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Comparison of Neural Network and PID Control Techniques Based on a Case Study

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Abstract: The performance of a developed Neural Network Controller (NNC) was compared with that of a classical Proportional-Integral-Derivative (PID) algorithm embedded in a Distributed Control System (DCS) using data from a local refinery distillation column. The control techniques were compared through experimental studies. Data collected from a working DCS using PID algorithm was used to develop the Neural Network Controller (NNC) under identical conditions with respect to set-point regulation and load disturbance regulation in real time. It was found that the NNC demonstrated better performance than the classical PID and offered some advantages. It could be inferred from the study that the better performance of the NNC is due to its behavioral characteristics.

Key words: Neural control, PID control and comparison, fixed gain, mathematical modeling, parameters, Nigeria

INTRODUCTION

The classical (PID) control technique has been the basis of simple control systems. Its simplicity has been the main reason for its wide applications in industry. Since, classical controllers are fixed-gain feedback controllers, they cannot compensate for parameter variations in the plant and cannot adapt to changes in the environment. In classical conventional techniques, mathematical modeling of the plants and parameter tuning of the controller have to be done before implementing the control algorithms by the controller during operation. Most systems from control perspective, exhibit nonlinear behaviors; furthermore, mathematical modeling of these systems is often difficult. Therefore, classical controller is not ideal for nonlinear control applications. The need to overcome such problems and have a controller well-tuned not only for one operating point but also for a whole range of operating points has motivated the option of neural network control techniques and the idea for an adaptive controller.

In the last three decades, numerous alternative control techniques such as neural and fuzzy control have been proposed instead of conventional classical technique. Development of Artificial Neural Network (ANN) theory has inspired new resources for possible implementation of better and more efficient control. ANN has capability of learning the dynamical systems that estimated input-output functions. ANN does not need the mathematical modeling of the plants. However, ANN has to be trained and they need some information (not based on mathematical model but sometimes taken measurement data from the plant). Generally, input-output characterization or desired output of the plant is sufficient. There have been some studies such as Rivals and Personnaz (1996) and Jones and Than (1987) in which the techniques are compared in the last decade. Unfortunately, most of these studies are based sometimes partly on simulations. In this study, the performance of NNC and classical PID controllers are compared using data from a practical crude oil distillation column control.

MATERIALS AND METHODS

Description of the study process: Distillation is by far the most important and widely used separation process in a petroleum refinery. It is an energy-separating agent that uses differences in relative volatilities or differences in boiling points, to achieve dissociation of different elements. The separation is achieved by heating the liquid to vaporize the lightest components. These vapors flow into an overhead condenser which cools the vapor back into a liquid which is then collected.

Crude oil is made up of components varying from light gases that boil below ambient temperature, to very heavy materials that cannot be distilled even at temperatures above 538°C (1000°F).

In crude oil distillation, hot crude is pumped into a distillation column and the lightest hydrocarbons present, rise to the top and are removed. The next-heavier products are drawn off at successively lower points on the column (Fig. 1).

The material that is too heavy to vaporize under atmospheric distillation conditions is removed from the

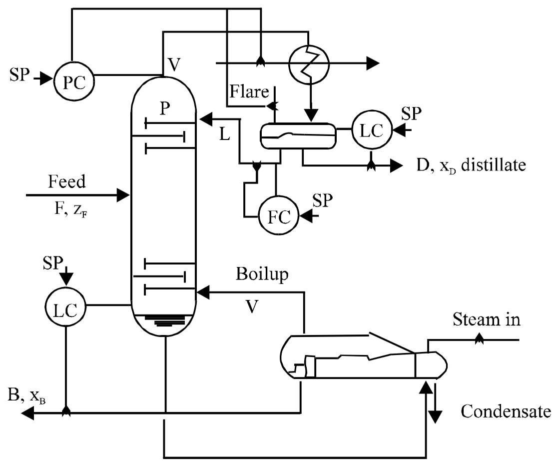

Fig. 1: A simple distillation column

bottom of the column. The bottom products can be fractionated further by a second distillation carried out under reduced pressure or can be send to the Fluid Catalytic Cracking Unit (FCCU) for further processing.

Classical three mode controllers: The basic PID controller responds to error by a correction that is an algebraic superposition of three actions. The first is the proportional action. It changes power in proportion to the value of error and in the direction that reduces the error. The second is the integral action.

It adjusts power incrementally, in proportion to the time integral of previous errors. The last component is the derivative action.

It adjusts power in proportion to the rate of change of error in the direction that reduces the rate of change, damping the response to avoid overshoot. Therefore, at any time t, controller output, m (t) is the weighted sum of the above three terms:

$$m(t) = K_C(e(t) + K_R \int e(t)dt + K_D \frac{de(t)}{dt} \tag{1}$$

where, K_C, K_R and K_D are constants that need to be tuned according to stability analysis to ensure that the system will not oscillate (Hooffman *et al.*, 1995). This type of algorithm generally model process dynamic in form of feedback loop as shown in Fig. 2.

The PID algorithm was embedded in a Distributed Control System (DCS) where the computer system using direct digital control takes the place of the controller. A set of instruction in the computer program tells the computer to periodically perform the following computation (Hooffman *et al.*, 1995).

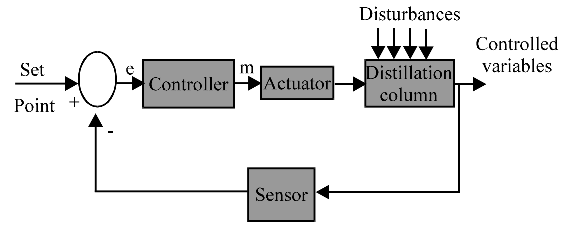

Fig. 2: Feedback control loop

$$\Delta P - K_c[(e_0 - e_1) + \frac{1}{T_R}(e_0)(\Delta t) + T_D \frac{(m_0 - 2m_1 + m_2)}{\Delta t}] \tag{2}$$

Where:

ΔP = The incremental change in the controller output
e_0 = The error at present time
e_1 = The error at previous check
m_0 = The measurement at present time
m_1 = The measurement at previous check
m_2 = The measurement at the second previous check
Δt = The time interval between check

The above operation is carrying out for each control loop Fig. 2.

Artificial Neural Network (ANN) for process modeling: There are many different types of neural networks. The most widely used ANN is known as Multilayer Perceptron (MLP) using the Back propagation algorithm. This type of ANN is excellent at prediction and classification tasks. This type of network has 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 network is back propagated through the network for the updating of weights. The back propagation algorithm is generally represented by Mars *et al.* (1996) and Schalkoff (1997):

$$w_{ij}^{k+1} = w_{ij}^{k} + \eta \delta_j I_i f'(s) \tag{3}$$

Where:

w^k_{ij} = Stands for the weights of the connection from unit i in layer, k to unit, j in layer k+1

η = A small constant called the learning rate
δ^k_j = The signal error
I_i = Input vector to the network
$f'()$ = The derivative of the network transfer function
s = The sum of all the weights (Narandra, 1996)

The recursive Eq. 3 is the key to back propagation learning. It allows the error signal of a lower layer (δ^k_j) to be computed as linear combination of the error signal of upper layer (δ^{k+1}_j). In this manner, the error signals (δ^k_j)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 (Principe *et al*., 2000; Narendra and Parthasarathy, 1990; Tham *et al*., 1991).

In process modeling the ANN received process inputs (Controlled variables and disturbances) and predicts process outputs (Values used to effect changes). The error between the desired outputs and the obtained are used to validate the effectiveness of the model and fine-tune the weights to more accurately map the process dynamics. With clever techniques the ANN approach can predict both the static and dynamic conditions and also account for process lag and dead-times.

Neural Network Controller (NNC) implementation: The input values to the Neural Network Controller (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 (Fig. 3).

The developed NNC for the control of the distillation column has 25 nodes distributed over three layers. The inputs to the network are 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 (Tonnang, 2004).

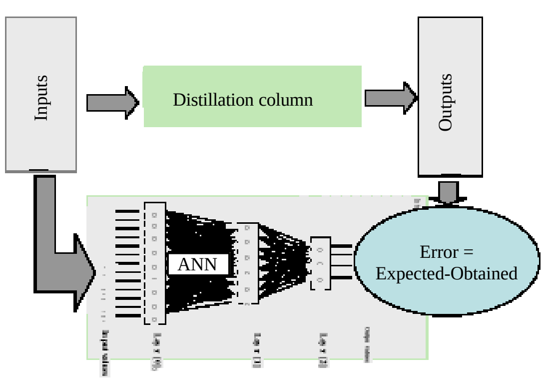

Fig. 3: Distillation column modeling

The developed NNC was validated using field data obtained from the 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 obtained data of, 40 patterns were divided into three major groups. A data pattern is made up of 17 measured values of the process variables which consists of 13 inputs values and 4 output values. The three groups (Based on the fluid flow rate into the distillation column) are for training, validation and testing.

RESULTS AND DISCUSSION

Using the network describe earlier, multiple training sets were utilized to estimate the effectiveness of NNC versus PIC controller (Narendra and Parthasarathy, 1990; Tonnang, 2004).

The graphs of controller outputs obtained values (From NNC) and expected values (From PID) are shown in Fig. 4-7. In the ideal case when the data does not contains

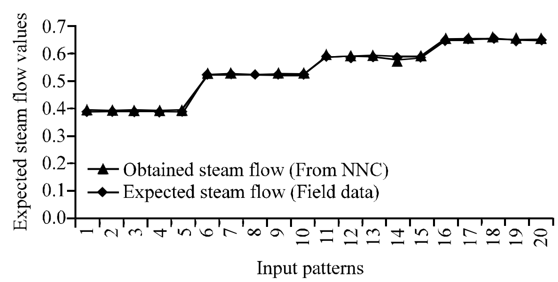

Fig. 4: Comparison between the obtained values (From NNC) and the expected values (Field data) of the steam flow R = 0.9996

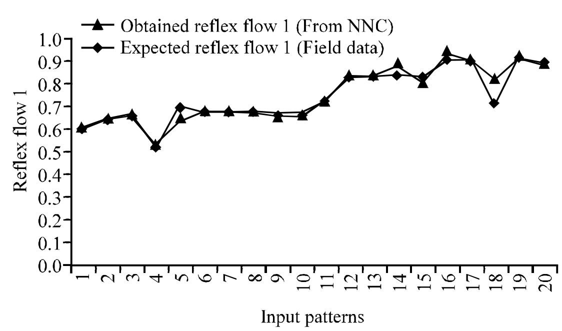

Fig. 5: Comparison between the obtained values (From NNC) and the expected values (Field data) of reflux flow 1 R = 0.9618

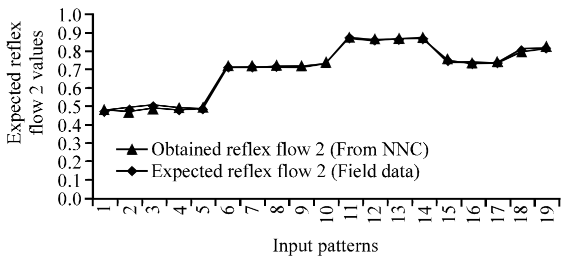

Fig. 6: Comparison between the obtained values (From NNC) and the expected values (Field data) of the reflux flow 2 R = 0.999

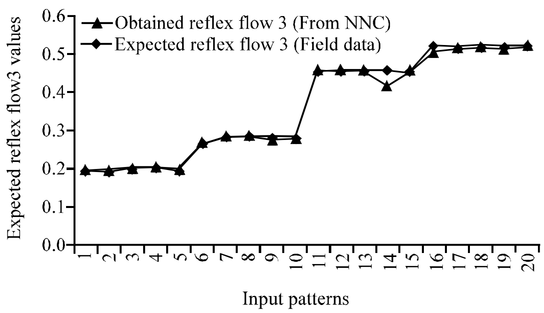

Fig. 7: Comparison between the obtained values (From NNC) and expected values (Field data) of the reflux flow 3 R = O.9972

noise and the network is perfectly accurate, the obtained outputs values (From NNC) always tract the expected values (From PID). However, this perfect correlation is unlikely to occur due to the process behavior and the controller internal structure.

To compare the performances of the conventional PID and the NNC, individual graphs were plotted for the controller outputs parameters (Steam flow, reflux flow 1, reflux flow 2 and reflux flow 3).

Figure 4 shows the comparison between the obtained values (From NNC) and the expected values (From PID) of the steam flow. There is an excellent agreement between the two curves. Their trajectories perfectly track each other this is because during the distillation process, the process control engineers often maintain the steam flow at a particular value, the steam flow does not change for a given feed flow. This result confirms the ability of NNC in learning process behavior from data base population by self-tuning its parameters which is impossible for the standard PID controller.

Figure 5 shows the comparison between the obtained values (From NNC) and the expected values (From PID) of reflux flow 1. There is a deviation of trajectory between the two curves. The same situation occurred in the graphs of Fig. 6 and 7 showing comparison between the obtained values (From NNC) and the expected values (From PID) 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. This results in increase of energy consumption and reduces the column capacity. The NNC due to its power in mapping the process nonlinearity and loops interactions correct the deviation by straightening the curves trajectory. This should reduce the energy consumption, optimize the column capacity and speed up the process of product separation.

CONCLUSION

This study has shown that neural network and PID control techniques can be easily implemented for real time control application. Moreover, it has presented a practical comparison of neural and classical PID control approaches. The researches shows that the superiority of neural control technique is due to its internal structure and design. Neural paradigm can accommodate multiple inputs and multiple outputs in a single controller.

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