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Artificial Neural Networks for Identification and Control of a Lab-Scale Distillation Column using LABVIEW

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Abstract**—**LABVIEW is a graphical programming language that has its roots in automation control and data acquisition. In this paper we have utilized this platform to provide a powerful toolset for process identification and control of nonlinear systems based on artificial neural networks (ANN). This tool has been applied to the monitoring and control of a lab-scale distillation column DELTALAB DC-SP. The proposed control scheme offers high speed of response for changes in set points and null stationary error for dual composition control and shows robustness in presence of externally imposed disturbance.

Keywords**—**Distillation, neural networks, LABVIEW, monitoring, identification, control.

I. INTRODUCTION

ANN is attractive due to its information processing characteristics such as nonlinearity, high parallelism, fault tolerance as well as capability to generalize and handle imprecise information [1]. Such characteristics have made ANN suitable for solving a variety of problems. The application of ANN in chemical engineering began with pioneering works [2], and in subsequent years the number of research publications on ANN in chemical engineering was steadily increased. Most of these publications cover five major areas: process control, dynamic modeling, forecasting fault diagnosis, and optimization.

In the area of process control, ANN was applied through adaptive control or model-based control. By monitoring the on-line process data, ANN could be used to adjust controller parameter for optimal performance. Dynamic modelling using ANN was also well practising in process industries. By exploiting the relationship among the process variables, ANN model was developed as estimator and to be implemented in advance control techniques (soft sensors). Similar to dynamic modelling, forecasting can also contribute in process industries by using prediction based on the history data. ANN was also useful in fault diagnosis since it has the ability to store knowledge about the process and learn from the quantitative historical fault information. ANN was implemented in plant optimization for optimal parameter searching to ensure process plant is always safe and productive.

Distillation column is the most common unit operation in the chemical industry and understanding its behaviour has become the most challenging job for chemical engineers. As distillation column can be viewed as an integrated and complex system, the operation and control of column become very difficult. Basically, there are five basic variables required to be controlled to achieve efficient operation, composition of distillate stream, composition of bottom stream, liquid level of reflux drum, liquid level of base column and column pressure. Distillation dynamics and control were well studied in past decades especially for composition control [3]. In practice, on- line analyzer for composition is rarely used due to its costs and measurement delay. Therefore composition is often regulated indirectly using tray temperature close to product withdrawal location. In order to achieve control purpose, many manipulated variables could be used, such as reflux flow (L), distillate flow (D), bottom flow (B) and vapour flow (V). This gave rises to many control strategy with different combination of manipulated variables configurations [4] reported some practical configurations alternatives and their comment for the distillation control scheme mainly refers to composition control. However, using temperature for composition control is not always satisfactory. This is because by maintaining constant temperature does not guarantee the ability to maintain a constant composition. Since the temperature-composition relationship only hold when pressure is kept constant and fluctuations in the column pressure resulting from disturbances.

Focusing on the distillation control problem, several control schemes based on knowledge of the plant neural model have been reported, such as predictive control, inverse model control and adaptive control [5].

LABVIEW is a powerful and versatile graphical programming environment that was developed primarily to

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facilitate instrumentation control and data acquisition and analysis [6]. Applications created with LabVIEW are referred to as virtual instruments (VIs) created as block diagrams. Input and output interfacing with the VI is performed in another window called the front panel. The graphical icon based source code and interfacing creates very user-friendly applications and eliminates typing in lengthy character-based code. Besides, LABVIEW enables to interface directly to instruments, sensors and actuators. This visual computing environment has been applied to a wide variety of control problems such as in bioprocess control [7], thermal systems control [8], and processing AC servo motor control [9] in this case using neural networks as control methodology.

In this paper we have utilized this platform to provide a powerful toolset for process identification and control of nonlinear systems based on artificial neural networks (ANN). This tool has been applied to nonlinear lab-scale distillation column DELTALAB DC-SP, with up to five control loops. Also LabVIEW environment has been employed as a graphical user interface for monitoring the neurocontrolled distillation column, by visualizing both the closed loop performance and the user selected control conditions. The proposed control scheme offers high speed of response for changes in set points and null stationary error for dual composition control and shows robustness in presence of externally imposed disturbance.

II. Description of the LABVIEW based Monitoring System

A lab-scale experimental distillation column coupled to a PC computer was used to evaluate the performance of the identification and control software developed in LABVIEW. We have selected a 9 trays column with heated electrically boiler and water refrigerated tubular condenser, for separating a mixture of methanol and water.

TABLE I
CONTROL CONFIGURATION FOR DISTILLATION COLUMN

Control Loop	Controlled variable	Manipulated variable
TT1	Temperature of the feed solution.	Feed heat resistance.
PDT1	Column differential pressure.	Boiler heat resistance
TIC2	Head temperature.	Reflux valve.
LIC1	Condensate level.	Light product valve.
LIC2	Boiler level	Heavy product valve

The system is equipped with temperature sensors, differential pressure sensors and flow meters for plant state sensing, together with plant actuators for flow, temperature and level control. The control strategy is given by the manipulated and controlled variables as indicated in Table I The configuration flowchart of the lab-scale distillation column DELTALAB DC-SP is shown in Fig. 1.

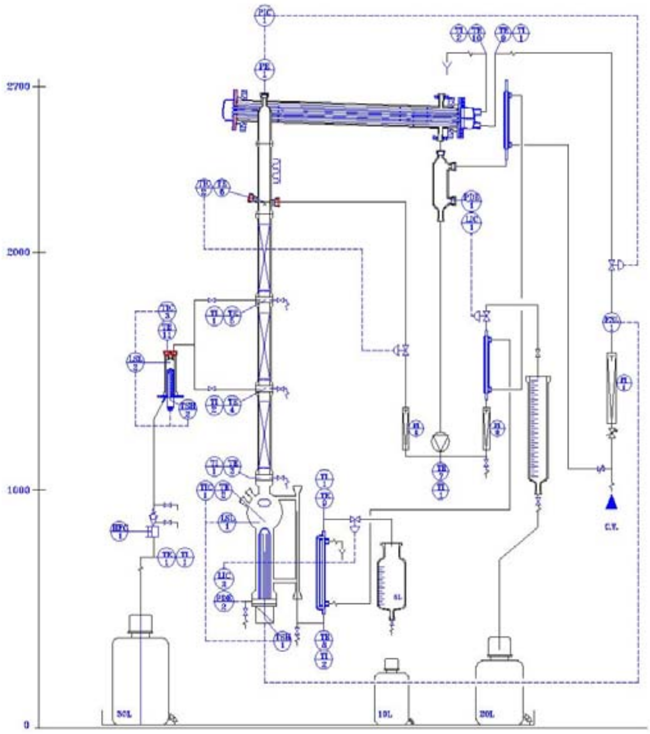

Fig. 1 Flowchart of distillation column DC-SP

The operation involves charging the boiler with the mixture to be separated using the feed pump, turning on the heating, bringing the column to equilibrium under total reflux conditions (start-up procedure). At the end of the start-up period, composition and temperature profiles are established. These initial profiles basically depend on the geometry of the column and the composition of the mixture charged into the boiler. During the operation period, the quality of the top product collected depends on the reflux flow rate and heat input flow. The reflux ratio is varied using the pneumatic valve to change the relative quantities of material returning to the column and flowing to product storage, and the heat input is varied throughout a variable resistance voltage.

One of the main goals of the present work was to develop a system able to on-line monitoring and control the variables that take part in the distillation process, as well as to interact with the neural tool here developed.

The solution we propose is using a graphic user interface developed in National Instrument's graphical programming language LABVIEW. In this way, both the observation and manipulation of the variables and the communication with the neural tool are carried out using virtual instruments. In this way, LABVIEW was used for the tasks of acquisition, analysis, presentation of data and control in a friendly way to the user. In Fig. 2 we show details of the front-panel designed for the lab-scale distillation column.

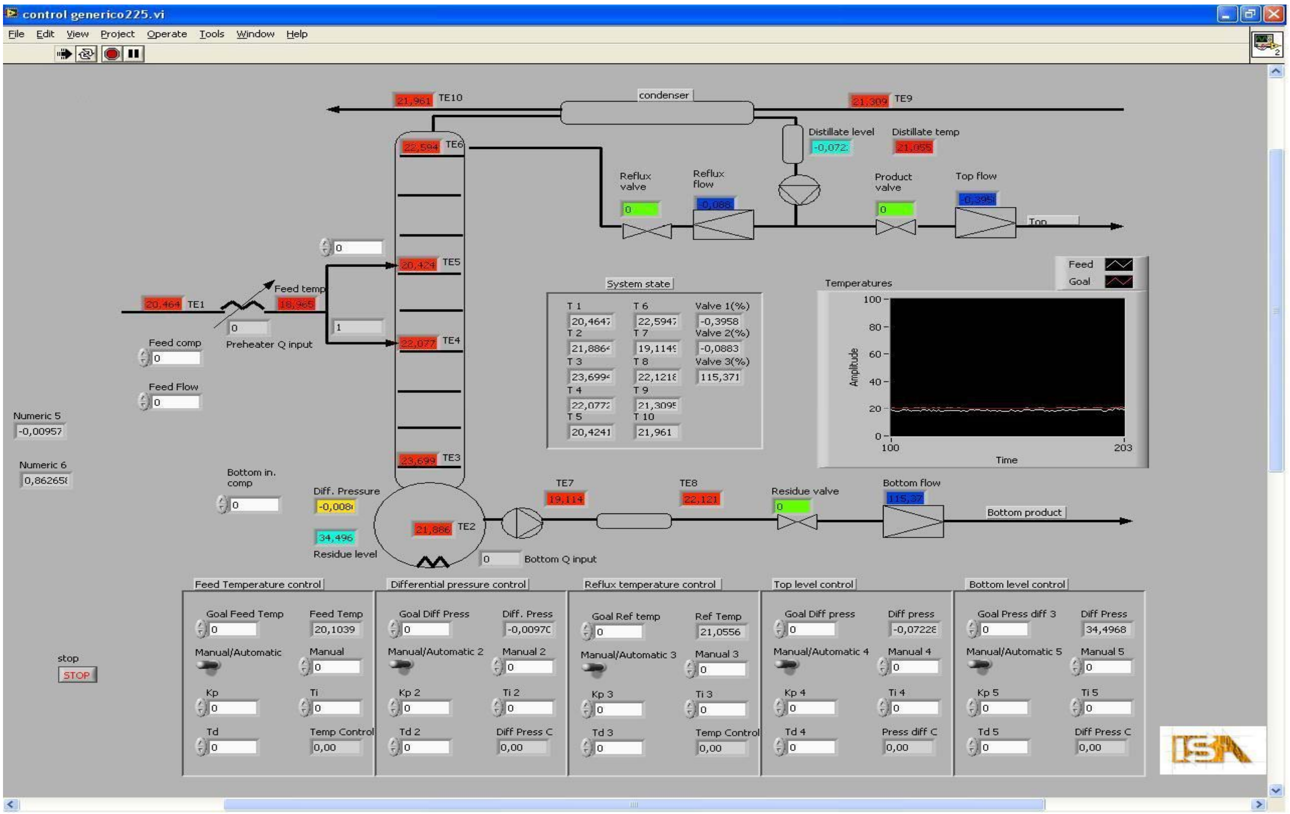

Fig. 2 Flowchart of distillation column DC-SP

III. Neural Identification and Control Tool

The general identification and control structure for the neural based control is shown in Fig. 3. The neural netwotk model uses the manipulated and previous controlled variables as inputs and the future controlled variables as outputs. The neural network controller uses instead the desired controlled variables, the previous controlled variables (or the feedback error variable) and the previous manipulated variables as inputs and the actual manipulated variables as outputs.

We have developed a neural identification and control tool for multivariable systems under the LABVIEW environment. The software can create and train nets with up to 5 layers of up to 40 neurons each one. Each neuron has a sigmoid function as activation function. The parameters of the system are the number of layers and the number of neurons in each layer, the numbers of iterations (in the training mode) and the maximum error. So in that way, the main program can stop either by total number of iterations reached, error reached or STOP button pressed.

The learning algorithm implemented is the adaptive backpropagation and the training I/O pattern set can be passed off-line (text file) or on-line. In Fig. 4 it is shown the VI program corresponding to the block diagram of the backpropagation algorithm.

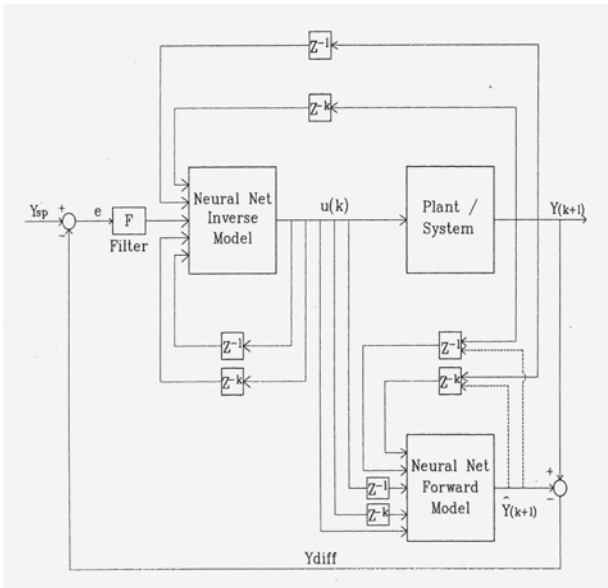

Fig. 3 Neural identification and control structure

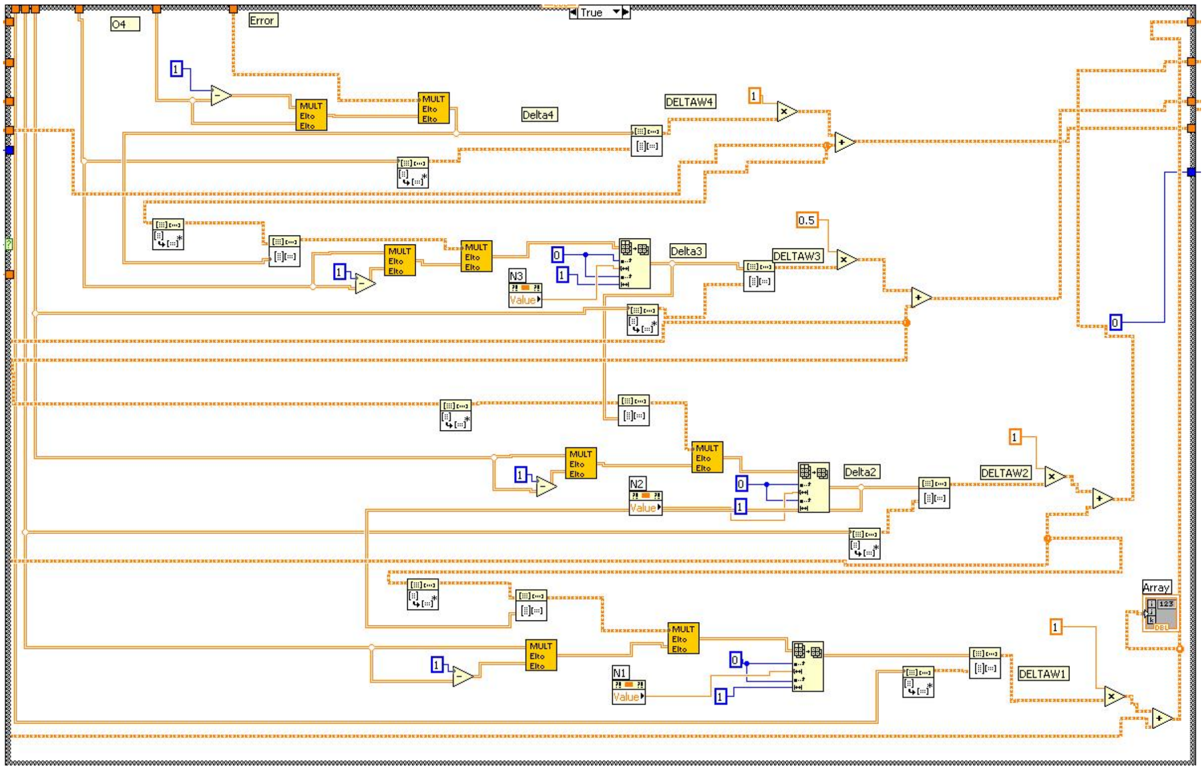

Fig. 4 Learning algorithm VI block diagram

In the system identification stage, it is developed a neural network model of the plant under control using the modelling error. In the control design stage, the neural network controller is trained as the inverse neural network model, so as to adjust the network controller weights using the propagation of the controlling error through the neural network model. In Fig. 5 it is shown the front panel corresponding to the neural identification stage.

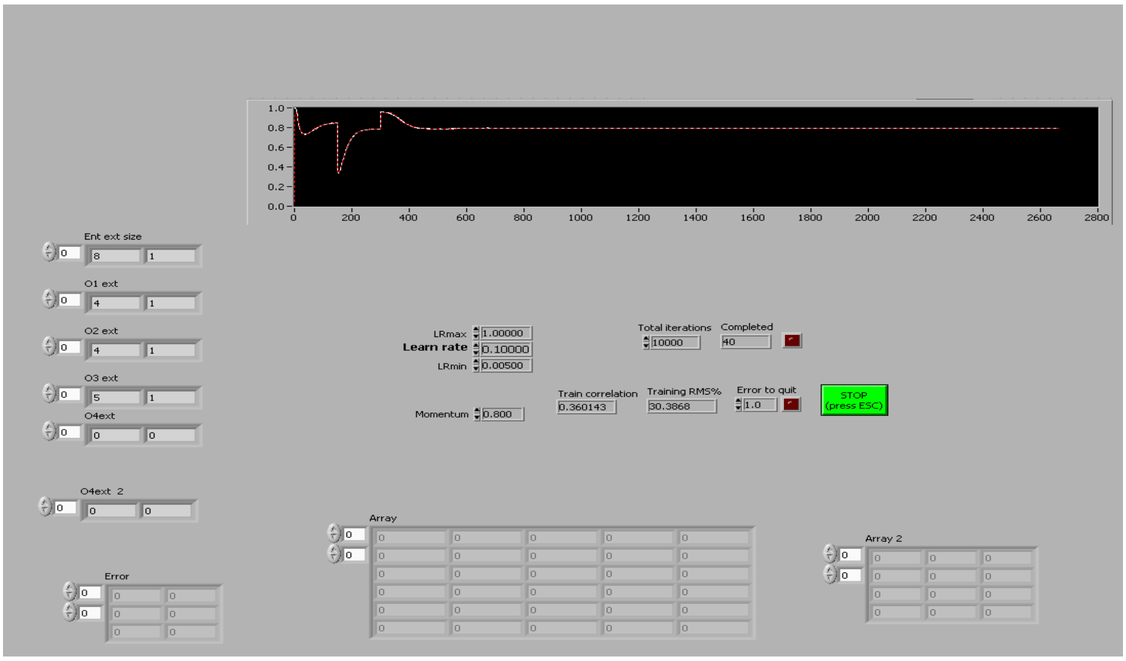

Fig. 5 Learning algorithm front panel for neural identification stage

IV. Results

The data for training both the plant's neural network model and controller were obtained operating the lab-scale distillation column at atmospheric pressure. The boiler was fed with 6 l of the binary mixture, composed of approximately 40 mol % methanol and 60 mol % water. Boiler heating power Q ranging and reflux flowrate L were selected as manipulated variables, while top and bottom product compositions X_D and X_B were considered controlled variables, computed from vapour temperature measurements and the equilibrium properties of the methanol-water system, with sampling time of 2 s. The feed variables (F, X_F, q) were treated as external process disturbances.

To obtain representative training data, varying feed flows, initial liquid composition values both in the column, boiler and condenser along with input values for the control actions were imposed on the column after a start-up process. The identification model has been carried out using an neural network given by $\hat{y}[k] = NN_I(y[k], y[k-1], y[k-2], u[k])$ after selecting the best structure among possible ones, with $u[k] = [L[k], Q[k]]$ and $y[k] = [X_D[k], X_B[k]]$ regularly spaced covering the operating range., resulting a two layer 8-17-2 net. The training set for the neural identification comprised 5200 data points belonging to the open loop operating range for plant inputs reflux flowrate L (0-5E-06 m3/h) and heat flow Q (0-2000 J/s) for fixed feed rate conditions F = 1E-06 m3/h, X_F = 0.4, and q = 1. An additional data set consisting of 260 data points was used to test the neural network model afterwards.

The training set for neural control comprised 1600 data points belonging to the closed loop operating range for desired and actual top and bottom compositions values X_D (0.0-1.0) and X_B (0.0-1.0). An additional data set consisting of 320 data points was used to test the neural network controller also. The controller has been carried out using an neural network given by the structure $u[k] = NN_c(e[k], e[k-1], e[k-2], u[k-1])$ after selecting the best structure among possible ones, resulting a two layer 7-15-2 net, with $e[k] = [X^{SP}{}_D[k] - X_D[k], X^{SP}{}_B[k] - X_B[k]]$ stands for the feedback error (*SP* 'set point').

In Fig. 6, we show the neural controller behaviour facing changes in both top and bottom distillate composition and presence of disturbances in the feed flow. The neural controller exhibit adequate control action to compensate a dual pulse step change in distillate composition from 94% to 97% and bottom composition from 0.05% to 0.03%, together with a change in feed composition to 0.32 at t = 6E+04 s Changes in the reflux and heat flows are determined by the neural network model-based controller for the column, remaining inside the operating range.

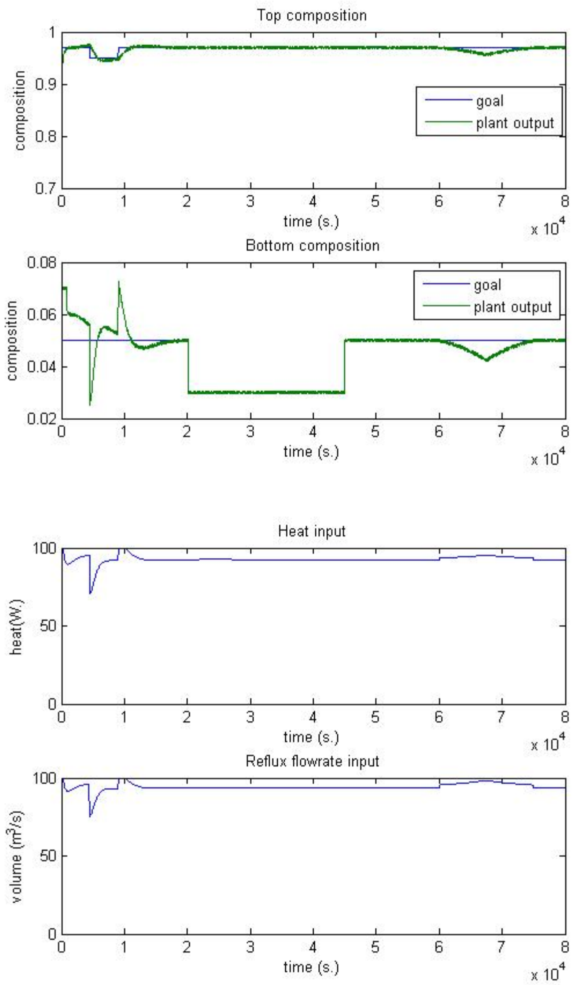

Fig. 6 Response of the distillation control system to step changes in top and bottom compositions and change in feed composition

V. Conclusion

A neural based control and identification tool is constructed by using LABVIEW platform. This tool has been applied to the control of a lab-scale distillation column DELTALAB DC-SP which is characterized by nonlinear behavior, transport delays and subject to constraints and disturbances including non linear hydrodynamic effects. The results obtained demonstrate the potential use of this control strategy in process engineering providing the user with ease of graphical programming and its functionality for interfacing directly to instruments, sensors and actuators. Future works are directed towards the stability analysis involved in the neural control task, since nonlinear and multivariable dynamics are present.

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