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NEURAL NETWORK CONTROLLER FOR A CRUDE OIL DISTILLATION COLUMN

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ABSTRACT

The development of neural network that could be used for the control of an industrial process is discussed. Field data from a working distillation column or fractionator of crude oil refinery in Nigeria was used for the development and testing the effectiveness of the controller. The developed controller performed optimally when compared with the installed distributed control system based on proportional integral and derivative algorithm in the company with well over 95% correlation between the expected data and obtained data.

Keywords: neural networks controller, distillation column, crude oil fractionator.

Nomenclature

Inputs NNC

i1 = Ff: Feed flow
i2 = Ft: Feed temperature
i3 = Tt: Top temperature
i4 = Bt: Bottom temperature
i5 = Rt1: Reflux temperature1
i6 = Rt2: Reflux temperature2
i7 = Rt3: Reflux temperature3
i8 = Bf: Bottom flow / atmospheric residual flow (ARF)
i9 = Df1: Distillate flow 1 / Naphthalene
i10 = Df2: Distillate flow 2 / Kerosene
i11 = Df3: Distillate flow 3 / Light Diesel Oil (LDO)
i12 = Df4: Distillate flow 4 / Heavy Diesel Oil (HDO)
i13= Tp: Top pressure

Outputs NNC

O1 = Sf: Steam flow
O2 = Rf1: Reflux flow 1 / Top pump around
O3 = Rf2: Reflux flow 2 / Kerosene pump around
O4 = Rf3: Reflux flow 3 / LDO pump around

1. INTRODUCTION

The problem of control loop interactions in industrial process control is well known. Most unit operations in the process industries are multivariable, and some of these variables are required to be maintained at particular values (set point) during process operations. Distillation column is the common separation unit used in the chemical and refinery industry to achieve product stripping and purification. This unit not only exhibits interaction, but is also very energy consuming, and the energy requirements are closely linked to the desired separation. For specified product composition, the energy requirement can be minimized if satisfactory simultaneous control of the terminal composition can be achieved despite disturbances to the column. Distillation column control is difficult, to control due to the strong process interactions, and the nonlinear dynamic behavior of the processes within the column.

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.

Controlled variables are usually obvious. They are normally identified when process objectives are defined and understood. Load variables are also easily identified. However, identification of manipulated variables can be more difficult. There are general guidelines for identifying which manipulated variables are to be associated with which controlled variable such as [13]:

- Manipulate the stream that has the greatest influence on the associated controlled variable.
- Manipulate the smaller stream if two streams have the same effect on the controlled variable.
- Manipulate the stream that has the most nearly linear correlation with the controlled variable.
- Manipulate the stream that is least sensitive to ambient conditions.
- Manipulate the stream least likely to cause interaction problems.

The above rules are used for the basic control principle, and sometimes yield conflicting results. Over the years, several methods for multivariable parameters adaptive control have been proposed [5, 13]. Most of these methods were derived as direct extension of the principle of single-input single-output (SISO) counterparts. However, majority of distillation column process are multiple-inputs multiple-outputs (MIMO) as shown in [7], and the SISO are unable to address the nonlinear dynamics of the process. Still date, good numbers of these SISO strategies for fractionator control is implemented using proportional integral and derivative (PID) algorithm. The PID algorithm is the basic feedback mechanism for correcting errors between the current condition (measurement) and what is desired (set point). The PID assumes a linear process. Adaptive control and other techniques are used when nonlinearity are encountered. However, we are still far from meeting the goal of optimizing the operations of the distillation column at minimal cost. Efforts have been made to improve PID performance by considering the dynamic nature of the fractionator, the nonlinearity of the system, and associated the coupling effects. These efforts include feed forward and feedback control, adaptive gain technique self tuning, etc. [2, 7, 8, 13, 15].

In the recent years, model based control system (MBCS) have been gaining popularity [13]. They include internal model controller (IMC), model algorithmic controller (MAC), and neural networks controller (NNC). Process model control uses algorithm to approximate the process model directly for control in order to overcome the coupling effect in the distillation column. Most of these methods are nonlinear, all are predictive, and many are MIMO [13].

The purpose of this study was to develop a powerful controller allowing perfect control of a complex process as a distillation column. This reliable controller was developed with artificial neural networks, which is a distributed structured paradigm that perfectly mapped the nonlinearities of the crude oil fractionator process. The modeling procedure, the experimental set-up and prediction results are described in the following sections.

2. MATERIALS AND METHODS

2.1 Data collection and preparation for the NNC training process

The developed NNC was validated using field data obtained from a working fractionator for crude oil refining company in Nigeria, owned by the Nigeria National Petroleum Cooperation (NNPC). The refinery is the Port-Harcourt Refining Company (NNPC-PHRC). The collected data contained information from 1994, when the process was working at 1000 m^3/hr of Feed flow rate to 2004 when the capacity dropped to 600 m^3/hr. These data were used to mimic the behavior of the process for a 10 year period. The data obtained there-of, 40 patterns were divided into three major groups because early stopping technique was applied. A data pattern was made up of 17 measured values of the process variables, which consists of 13 input values and 4 output values. The three major groupings (based on the quantity of fluid flow rate into the distillation column) are for training, validation, and testing the performance of the NNC, respectively. The performance of our developed NNC was demonstrated during a step called the running phase. This was achieved by using randomly chosen input data from the training and validation sets, added to some datasets that were not used for both exercises. The data were appropriately scaled to obtain satisfactory range (between 0 and 1) that could easily be handled by the NNC as a sigmoid transfer function was used.

2.2 Fractionation process and description of the fractionator

The separation of crude oil by distillation is a physical process based on the fact that different chemical compounds have different boiling points. For example, pentane, C_5H_{12}, boils at 36 °C, while nonane, C_9H_{20}, boils at 128 °C. Because the separation is only based on the physical process, no chemical bonds are broken during distillation and no chemical reactions take place at this stage. The column also called fractionator or tower contains a series of collecting trays, one above the other (Figure-1).

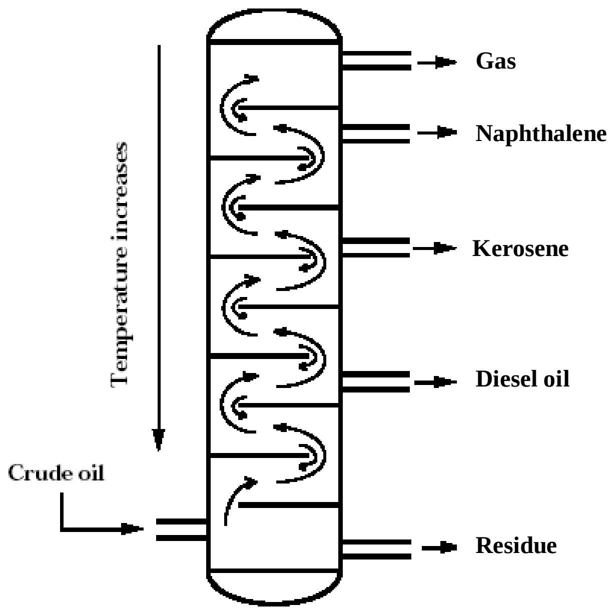

Figure-1. Schematic representation of a fractionator.

The temperature inside the tower is carefully controlled so that the highest is obtained where the crude oil enters the tower and gradually decreases from the bottom to the top of tower. Thus each collecting tray is a little cooler than the one beneath it. As the hot oil enters the tower, the largest molecules evaporate and become gas. This gas gradually ascends the tower and its temperature decreases (Figure-1) with the decrease in temperature. The molecules in the gas find it more

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difficult to stay apart [5], as the larger molecules in the gas begin to stick to one another and form liquid in the fractionator's trays. Some of this liquid drips down from each tray to the tray below. Overall, gas moves up the tower from below and liquid drips down the tower from above. Each tray tends to accumulate those molecules that can be either gas or liquid at the tray's temperature. Any molecules that tend to be gaseous at that temperature will move up the tower to the trays above. Any molecules that tend to be liquid at that temperature will drip down the tower to the trays beneath. Thus each tray concentrates a particular group of molecules. However this concentrating process doesn't produce pure chemicals. The liquid in a particular tray still contains a number of different molecules. While one range of sizes is most likely to accumulate in that tray, it will also contain some smaller and larger molecules that manage to find their way into the liquid. In general, nature always tries to maximize the randomness of a liquid. The same statistical rules that govern the flow of heat responsible for the laws of thermodynamics make it very difficult to purify chemicals completely. The fractionator finally separates the crude oil into several parts, including diesel oil, kerosene, and naphthalene.

2.3 Artificial neural networks (ANN)

Artificial neural networks initially grew from the full understanding of some ideas and aspects about how biological system works, especially the human brain. In biology, the cell body of neuron is called the soma. The spine-like extensions of the cell body are dendrites. They usually branch repeatedly and form a bushy tree around the cell body and provide connections to receive incoming signals from other neurons. The axon extends away from the cell body to provide a pathway for outgoing signals. Signals are transferred from one neuron to another through a contact point called a synapse. Although the synaptic junctions can be formed between axon and cell body, the most common synaptic junction is between the axon of one neuron and the dendrite of another. There are two classes of synapses: a) the excitatory synapse, which tends to promote the activation of neurons, b) the inhibitory synapse, which plays the opposite role of excitatory. When a neuron is activated, or fired, (this could be caused by an external stimulus), an impulse signal travels down along the axon, until it reaches a synapse. At this point some kind of chemical transmitter is released to promote or inhibit the firing of the receptor neuron [6, 10].

Research in the neuroscience has demonstrated that the excitation and inhibition of a synapse can be enhanced by the activities of neurons, and this synaptic plasticity is believed by many researchers to be the neuronal mechanism of learning and memory function of the brain; this synaptic plasticity learning theory is the biological foundation of ANN [11, 14].

Like biological neuron networks, ANN is made of 'neuron' and 'synaptic connections' which are highly simplified abstracts of their counterparts in real neural networks. The neurons in the ANN are usually called units, node, or processing elements, and the efficacy of the synaptic connection, which is a measurement of excitability and inhabitability, are usually called weights. Neural networks systems (NNS) are typically organized in layers. Layers are made up of a number of interconnected nodes (artificial neurons or processing element), which contain an activation function.

The data are presented to the networks via the input layer, which communicates to one or more hidden layers where the actual processing is done through a system of weighted connections. The hidden layers are then linked to an output layer, which generates the output. The neural networks contain some sort of learning rule that modifies the weights of the connections according to the input patterns that it is presented with [3, 12]. The neural networks have the capability to learn, memorize and create relationships amongst data. There are many different types of neural networks. The most widely used and the one applied in this study were known as the multilayer perceptron (MLP) train with back propagation algorithm [6, 10].

2.4 Multilayer perceptron (MLP) using back propagation algorithm

This type of ANN is excellent at prediction and classification tasks. Their networks have two modes of operation during the training or learning phase: Feed forward computation and the weights updating operation. In feed forward computation, when an input pattern is presented to the input layer, the units in the next layer use the weighted sum of inputs and the activation function to calculate their outputs. These outputs are passed forward for computation in the next layer until the output layer is reached. During the weight updating operation, an error signal, which is based on the discrepancy between the desired response and the actual output of the networks, is back propagated through the networks for the updating of weights. The back propagation algorithm is generally represented as follows:

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

where w_{ij}^{k} stands for the weights of the connection from unit i in layer k to unit j in layer $k+1$, η is a small constant called the learning rate, δ_j^{k} is the signal error, I_i is input vector to the networks, $f'(s)$ is the derivative of the networks transfer function and s is the sum of all the weights.

The recursive formula (1) is the key to back propagation learning. It allows the error signal of a lower layer (δ_j^{k}) to be computed as linear combination of the error signal of upper layer (δ_j^{k+1}). In this manner, the error signals (δ_j^{k}) are back propagated through all the layers from the top to the down. This also implies that the influences from an upper layer to a lower layer (and vice versa) can only be affected via the error signals of the intermediate layer.

Therefore it serves as a feedback mechanism that can be easily used in process control systems [10, 11].

3. RESULTS AND DISCUSSIONS

3.1 Architecture of the developed NNC

The developed NNC (Figure-2) for the crude oil fractionator has 25 nodes distributed over three layers.

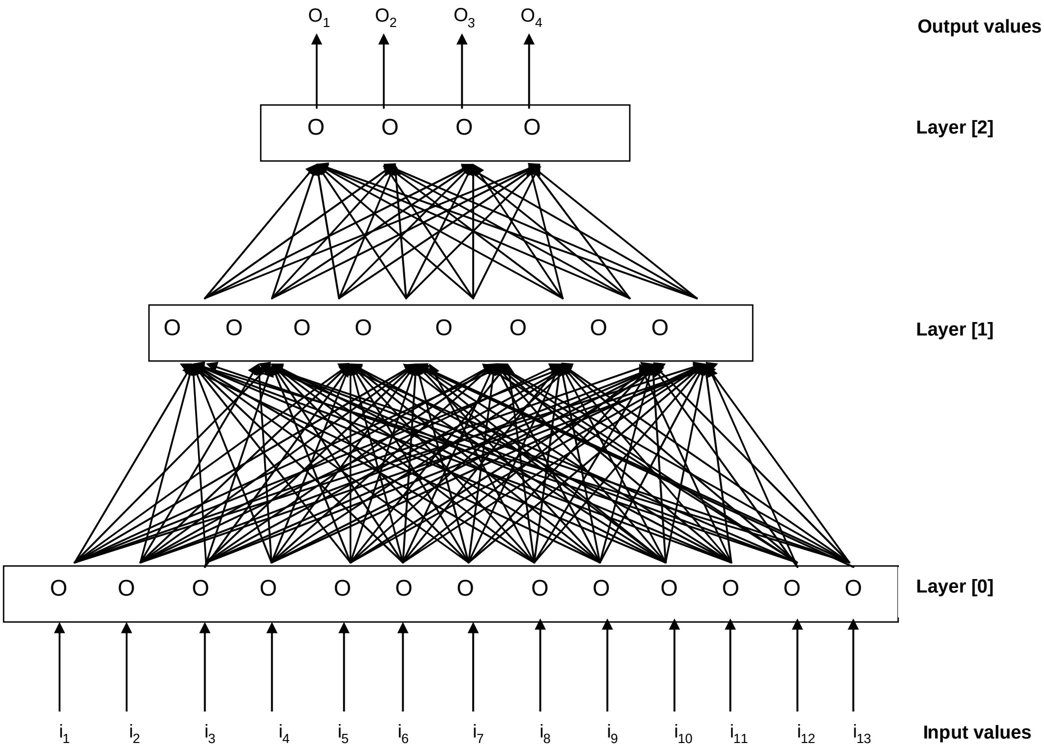

Figure-2. Architecture of the developed NNC.

The input to the networks is layer {0}, the middle hidden layer is layer {1} and the output layer is layer {2}. Layer {0} has 13 nodes, layer {1} has 8 nodes and layer {2} has 4 nodes. All nodes are feed forward, that is, the nodes in the input layer {0} are connected to the nodes in the middle layer {1} and the middle layer nodes are connected to the output layer {2}. The outputs of the NNC (steam flow, reflux flow 1, reflux flow 2 and Reflux flow 3) are used as manipulated variables for the process. The NNC was implemented by of a computer program wrote in object oriented C++ language [4]. The Flow Chart of the developed software is shown in Figure-3. The diagram is divided in two main sections for training and for running.

3.2 The developed NNC for the crude oil fractionator control

Figure-4 shows the overview of the developed NNC mounted to control the crude oil fractionator. The tower or column receives crude oil and steam flow as inputs. Naphthalene, Kerosene, Light Diesel Oil and Heavy Diesel Oil are its outputs. Stripping (distillate flows) is sent to the storage tank, while some quantity of Naphthalene, Kerosene and Light Diesel Oil (reflux flows) are returned into the column. The input values to the NNC are: distillate flows, feed flow, feed temperature, top temperature, bottom temperature, bottom composition, reflux temperature, and the tower pressure. Its output values are used to adjust the reflux flows and steam flow.

3.3 The NNC performance

A linear regression analysis was performed on the NNC output values and the expected output values. We estimated the correlation coefficients of 99%, 96%, 96% and 99% between the obtained values (from NNC) and the expected values (field data) for steam flow, reflux flow 1, reflux flow 2, and reflux flow 3, respectively. The results show that our NNC was not only trained but has undergone effective learning, and is capable of optimally mapping the nonlinearity existing among various variables of the process.

The company where the field datasets were collected was using a distributed control system (DCS) implemented by PID algorithm. To compare the performances of the conventional PID and the NNC, individual graphs for the controller outputs (steam flow, reflux flow 1, reflux flow 2 and reflux flow 3) were plotted.

Figures 5 to 8 display the trajectories of the different NNC outputs. Figure-5 illustrates the obtained values and the expected values of the steam flow.

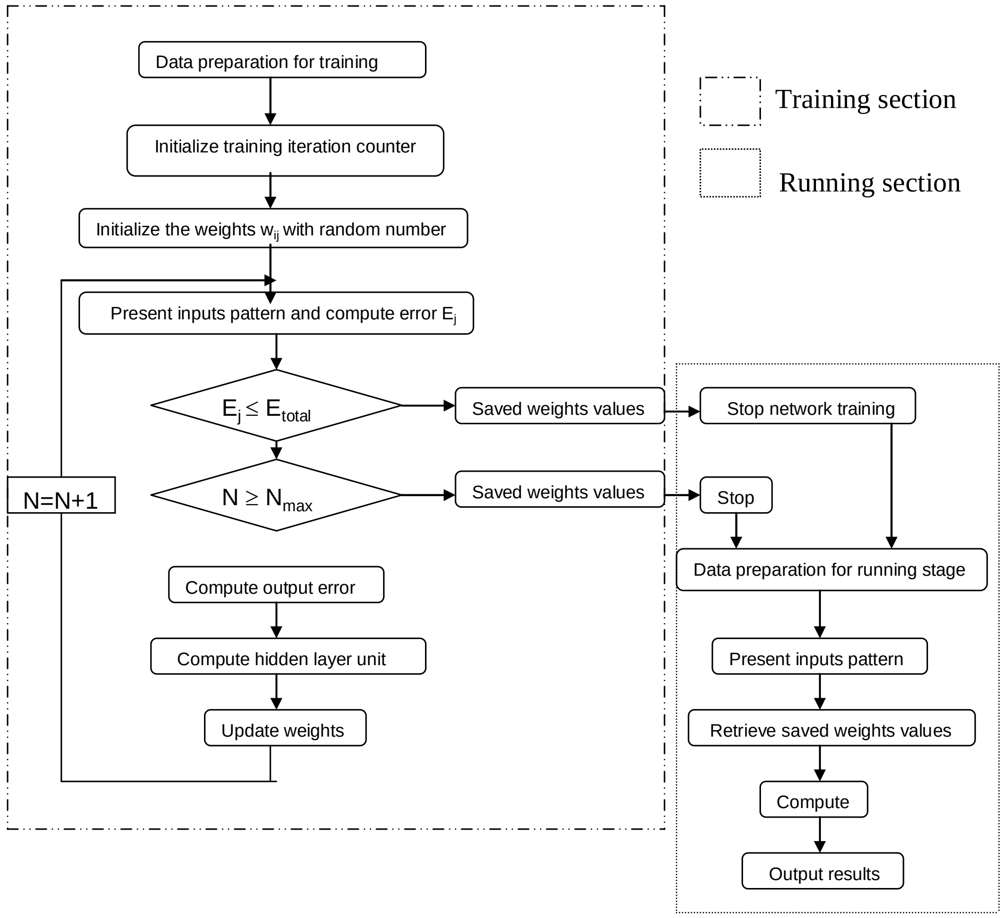

Figure-3. Flow chart of the developed NNC.

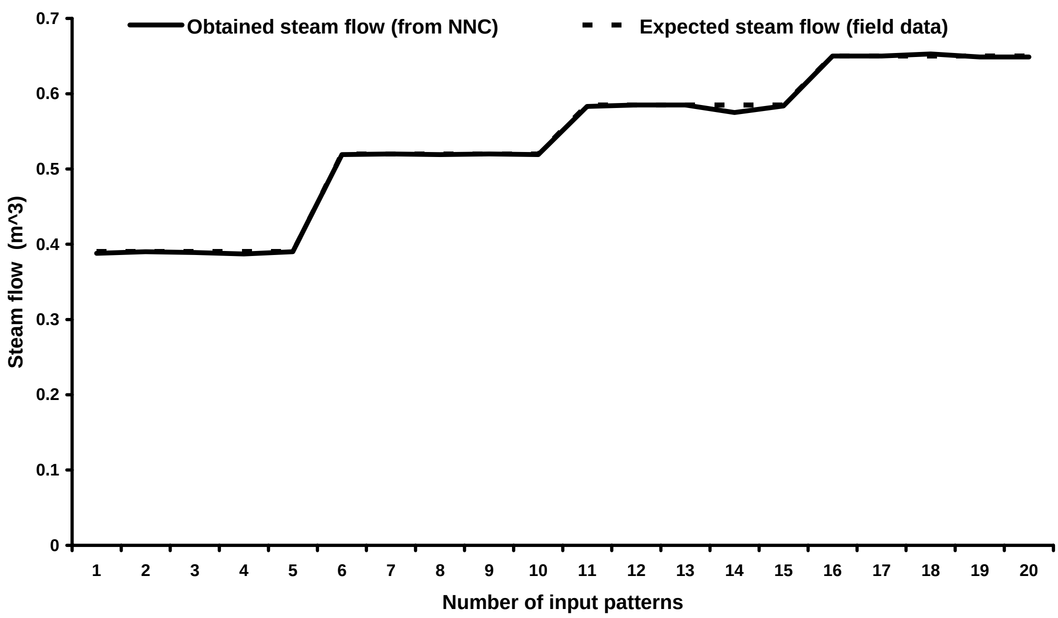

Figure-5. Empirical trajectories of the steam flow and its predictions by the NNC.

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There is an excellent agreement between the two curves. In others words, both graph trajectories present perfect tracking of each other; this is because during the fractionation process, the process control engineers often maintain the steam flow at a particular value. The steam flow value always remains constant for any chosen value for feed flow that is why field data follows smooth direction. The NNC, by its ability of learning process behavior from database, perfectly reproduces an identical curve for the variable.

Figure-6 shows the obtained values and the expected values of reflux flow 1.

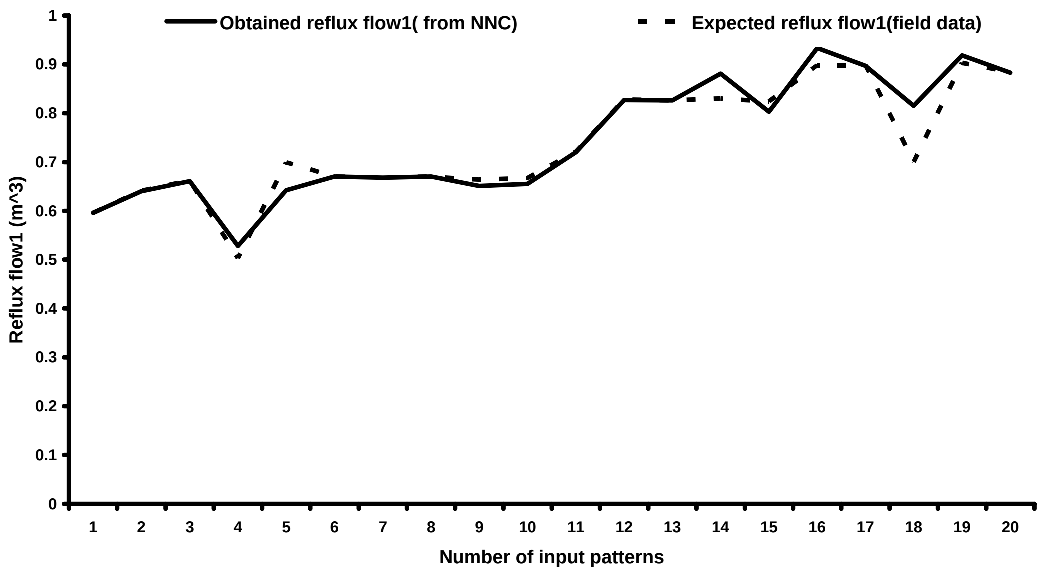

Figure-6. Empirical trajectories of the reflux flow 1 and its predictions by the NNC.

There is a deviation of trajectory between the two curves. The same situation occurred in the graphs of Figures 7 to 8 representing the obtained values and the expected values of reflux flow 2 and reflux flow 3 respectively. These results demonstrate an excessive use of reflux flows by the PID controller to meet product specifications, which resulted in increase of energy consumption, and reduction on the column capacity.

The NNC due to its power in mapping the process nonlinearity and loops interactions corrected the deviation by straightening the curves trajectory. In practice, this should reduce the energy consumption, optimize the column capacity and speed up the process of product separation [1]. From these results, the following interpretation could be offered. The NNC makes use of the history and current values of the process parameters to predict the behavior of the fractionator in the future and takes action based on these predictions.

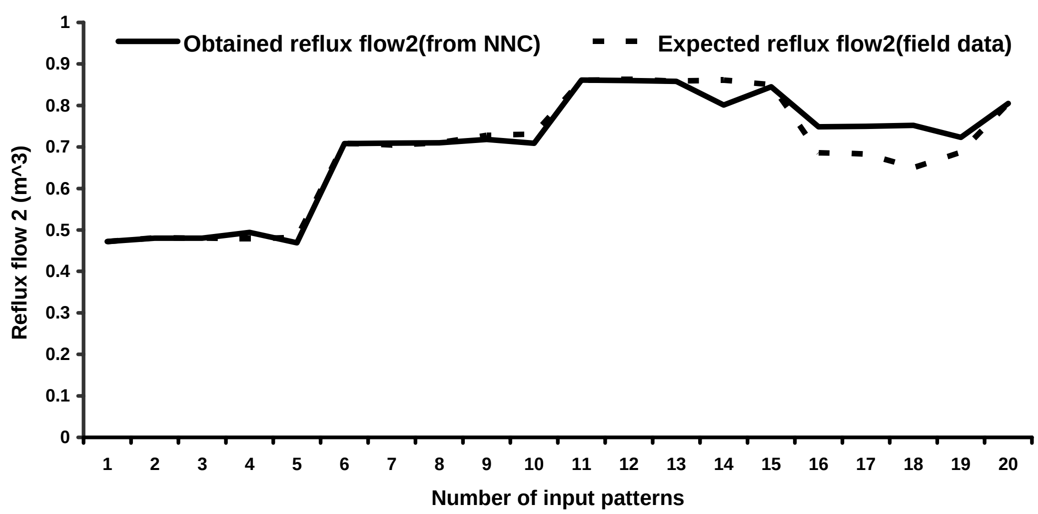

Figure-7. Empirical trajectories of the reflux flow 2 and its predictions by the NNC.

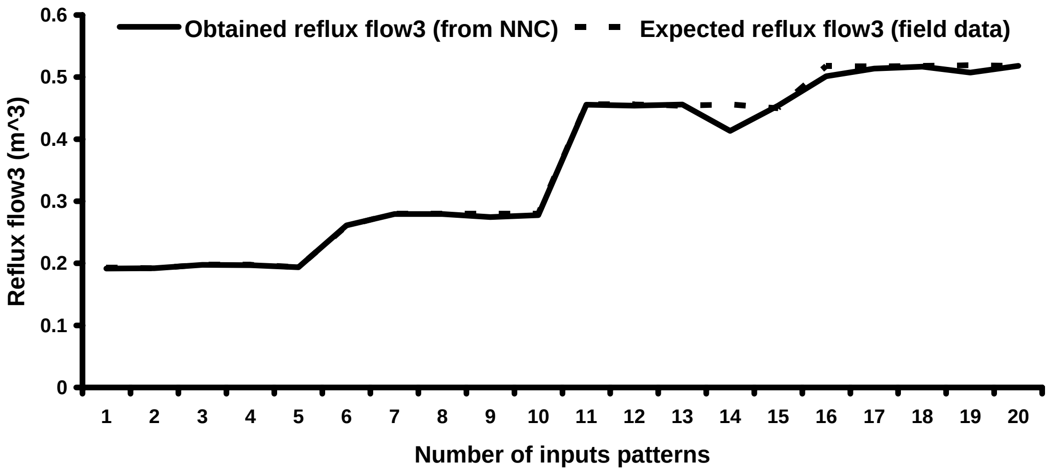

Figure-8. Empirical trajectories of the reflux flow 3 and its predictions by the NNC.

In practice, it allows the NNC to predict if a controlled variable is likely, in the time period of the prediction horizon, to deviate from its specification or violate a plant limit. If so, control action can then be taken to correct the condition before there is ever an actual deviation or violation detected. These features render the NNC more automatic and powerful than the PID controller.

The work has shown that because of its distributed representation, the neural controller promises the ability of adaptation, learning, and generalization to nonlinear problems as the control of crude oil fractionator. The developed NNC is capable of mapping the interactions and nonlinear dynamics of the process. The back propagation algorithm used is characterized by its ability of searching the entire weight space at the same time without knowing the mapping realized by the hidden layer. Instead of utilizing the basic PID equation, the networks build an internal nonlinear model relating the controlled and corresponding manipulated variables. It builds this model by learning from datasets of known measurements and process responses. This dynamic response is recorded for the training datasets. Thus making the NNC useful and more robust than the standard PID. Because the neural paradigm can accommodate multiple inputs and multiple outputs, an entire fractionator process can be built into a single controller.

The NNC is yet to give total satisfaction. It presents some disadvantages. The first is computational complexity, the second is the presence of nonlinear processes with many degrees of freedom, and the third is uncertainty due to noise and disturbances that can easily affect the system especially at the training stage. The greater the ability to deal with these difficulties, the more intelligent and preferment the control system will be.

Future work on NNC could be undertaken with emphasis on the time delay between each input variable and the output variables. For example with the neural networks matrix assessment, a relative importance of the different input variables upon the output variables can be known [9].

ARPN Journal of Engineering and Applied Sciences

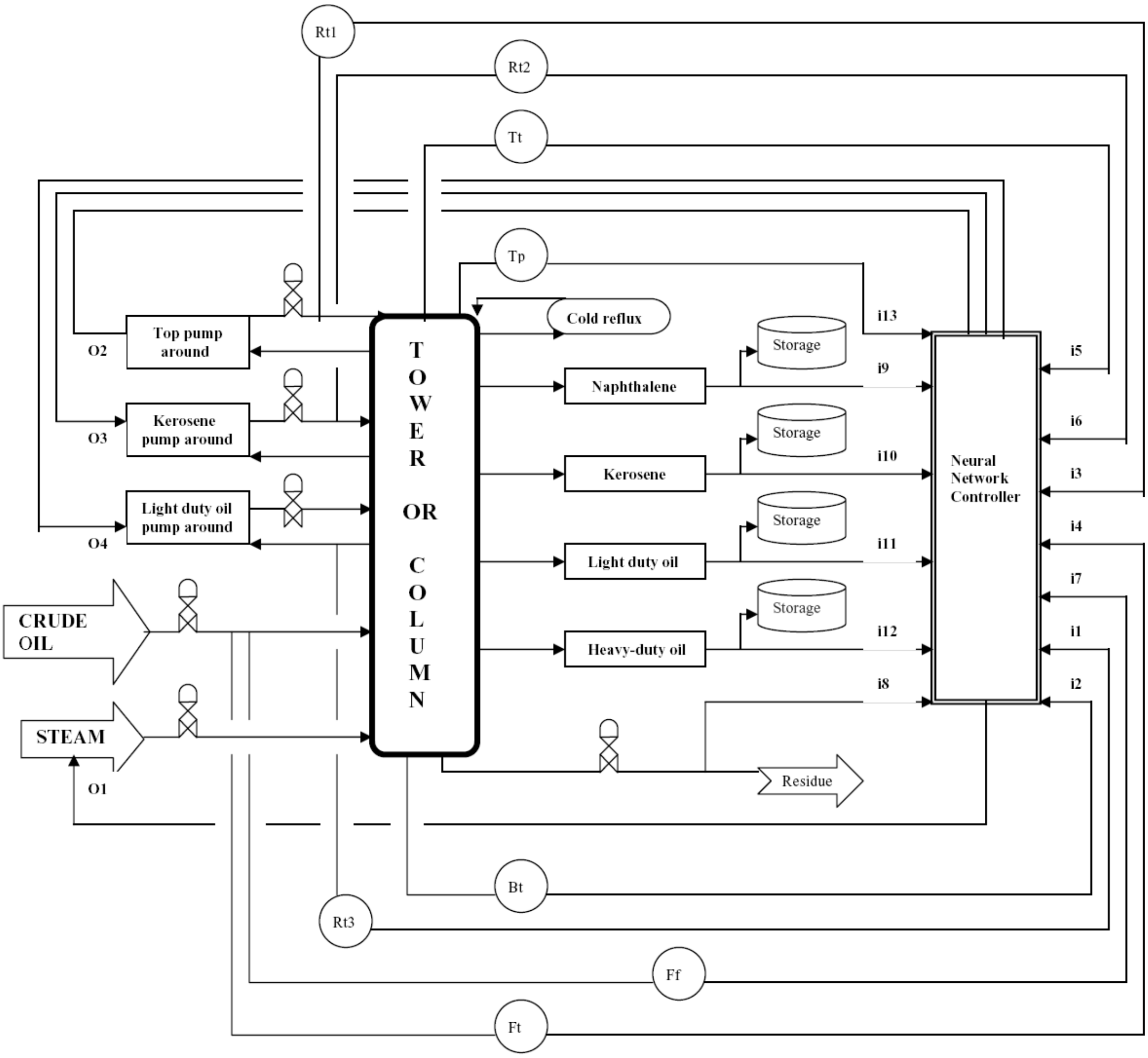

Figure-4. Overview of the developed NNC mounted to control the crude oil fractionator.

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REFERENCES

[1] Alpbaz M., Karacan S., Cabbar Y., Hapoglu H. 2002. Application of model predictive control and dynamic analysis to a pilot distillation column and experimental verification. Chemical Engineering Journal. 88: 163-174.

[2] Thirunavukkarasu I., George V.I., Kumar S.G., Ramakalyan A. 2009. Robust stability and performance analysis of unstable process with dead time using Mu synthesis. ARPN Journal of Engineering and Applied Sciences. 4(2): 1-5.

[3] Hoffman H.L., Lupfer D.E., Kane L.A., Jensen B.A. 1995. Distillation column, basic and advance controls Process control. Instrument engineer handbook 3rd Edition. Butherworth Heinemann.

[4] Jeoy R. 1997. Object-oriented neural networks in C++. Academic Press.

[5] Jones R.W., Than M.T. 1978. Multivariable adaptive control: a survey of method and application. In: O'reilly, J. (ed) Multivariable control for industrial application. Peter peregrinus London.

[6] Jose C.P., Neil R.E., Curt W. 2000. Neural and adaptive systems. Fundamentals through simulation. John Wiler and Son Inc.

[7] Lawrynczuk M. 2007. A family of model predictive control algorithms with artificial neural network.

Journal of Applied Mathematics and Computer Sciences. 17: 217-232.

[8] Mohammad M., Montazeri A., Poshtan J., Jahed-Motlagh M.R. 2008. Wiener-neural identification and predictive control of more realistic plug-flow tubular reactor. Chemical Engineering Journal. 138: 274-282.

[9] Nikravesh M., Farell A.E., Stanford T.G. 1997. Dynamic neural network control for non-linear systems: optimal neural network structure and stability analysis. Chemical Engineering Journal. 68: 41-50.

[10] Phil Mars, CHen J.R., Raghu N., Fidler J. K. 1996. Learning algorithms. Theory and application in signal processing, control and communications. CRC Press.

[11] Robert J., Schanlkoff. 2000. Artificial neural networks. McGraw-Hill.

[12] Gowri T.M., Reddy V.V.C. 2008. Load Forecasting by a Novel Technique using ANN. ARPN Journal of Engineering and Applied Sciences. 3(1): 19-25.

[13] Than M.T., Morris A.J., Wood R.K. 1991. Multivariable and multivariate self-tuning control: a distillation column case study. IEEE proceeding symbol {126}D control theory and applications. 138: 9-24.

[14] Tonnang Z.E.H. 2004. Distillation column control using Artificial Neural Networks. M.Sc Thesis. Microprocessors and Control Engineering, Department of Electrical and Electronics Engineering, Faculty of Technology, University of Ibadan, Ibadan, Nigeria.

[15] Chary D.V.M., Amarnath J. 2010. Complex neural network approach to optimal location of facts devices for transfer capability enhancement. ARPN Journal of Engineering and Applied Sciences. 5(1): 21-25.