EXPERT SYSTEM DESIGN AND CONTROL OF CRUDE OIL DISTILLATION COLUMN OF A NIGERIAN REFINERY USING ARTIFICIAL NEURAL NETWORK MODEL

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ABSTRACT

This research work investigated the expert system design and control of crude oil distillation column (CODC) using artificial neural network model which was validated using experimental data obtained from functioning crude oil distillation column of Port-Harcourt Refinery, Nigeria. MATLAB program was written for the artificial neural network back-propagation algorithm using the implementation steps of the artificial neural network. Out of the one-hundred and thirty (130) experimental data sets obtained, ninety percent (90%) were used for training the network while the remaining ten percent (10%) were used for testing the network to determine its prediction accuracy. The neural network architecture for the design of the crude oil distillation column was fourteen inputs with one hidden layer and seven outputs (14-1-7); and thirteen (13) inputs with one hidden layer and six (6) outputs (13-1-6) for the neural network controller. The accuracies obtained for the design were 94%, 99%, 92%, 93%, 81%, 95% and 90% for temperature at which 100% (T_{100}) of Kerosene, 90% (T_{90}) of Diesel and 10% (T_{10}) of AGO were distilled; and naphtha, kerosene, diesel and AGO flow rates respectively. The maximum relative error between the experimental data and the calculated data obtained from the output variables of the neural network for CODC design was 1.98% error. The accuracies obtained for the neural network controller (NNC) were 98%, 99%, 99%, 93%, 97% and 97% for the stripping steam to main column, LDO stripper, HDO stripper, reflux flow 1, reflux flow 2 and reflux flow 3 respectively. The little deviation between the output variables of the experimental and calculated data for the cases of NNC predictions for reflux flows 1, 2 and 3 resulted from their excessive usage by the PID controller of the refinery considered to meet the product specifications. Hence, artificial neural network model is an effective tool for the design and control of crude oil distillation column.

Keywords: *Crude Oil Distillation Column, Control, Artificial Neural Network Model, Architecture, Input and Output Variables, Design, Back-Propagation Algorithm, PID Controller.*

1. INTRODUCTION

An expert system is a computer system employing expert knowledge to attain high levels of performance in solving the problems within a specific domain area [1]. Expert systems apply expertise to provide solutions for many complex systems in recent years [2]. They can be applied in the design of crude oil distillation column based on the information obtained from a functioning crude oil distillation column of a refinery. Crude oil distillation is the separation of the hydrocarbons in crude oil into fractions based on their boiling points. It is converted to petrol, diesel, kerosene, aviation fuel, bitumen, refinery gas and sulphur [3]. These fractions are mixtures containing hydrocarbon compounds whose boiling points lie within a specified range. Hence, distillation is the first step in refining crude oil. The separation is done in a large tower that is operated at atmospheric pressure. The tower contains a number of trays where hydrocarbon gases and liquids interact. The liquids flow down the tower and the gases up. The fractions that rise highest in the column before condensing are called light fractions, and those that condense on the lowest trays are called heavy fractions. The very lightest fraction is refinery gas, which is used as a fuel in the refinery furnaces. Next in order of volatility come gasoline (used for making petrol), kerosene, light and heavy gas oils and finally long residue [4].

The crude separation process involves many complex phenomena which have to be controlled in its best placement. The input variables of crude distillation column are usually energy supply inputs, reflux ratios and product flow rates, while the output variables are the oil product qualities, system operating performance or the plant profit [5]. If specifications of oil products cannot be reached, the oil supply can cause some problems in plant management. Controlling distillation column starts by identifying controlled, manipulated and load variables. Controlled variables are those variables that must be maintained at a precise value to satisfy column objectives. These variables for crude oil fractionator normally include product composition, column temperatures, column pressure and accumulator levels. Manipulated variables are those that can be changed in order to maintain the controlled variables at their values. Common examples include reflux flow, coolant flow, heating medium flow and product flows. Load variables are those variables that cause disturbances to the column. Examples include feed flow rate and feed composition. Other disturbances are steam heater pressure, feed enthalpy, environmental conditions (rain, barometric pressure, and ambient temperature) and coolant temperature [4]. Figure 1.1 is the schematic representation of the inside of the distillation column.

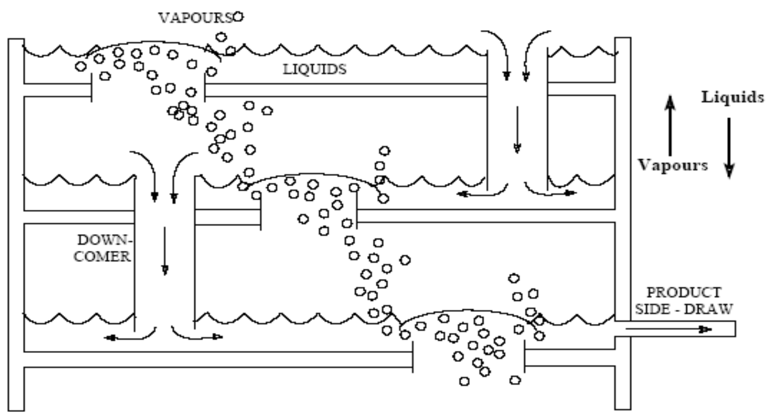


Figure 1.1: Schematic Representation of the Inside of the Distillation Column [6]

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems (such as the brain) process information. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems [7]. Bawazeer *et. al.* [3] proposed application of neural networks in oil refineries. The objective of their proposed work was to eliminate the dependency on laboratory and/or on-line sample analyzers for sampling of product qualities. The stream properties determined were naphtha 95% cut point and naphtha Reid vapor pressure. Santana *et. al*. [8] did modeling and simulation of the column with HYSYS of version 2.2 on their proposed work on thermodynamic analysis of a crude-oil fractionating process. The mixture was described as a 36 pseudo-component, using the TBP distillation curve of the feed mixture. The products streams specifications were also described as ASTM D-86 curves. To proceed with the thermodynamic analysis, flows, temperature, pressure, enthalpy, entropy, stream composition and equilibrium constants for each feed, internal liquid and vapor streams had to be extracted from the simulation. Okeke *et. al*. [9] worked on design and optimization of a refinery crude distillation unit in the context of total energy requirement. Kanthasamy [10] developed a mathematical model based on total mass balance, component balance and enthalpy balance based on first principles. A suitable algorithm was developed to solve the model equations in MATLAB environment. He proposed nonlinear model predictive control (NMPC) of a distillation column using Hammerstein model and nonlinear autoregressive model with exogenous input (NARX). Kansha *et. al*. [11] investigated the application of the self-heat recuperation technology to crude oil distillation. The heat energy analysis was conducted by following the self-heat recuperation technology. The simulation was conducted by PRO/II Ver. 8.1 to calculate the energy required.

In recent years, the research of crude distillation process was focused on the subject of process control and optimization [12]. Yu *et. al*. [13] worked on an on-line soft-sensor for control and optimization of crude distillation column. The developed soft-sensor was installed in an industry crude distillation process and worked well in on-line applications. Torgashov [14] proposed non-linear process model-based self-optimizing control of complex crude distillation column. The control system was based upon a nonlinear process model. The self-optimizing control strategy was used for the maintenance of the optimal steady-state of a complex crude distillation column. The optimal distillation operation under immeasurable feed composition disturbances was examined. Riverol *et. al*. [15] proposed the integration of fuzzy logic based control procedures in cryogenic distillation column in which they noticed that the automation of complex industrial processes was a difficult problem due to the extremely non-linear and variable system behaviour or conflicting goals within the different process phases. Macías-Hernández *et. al*. [16] worked on soft sensor for predicting crude oil distillation side streams using evolving Takagi-Sugeno fuzzy models. They concluded that the results obtained with this tool were stable and probably could go online. The results presented included the online prediction of soft sensors for distillation and inflammability of kerosene side stream.

Zalizawati [17] proposed the development of multiple-input multiple-output (MIMO) and multiple-input single-output (MISO) neural network models for continuous distillation column. The input-output data for the neural network model was generated from the validated general first principle model. Based on the input-output analyses, reboiler heat duty, reflux flow rate and tray temperatures were selected as the inputs for the neural network model. Seven different profiles were designated to excite the first principle model to generate the input-output data. These sets of data were then divided into training, validation and testing data. The results showed that the first principle and the neural network models which were developed were in good agreement with the experimental data. Haydary *et. al*. [18] performed steady-state and dynamic simulation of preflash and atmospheric column (Pipestill) in a real crude oil distillation plant using ASPEN simulations. Steady-state simulation results obtained by ASPEN plus were compared to real experimental data. Experimental ASTM D86 curves of different products were compared to those obtained by simulations. Steady-state simulation results were in good agreement with experimental data. Non-linear model predictive control (NMPC) of a distillation column using Hammerstein model and nonlinear autoregressive model with exogenous input (NARX) was proposed by Kanthasamy [10] in which he concluded that the model results showed a high level of consistency with the experimental results. Kozarev *et. al*. [19] proposed computer aided steady state control of crude oil distillation. An algorithm and computer program for a feed design was developed with simple non-iterative mathematical models of crude oil distillation tower together with an appropriate adaptation technique. During the past two decades, there has been a growing awareness among academia and industrial practitioners regarding the control of crude oil distillation column.

2. MODELLING EQUATIONS

2.1 The Back-Propagation Algorithm

The binary sigmoidal transfer function considered as the activation function for each node in the network is defined thus [20]:

$$y_k = F_N(Z_k) = \frac{1}{1+\exp^{(-Z_k)}} \quad \text{......................................} \qquad 2.1$$

where y_k is the Sigmoidal Transfer function and limits the output of all nodes in the network to be between 0 and 1; Z_k is the sum of the inputs x_j multiplied by their respective weights.

$$Z_k = \sum_j w_{kj} x_j \quad \text{......................................} \qquad 2.2$$

w_{kj} is weight of the jth input to the kth neuron of the output layer and x_j is the jth input to the neuron.

The error function is calculated thus:

$$error = \frac{1}{2}\sum_{j=1}^{m}[d_j(n) - y_j(n)] \quad \text{................................} \qquad 2.3$$

Where d_j = practical data of jth output neuron

y_j = computed data of jth output neuron

m = neuron number

n = training step

The Back Propagation Algorithm for training the artificial neural network and updating the weights is calculated thus:

$$w_{ij}^{k+1} = w_{ij}^{k} + \eta\delta_j^k I_i f'(s) \quad \text{......................................} \qquad 2.4$$

where

w_{ij}^{k} = weights of the connection from unit i in layer k to unit j in layer k+1

η = learning rate (constant)

δ_j^k = signal error

I_i = input vector to the networks

2.2 Implementation Procedure for Artificial Neural Network

The back propagation algorithm stated was used as part of the implementation procedure for building the artificial neural network (ANN) for the crude distillation column. The coefficients of the model were discovered by training the neural network program using back propagation algorithms. The neural network program was trained by adjusting the weight coefficients until the difference between the predicted product quality and the measured product quality was within acceptable limits. When the coefficients had been determined, they would be tested by comparing the predicted quality to the measured quality for data sets which were not used in finding the coefficients. The major steps involved in implementing the ANN predictor are shown in Figure 2.1.

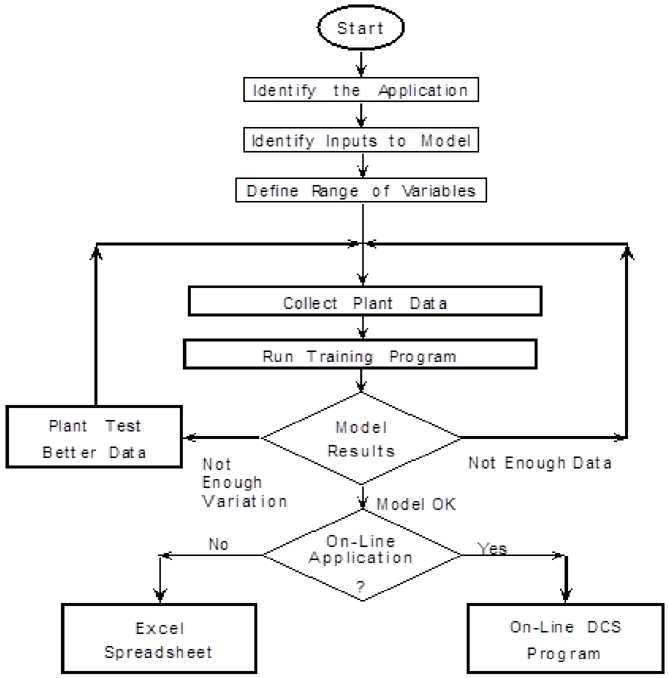


Figure 2.1: Major Steps for Implementing ANN in the Crude Oil Fractionation Process

2.3 Neural Network Architecture for the Design of the Crude Oil Distillation Column

The neural network architecture for the design of the crude oil distillation column (CODC) is fourteen inputs with one hidden layer (nine nodes) and seven outputs (14-1-7) making a total of 30 nodes distributed over the three layers. The inputs to the network are feed temperature of crude oil, kerosene flow ratio, AGO flow ratio, diesel flow ratio, crude oil flow rate, API gravity of crude oil, sulphur content of crude oil, compositions of C_2, C_3, i-C_4, n-C_4, i-C_5, n-C_5 and Cyclo-pentane in crude oil represented respectively as I1, I2, I3, I4, I5, I6, I7, I8, I9, I10, I11, I12, I13 and I14. The outputs from the NN architecture are temperatures at which 100% (T_{100}) of Kerosene, 90% (T_{90}) of Diesel and 10% (T_{10}) of AGO are distilled; and naphtha, kerosene, diesel and AGO flow rates represented respectively as O1, O2, O3, O4, O5, O6 and O7. Figure 2.2 is the neural network architecture for the design of crude oil distillation column.

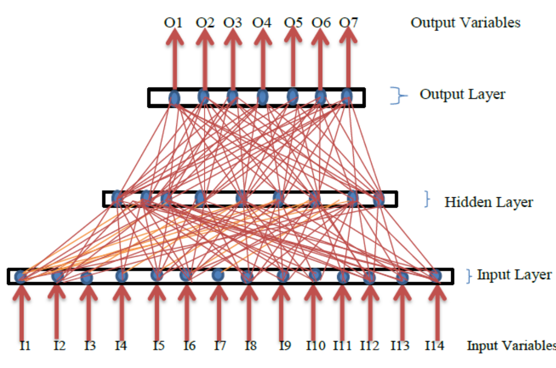


Figure 2.2: Neural Network Architecture for the Design of Crude Oil Distillation Column

2.4 Implementation Procedure for Artificial Neural Network Controller of the Crude Oil Distillation Column

The flow chart overview of the developed neural network controller (NNC) mounted to control the crude oil fractionator is shown in figure 2.3 below. The input variables for the neural network controller designed for the crude oil distillation column include the feed flow rate, feed temperature, top temperature, bottom temperature, reflux temperature 1, reflux temperature 2, reflux temperature 3, bottom flow, distillate flow 1, distillate flow 2, distillate flow 3, distillate flow 4 and top pressure. The expected output from the network include stripping steam to main column, LDO striper, HDO stripper, reflux flow 1, reflux flow 2 and reflux flow 3.

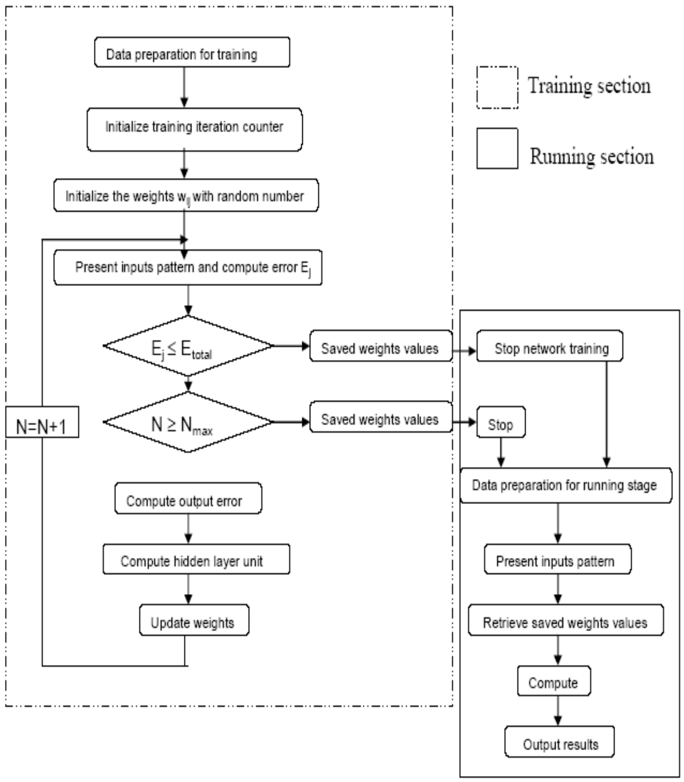


Figure 2.3: Flow Chart of the Neural Network Controller

2.5 Neural Network Controller (NNC) Architecture for Crude Oil Distillation Column

The inputs to the network are feed flow rate, feed temperature, top temperature, bottom temperature, reflux temperatures 1, 2 and 3; bottom flow, distillate flow 1 (Naphthalene), distillate flow 2 (kerosene), distillate flow 3 (Light Diesel Oil), distillate flow 4 (Heavy Diesel Oil) and top pressure represented as i_1, i_2, i_3, i_4, i_5, i_6, i_7, i_8, i_9, i_{10}, i_{11}, i_{12} and i_{13} respectively. The outputs from the NNC are stripping steam to main column, LDO stripper, HDO stripper, reflux flow 1 (Top Pump around), reflux flow 2 (Kerosene Pump around) and reflux flow 3 (Light Diesel Oil Pump around) represented as o_1, o_2, o_3, o_4, o_5 and o_6 respectively. The architecture for the neural network controller becomes thirteen (13) inputs with one hidden layer (nine nodes) and six (6) outputs (13-1-6) with a total of 28 nodes distributed over the layers. Figure 2.4 represents neural network controller architecture for crude oil distillation column.

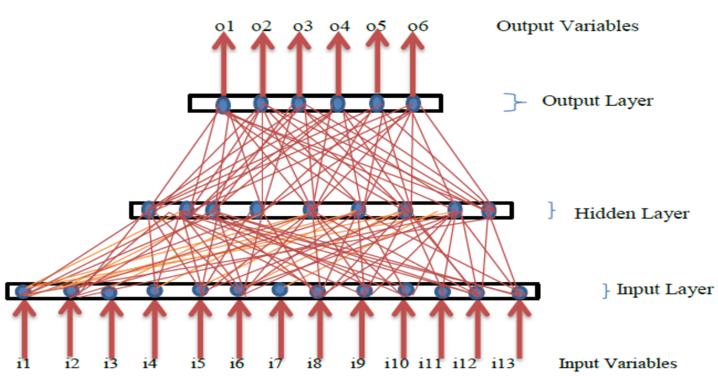


Figure 2.4: Neural Network Controller Architecture for Crude Oil Distillation Column

3. RESULTS

The artificial neural network model developed for both the design and controller of the crude oil distillation column was validated using experimental data obtained from functioning crude oil distillation column of Port-Harcourt Refinery, Nigeria. Out of the one-hundred and thirty (130) experimental data sets obtained, ninety percent (90%) were used for training the network while the remaining ten percent (10%) were used for testing the network to determine its prediction accuracy. MATLAB program was written for the neural networks model. Table 3.1 and 3.2 show the test comparison results obtained between the experimental data of the CODC and the calculated values from the trained neural network for the design and controller of the crude oil distillation column (CODC) respectively.

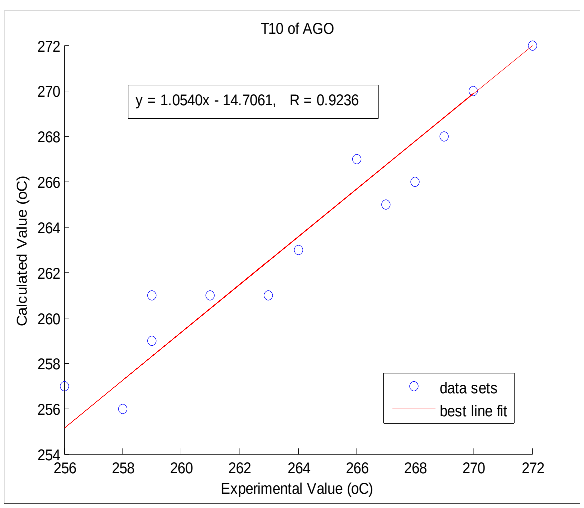
Table 3.1: Test Results Obtained from the Trained ANN for Crude Oil Distillation Column Design

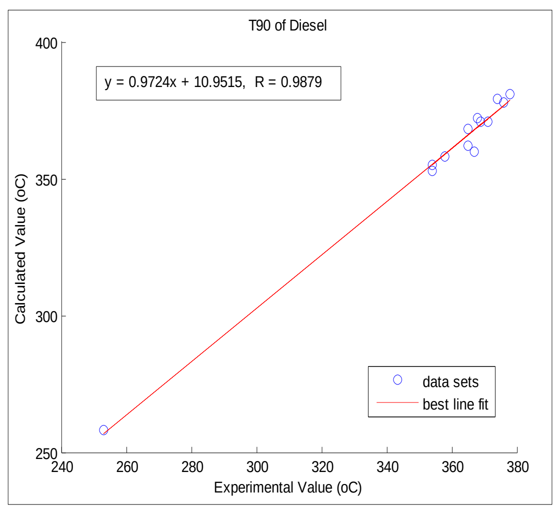
Test No	**T_{10} of AGO (^oC)**			**T_{90} of Diesel (^oC)**			**T_{100} of Kerosene (^oC)**		
	Comp.	**Exp.**	**Err.(%)**	**Comp.**	**Exp.**	**Err.(%)**	**Comp.**	**Exp.**	**Err.(%)**
1	261	263	0.76	379	374	1.34	255	253	0.79
2	257	256	0.39	362	365	0.82	267	263	1.52
3	261	259	0.77	258	253	1.98	261	263	0.76
4	265	267	0.75	360	367	1.91	258	256	0.78
5	263	264	0.38	353	354	0.28	266	269	1.12
6	259	259	0.00	358	358	0.00	258	259	0.39
7	261	261	0.00	371	369	0.54	278	278	0.00
8	268	269	0.37	371	371	0.00	272	271	0.37
9	270	270	0.00	368	365	0.82	247	243	1.65
10	266	268	0.75	355	354	0.28	268	266	0.75
11	256	258	0.78	381	378	0.79	253	249	1.61
12	267	266	0.38	378	376	0.53	254	254	0.00
13	272	272	0.00	372	368	1.09	273	275	0.73

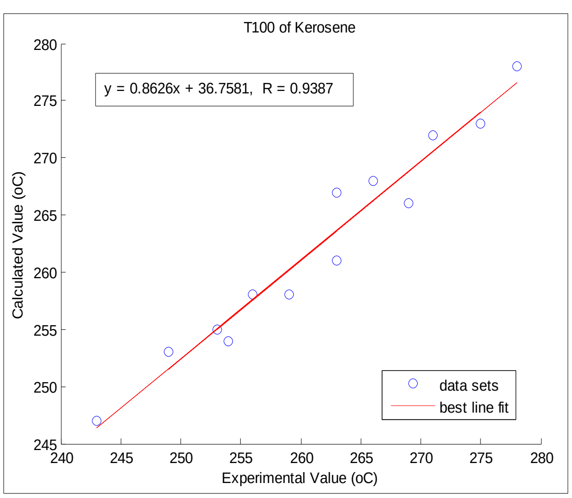
Test No	**Naphtha Flow Rate (m^3/hr)**			**Kerosene Flow Rate (m^3/hr)**			**Diesel Flow Rate (m^3/hr)**			**AGO Flow Rate (m^3/hr)**		
	Comp.	**Exp.**	**Err.(%)**	**Comp.**	**Exp.**	**Err.(%)**	**Comp.**	**Exp.**	**Err.(%)**	**Comp.**	**Exp.**	**Err.(%)**
1	205.2	205.6	0.20	142.8	143.9	0.76	42.7	42.9	0.47	237.0	236.8	0.09
2	210.0	209.8	0.10	139.3	138.9	0.29	42.0	41.8	0.48	235.6	235.8	0.09
3	201.9	201.3	0.30	142.9	142.3	0.42	45.5	45.6	0.22	233.8	233.8	0.00
4	203.1	203.5	0.20	138.4	139.8	1.00	42.6	42.3	0.71	235.4	235.4	0.00
5	207.1	206.8	0.15	143.8	142.4	0.98	44.3	44.3	0.00	232.1	231.3	0.35
6	203.5	203.8	0.15	141.1	141.9	0.56	41.9	41.8	0.24	232.9	231.7	0.52
7	201.5	201.3	0.10	142.8	142.9	0.07	43.1	42.8	0.70	231.9	231.9	0.00
8	204.3	204.6	0.15	138.7	138.7	0.00	41.6	41.9	0.72	233.9	233.6	0.13
9	202.0	201.7	0.15	142.9	143.3	0.28	43.8	43.9	0.23	232.3	233.6	0.56
10	203.8	203.8	0.00	143.9	145.6	1.17	42.2	42.8	1.40	233.9	232.5	0.60
11	204.8	203.6	0.59	145.1	144.9	0.14	44.6	44.6	0.00	239.3	238.9	0.17
12	202.9	202.9	0.00	144.1	144.2	0.07	42.5	42.3	0.47	231.8	231.8	0.00
13	205.7	204.3	0.69	143.7	142.5	0.84	43.5	43.8	0.69	234.5	234.8	0.13

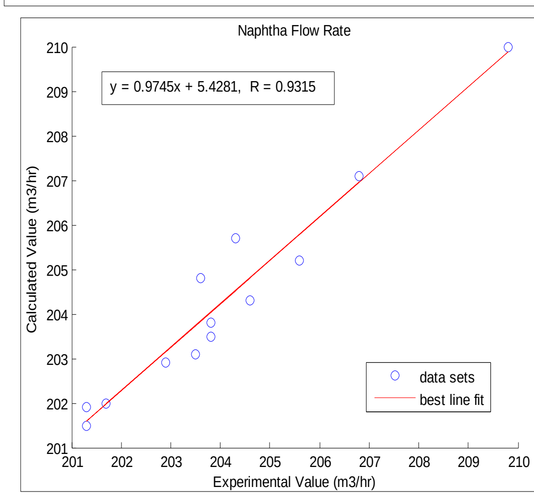
Table 3.2: Test results obtained from the trained neural network controller for CODC

Test No	**Stripping Steam to main column (kg/hr)**		**LDO Stripper (kg/hr)**		**HDO Stripper (kg/hr)**		**Reflux Flow 1 (m^3/hr)**		**Reflux Flow 2 (m^3/hr)**		**Reflux Flow 3 (m^3/hr)**	
	Comp.	**Exp.**	**Comp.**	**Exp.**	**Comp.**	**Exp.**	**Comp.**	**Exp.**	**Comp.**	**Exp.**	**Comp.**	**Exp.**
1	6631	6632	5603	5603	796.1	795.8	374.6	374.2	801.5	801.8	374.1	374.2
2	6631	6632	5603	5603	795.9	795.7	374.1	374.1	801.5	801.8	372.3	372.8
3	6630	6630	5603	5604	796.7	796.2	374.7	374.3	801.3	801.8	370.4	370.4
4	6631	6631	5605	5605	797.5	797.7	375.1	375.6	802.1	802.3	370.1	370.4
5	6636	6635	5613	5614	800.9	800.6	376.2	376.4	802.7	802.6	370.6	370.4
6	6637	6637	5613	5614	800.8	800.7	376.4	376.2	803.9	803.7	370.4	370.1
7	6641	6640	5614	5614	802.8	802.4	376.9	376.6	803.7	803.7	374.0	373.6
8	6641	6640	5616	5616	804.2	804.4	377.9	377.9	803.2	803.7	373.5	373.8
9	6641	6640	5616	5617	804.1	804.3	376.8	376.8	805.3	805.1	376.9	376.8
10	6645	6644	5622	5621	804.9	804.7	376.6	376.7	805.4	805.5	376.6	376.8
11	6649	6648	5622	5622	806.1	806.8	376.9	376.5	805.7	805.5	376.7	376.9
12	6650	6649	5622	5622	809.6	809.7	376.6	376.3	807.6	807.0	376.7	376.9
13	6650	6649	5623	5624	809.0	809.8	376.4	376.8	807.6	806.9	376.9	375.6









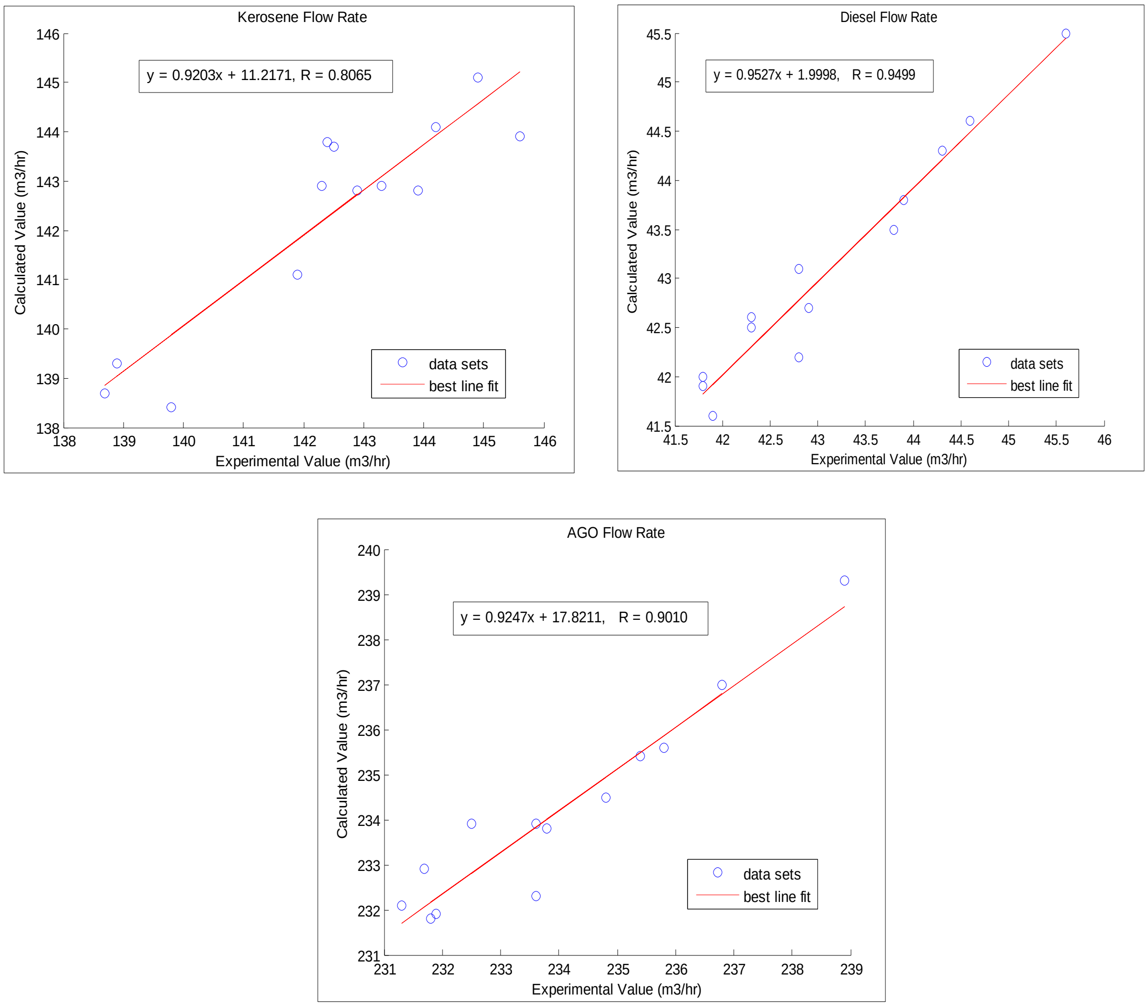


Figure 3.1: Linear Regression Analysis between the Experimental Data and Calculated Data for the Crude Oil Distillation Column Design

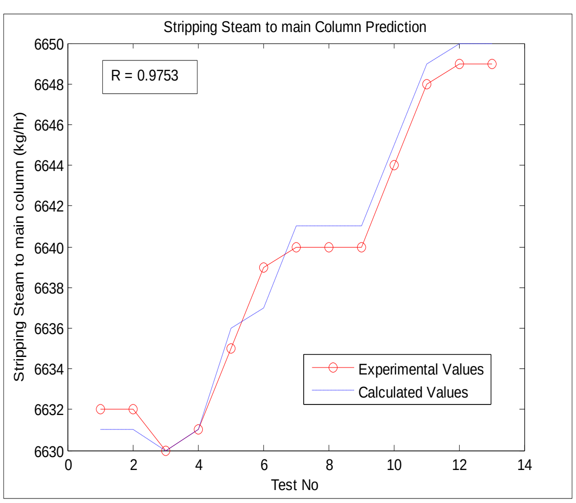


Figure 3.2: NNC for Stripping Steam Prediction

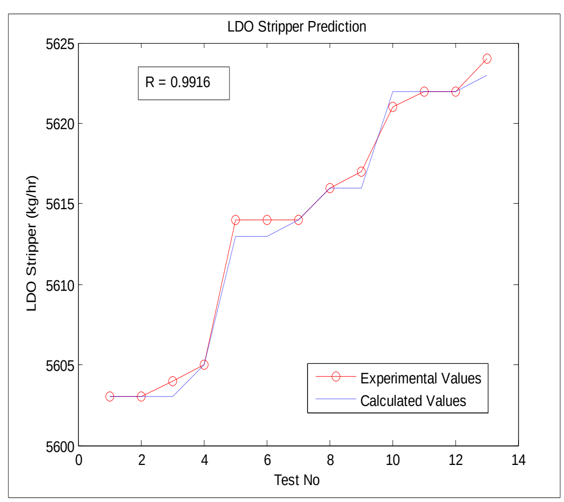


Figure 3.3: NNC for LDO Stripper Prediction

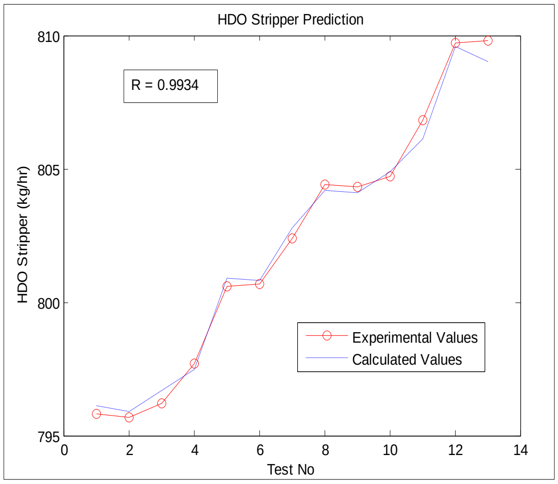


Figure 3.4: NNC for HDO Stripper Prediction

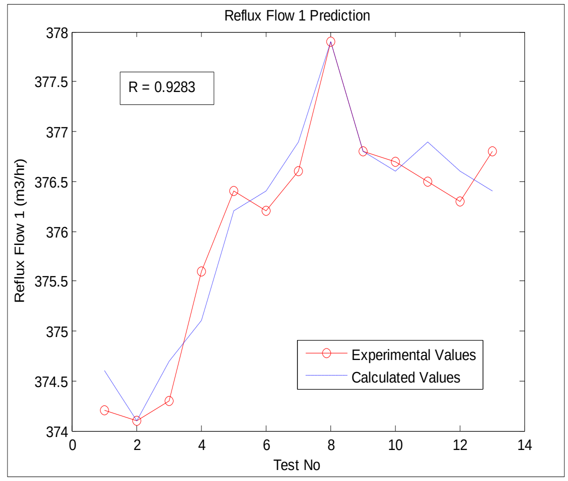


Figure 3.5: NNC for Reflux Flow 1 Prediction

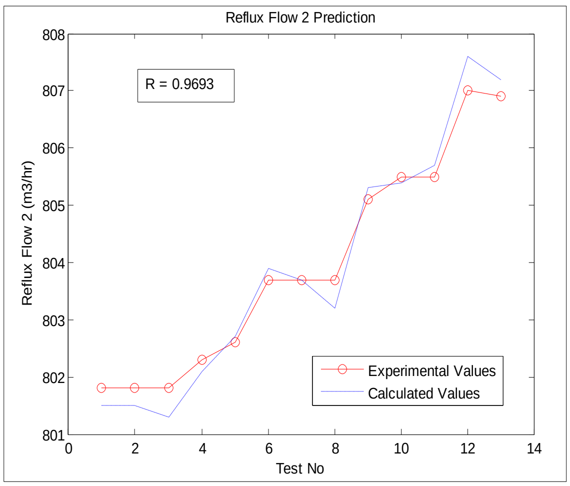


Figure 3.6: NNC for Reflux Flow 2 Prediction

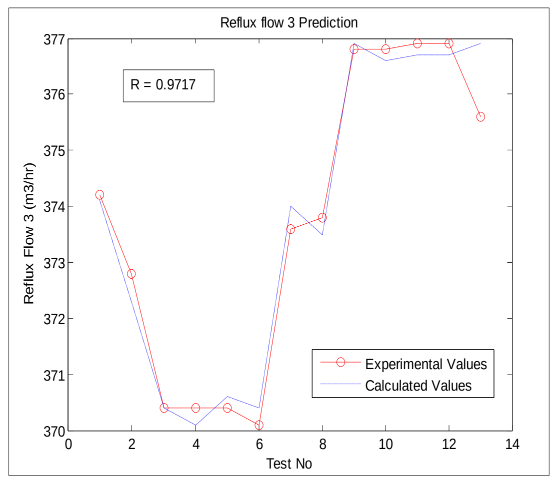


Figure 3.7: NNC for Reflux Flow 3 Prediction

4. DISCUSSION OF RESULTS

The maximum relative error between the experimental data and the calculated data obtained from the output variables of the neural network for CODC design is 1.98 error %. The linear regression analysis performed between the experimental data obtained from the refinery and the calculated data obtained from the neural network architecture for the CODC design is depicted in figure 3.1. The correlation coefficients obtained for T_{100} of Kerosene, T_{90} of Diesel, T_{10} of AGO, naphtha, kerosene, diesel and AGO flow rates are 0.9387, 0.9879, 0.9236, 0.9315, 0.8065, 0.9499 and 0.9010 respectively. This is an indication that the neural network model can be used to predict design variables (output variables) of the crude oil distillation column. For the neural network controller designed for the crude oil distillation column, the regression coefficients executed between the experimental and calculated data are 0.9753, 0.9916, 0.9934, 0.9234, 0.9283, 0.9693 and 0.9791 for the stripping steam to main column, LDO stripper, HDO stripper, reflux flow 1 (Top Pump around), reflux flow 2 (Kerosene Pump around) and reflux flow 3 (Light Diesel Oil Pump around) respectively. This result revealed that the neural network controller had been trained rigorously and can be used to predict the non-linear relation existing among the variables of the process. Individual plots for the neural network controller (NNC) outputs were done to find the correlation between the PID controller of the refinery (from which experimental data were gotten) and the neural network controller (from which calculated values were obtained). Figures 3.2, 3.3 and 3.4 are the NNC predictions for the stripping steam to main column, light diesel oil (LDO) stripper and heavy diesel oil (HDO) stripper with respective accuracy of 98%, 99% and 99% between the experimental and calculated values. This resulted from their maintenance at particular values for various inputs of the NNC. Figures 3.5, 3.6 and 3.7 depict the NNC prediction for reflux flow 1 (Top Pump around), reflux flow 2 (Kerosene Pump around) and reflux flow 3 (Light Diesel Oil Pump around) with 93%, 97% and 98% accuracy respectively. However, the output variables for both the PID controller (from refinery) and NNC deviated from each other to some extent for the cases of NNC predictions for reflux flows 1, 2 and 3 (figures 4.5, 4.6 and 4.7) respectively. This resulted from their excessive usage by the PID controller to meet the product specifications (T_{100} of Kerosene, T_{90} of Diesel and T_{10} of AGO, naphtha, kerosene, diesel and AGO flow rates). The accuracies for the NNC predictions for reflux flows 1, 2 and 3 are 93%, 97% and 98% respectively. Thus, the neural network controller is effective for the predictions of the output variables and maximally relating the non-linear behaviour existing among various variables of the process.

5. CONCLUSION AND RECOMMENDATIONS

The expert system design and control of crude oil distillation column using artificial neural network model had been done. MATLAB computer program had been written to simulate the artificial neural network back-propagation algorithm for both the design and control of crude oil distillation column using experimental data of Port-Harcourt refinery, Nigeria. The design of the crude oil distillation column and the neural network controller gave effective accuracies for their various output variables. The neural network controller is effective for the predictions of the output variables and maximally relating the non-linear behaviour existing among various variables of the process. Hence, artificial neural network model is an effective tool for the design and control of crude oil distillation column. There is need for improvement in the neural network model to curb uncertainty as a result of noise and disturbance which usually affect the system during the training stage. Also, it is highly recommended that computational complexity of the model should be reduced as the training requires using many data for its accurate prediction.

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