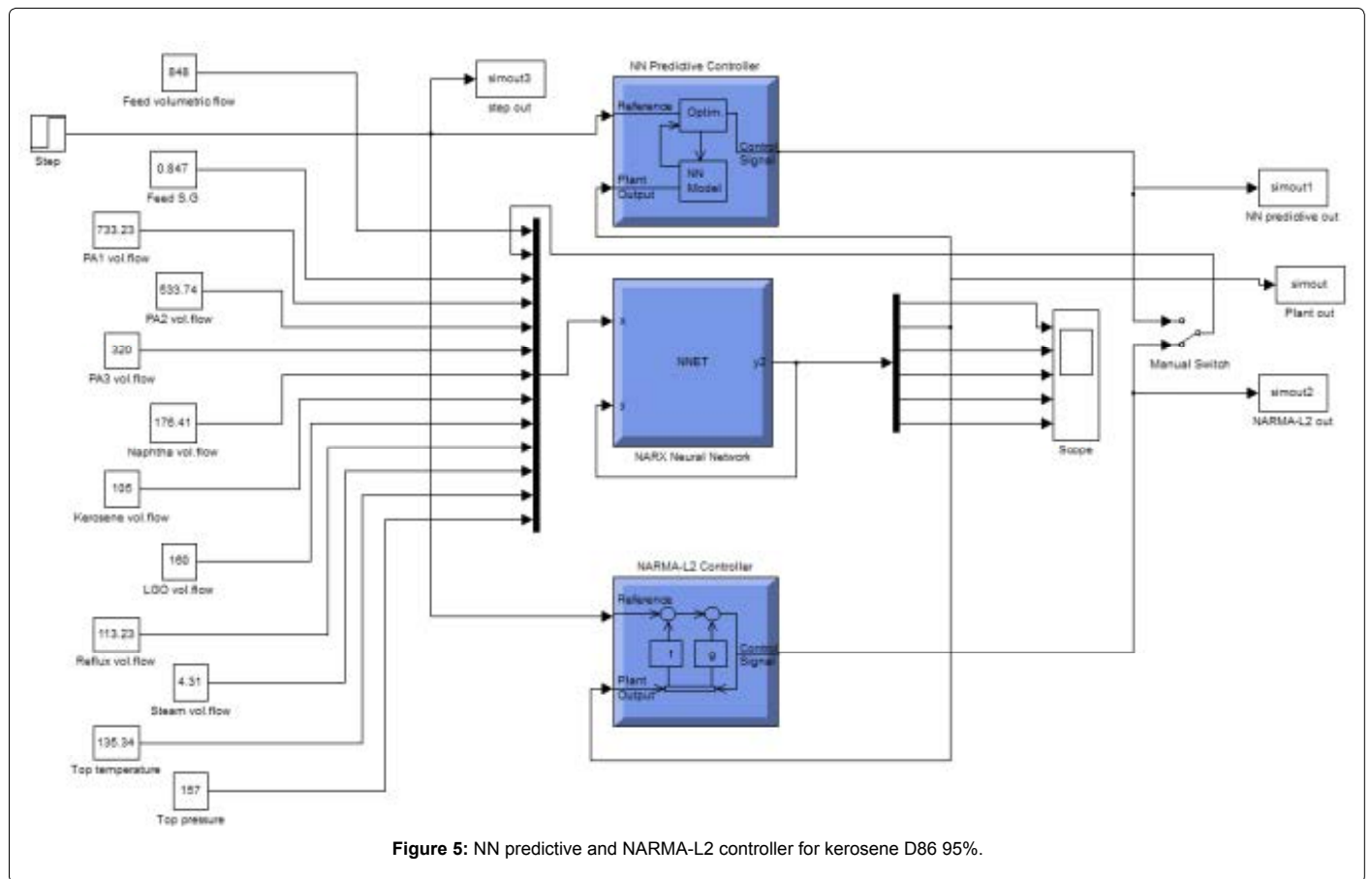


Figure 4: NN predictive and NARMA-L2 controller for naphtha D86 95%.



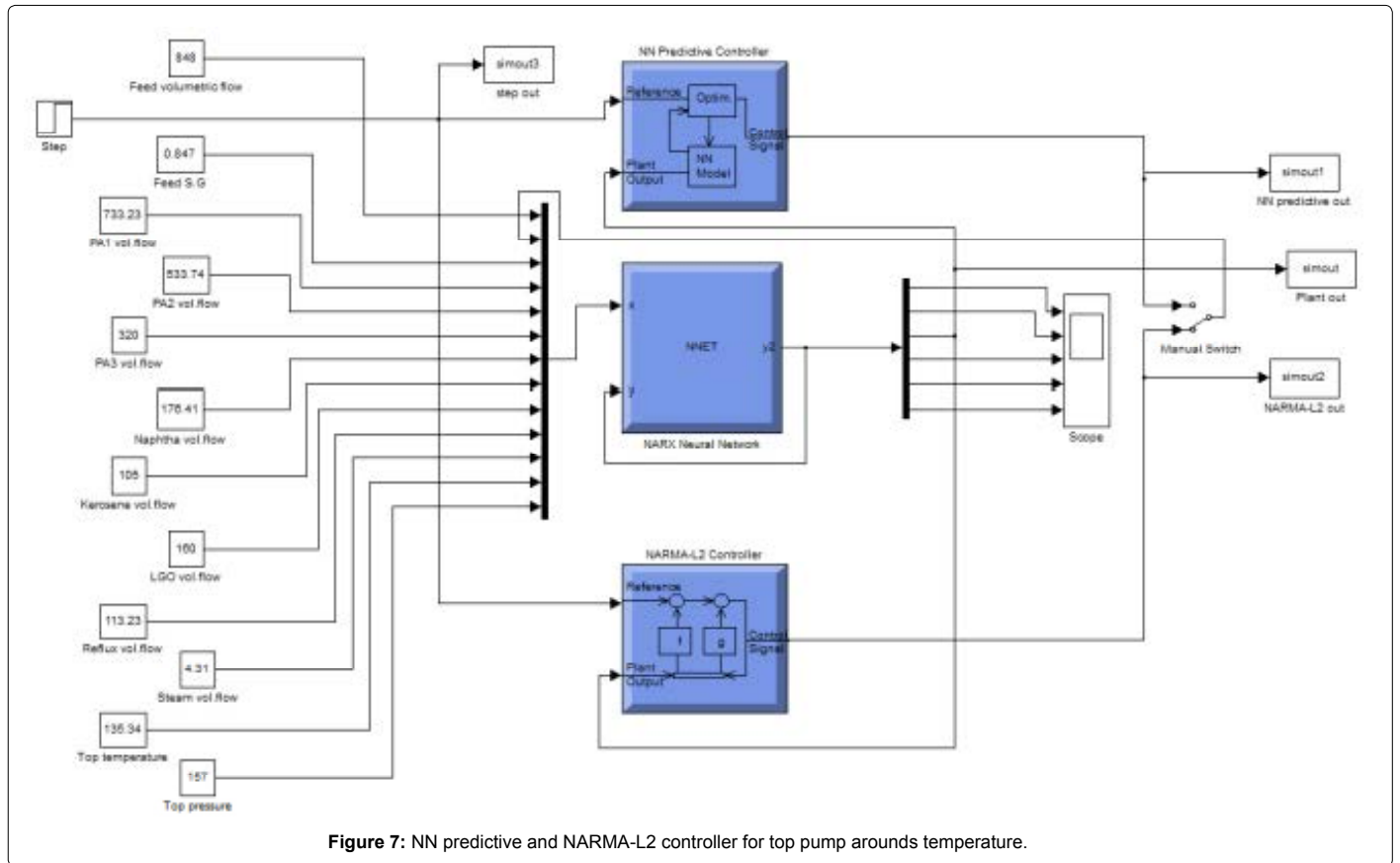


Figure 7: NN predictive and NARMA-L2 controller for top pump arounds temperature.

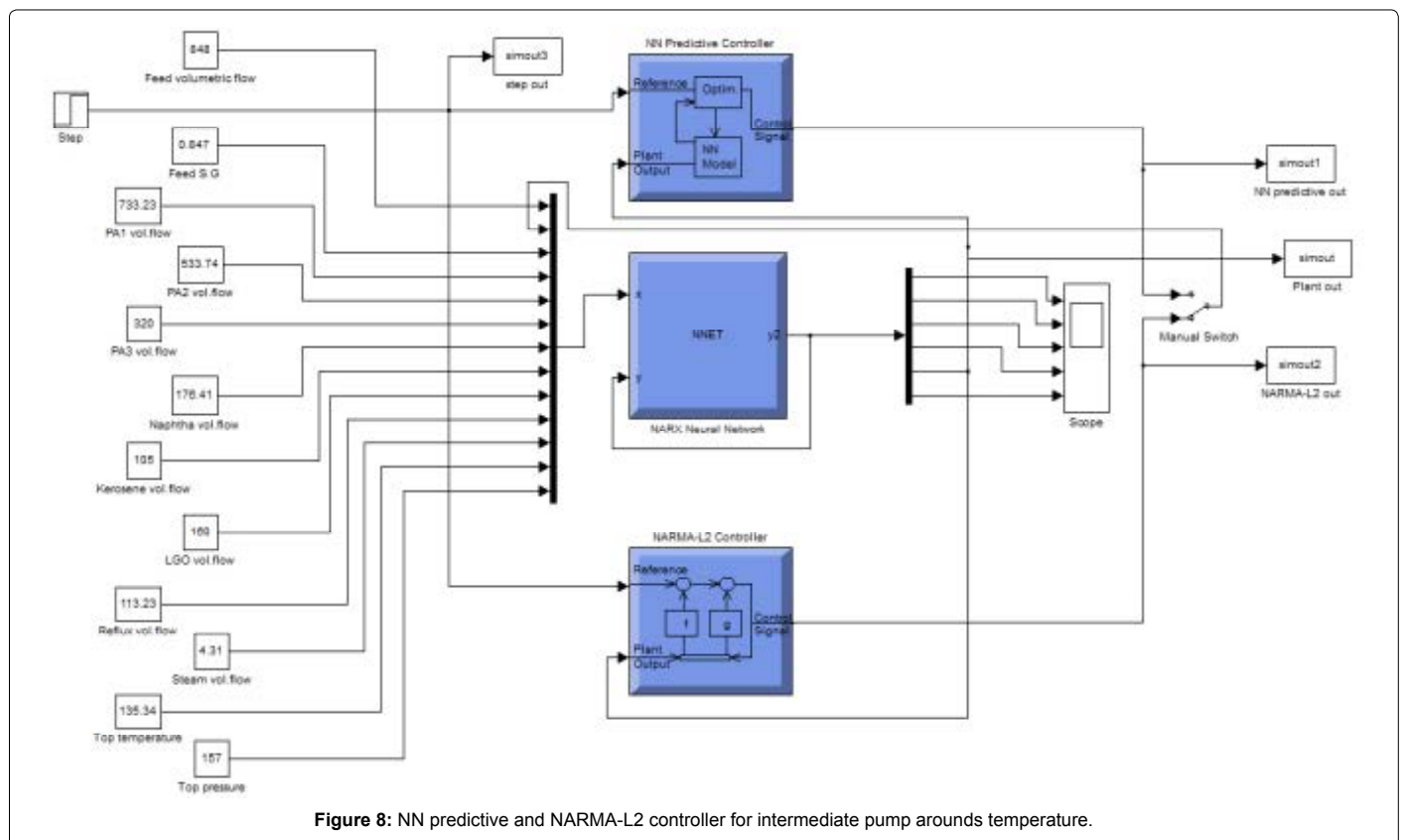
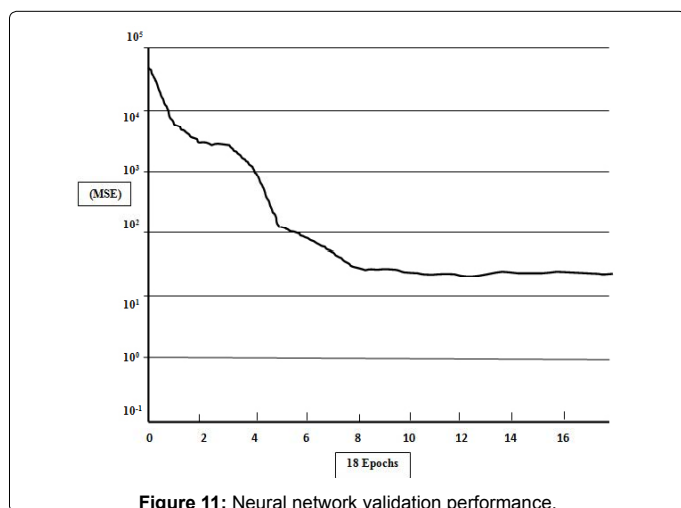
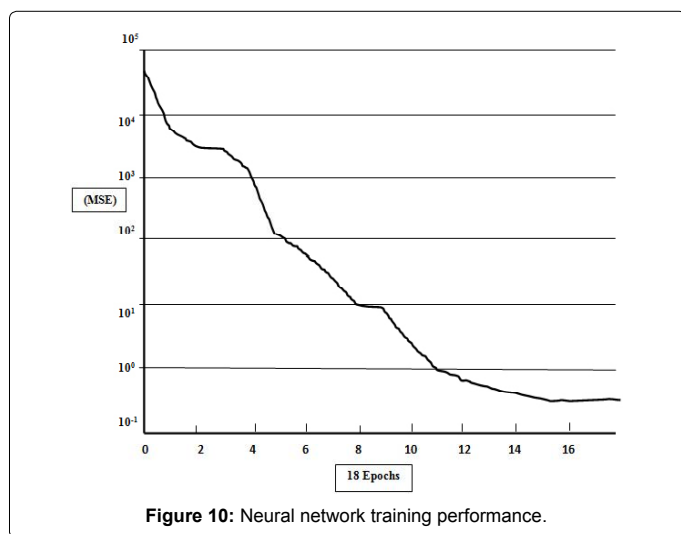
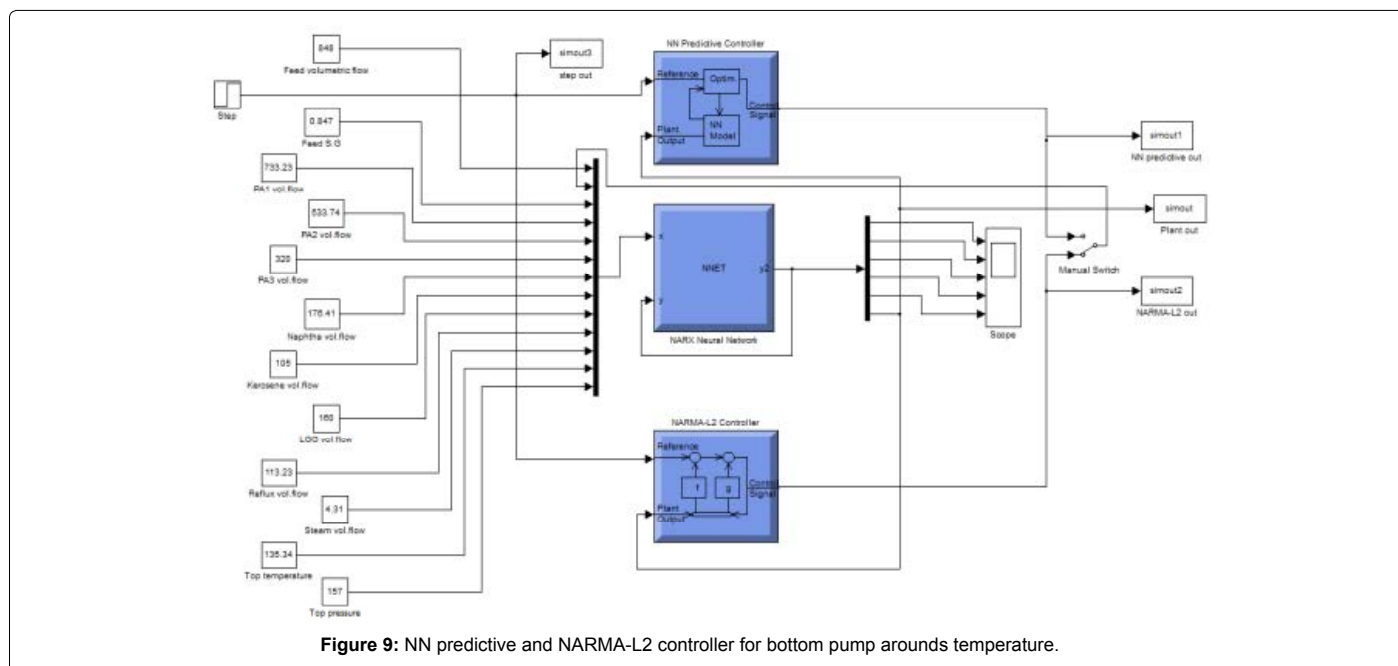


Figure 8: NN predictive and NARMA-L2 controller for intermediate pump arounds temperature.



Neural networks controller

The control system is designed for this model using neural network controller by using two methods, neural network predictive and NARMA-L2. The controlled variables are temperatures of top pumparound, intermediate pumparound, bottom pumparound, naphtha D86, kerosene D86 and LGO D86. A step change is made in feed temperature to test the controller as shown in Table 2. Also in these runs the changes in temperatures are within the limit of the training of the neural network due to the inherent property of neural networks and it is good in interpolation but is not good in extrapolation. Advantages of NN based controllers do not require any tuning of the control parameters also can take care of a nonlinear model of the process, compute the manipulated variables rapidly and produce less oscillation. Finally has less offset value and neural controller has more suitable. The temperature response reach the steady state value in less time and neural controller has lower over-shoot. Artificial neural network controller learns system and it has got generalization capabilities. The controllers based on this neural network model are able to take into account any significant process model mismatch. A step change in feed temperature from 340 to 350°C is carried out using neural network predictive and neural network NARMA-L2 controller to control the temperatures of naphtha, kerosene, LGO D86 95%, top, intermediate and bottom pumparounds. Figures 12-17 show the controller's behavior for naphtha, kerosene, LGO D86 95%, top, intermediate, and bottom pumparounds return temperatures. The comparison between the behavior of NN predictive and neural NARMA-L2 controllers are made by using mean square error criterion. It can be seen from Table 2 the MSE for NARMA-L2 controller is less than the obtained of neural predictive controller. The maximum MSE for NARMA-L2 is 103.1 while it is 182.7 for neural predictive. Both of these controllers are able to eliminate the offset without any overshoot. The satisfactory performance is due to the full representation of the non-linear dynamics of the crude oil distillation column. The NARMA-L2 controller responds as quickly as NN predictive. They indicate that the NARMA-L2 give smallest overshoots, shortest settling times and shows less oscillation, smoother and better control performance than the NN predictive controllers with smaller MSE error values acquired.

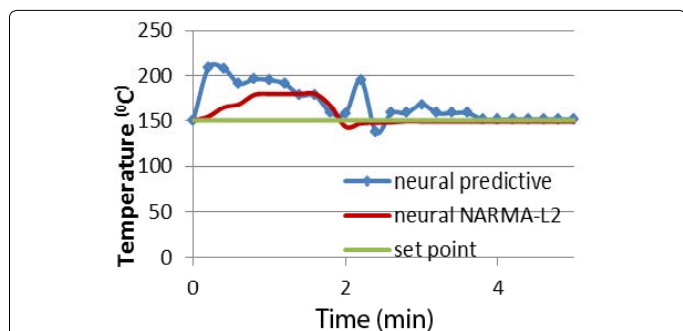


Figure 12: Comparison between neural predictive and NARMA-L2 controllers of naphtha D86 95% to a step change in feed temperature from 340 to 350°C at set point 150°C.

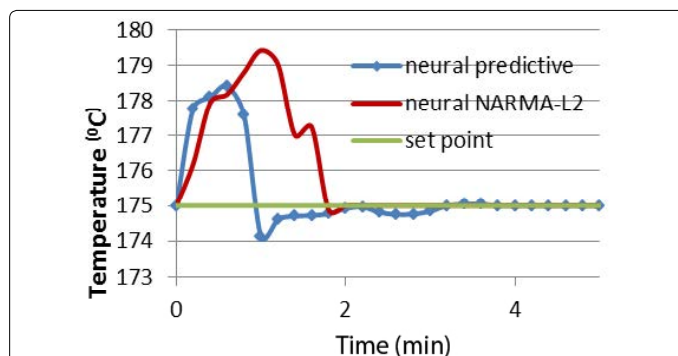


Figure 16: Comparison between neural predictive and NARMA-L2 controllers of intermediate pumparounds return temperature to a step change in feed temperature from 340 to 350°C at set point 175°C.

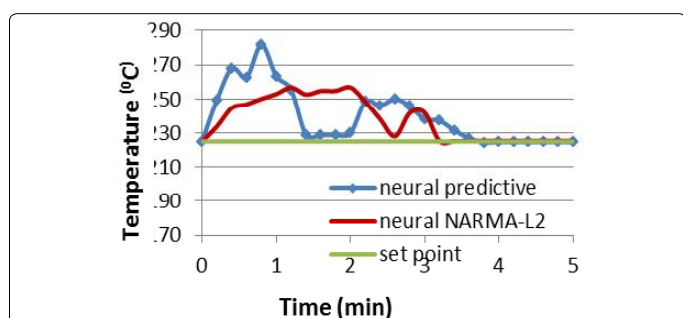


Figure 13: Comparison between neural predictive and NARMA-L2 controllers of kerosene D86 95% to a step change in feed temperature from 340 to 350°C at set point 225°C.

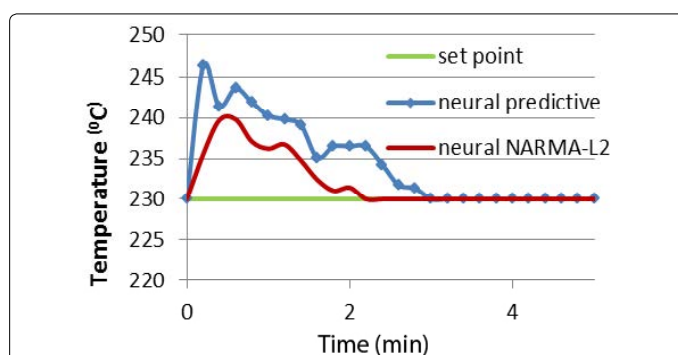


Figure 17: Comparison between neural predictive and NARMA-L2 controllers of bottom pumparounds return temperature to a step change in feed temperature from 340 to 350°C at set point 230°C.

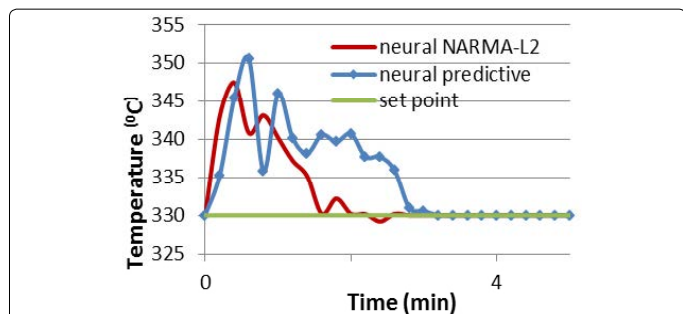


Figure 14: Comparison between neural predictive and NARMA-L2 controllers of LGO D86 95% to a step change in feed temperature from 340 to 350°C at set point 330°C.

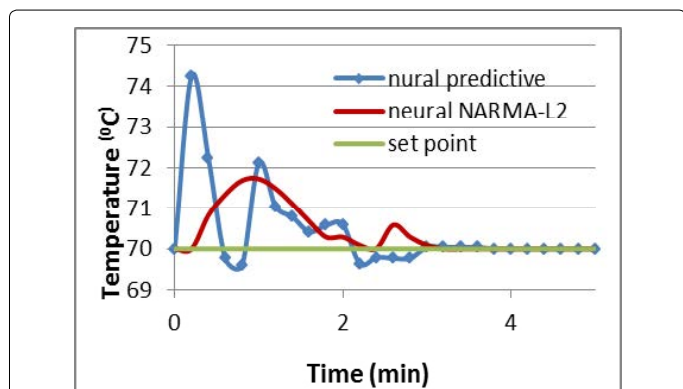


Figure 15: Comparison between neural predictive and NARMA-L2 controllers of top pumparounds return temperature to a step change in feed temperature from 340 to 350°C at set point 70°C.

Conclusion

The results presented in this paper have clearly shown the ability of neural networks to act as process controllers. The ANN is advance method can be used to model any nonlinear, complex and multivariable system. It gives the desired performance if trained well, for this study the ANN are useful tool for representing and predicting the plant output for specific input. Also the results have shown priority of neural network NARMA-L2 controller in crude oil distillation column. From simulation results which give a less offset value and the temperature response reach the steady state value in less time with lower over-shoot compared with neural network predictive controller. Finally the MSE of NARMA-L2 is less than MSE of neural network predictive control.

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