A Development of Tools For Monitorization and Control of Multivariable Neurocontrolled Systems with Application to Distillation Columns

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Abstract

The issues raised in advanced process control applications lead control engineers to be aware of the need of integrating advanced information processing capabilities in the process control loop. In this paper a SIMULINK based tool has been developed for analysis and design of multivariable neural based control systems. This tool has been applied to the control of a high purity distillation column also modeled in SIMULINK including non linear hydrodynamic effects. 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 an optimal response for both theoretical and practical challenges posed in process control task, in particular when both, the quality improvement of distillation products and the operation efficiency in economical terms are considered

1. Introduction

Artificial neural networks have been used extensively for a number of process engineering applications such as sensor data analysis, fault detection and nonlinear plant identification and control, specifically of distillation column and reactors in chemical engineering.

Focusing on the control problem, several control schemes based on knowledge of the plant model have been reported, such as generalized predictive control [1], inverse model control [2] and adaptive control [3] among others.

The lack of tools for the design of controllers based on neural network models is particularly pronounced. The reason for this might be that development of generic software for control system design is relatively difficult as several types of control designs exist. A few non commercial tools for system identification and control system design have become available. One of these is the system identification and control MATLAB-SIMULINK tool [4] which offers an useful guided user interface (GUI) for predictive control, model reference adaptive control and feedback linearization control, all based on neural networks.

In addition, [5] have developed two toolset for use with MATLAB, termed NNSYSID and NNCTRL for neural network based identification and control of nonlinear systems. These toolset allow the user to choose among several designs, such as direct inverse control, internal model control, feedback linearization and predictive control among others. However, these toolset are applied only to SISO nonlinear systems, being therefore invalid to be extended to general MIMO control problems as is frequently usual in process engineering.

On the other hand LabVIEW [6] and SIMULINK are properly two widely used graphical code development environment which allow system level developers to perform rapid prototyping and testing. Unlike text-based programming languages, such as C, MATLAB and Java, graphical programming involves block-based code development and offers a more intuitive approach to designing control systems. Besides, both environments can be linked together through the LabVIEW simulation interface toolkit (SIT) allowing control engineers to custom user interface to interactively verify SIMULINK models and easily deploy these models to real-time hardware

for control prototyping and hardware-in-the-loop testing, with proven results in industrial applications [7].

For many reasons, distillation remains the most important separation technique in chemical process industries around the world [8]. Therefore, improved distillation control can have a significant impact on reducing energy consumption, improving product quality and protecting environmental resources. However, distillation control is difficult because it is usually nonlinear, non-stationary, interactive, and is subject to constraints and disturbances.

In this paper a MATLAB-SIMULINK based tool has been developed for analysis and design of multivariable neural based control systems. This tool has been applied to the control of a high purity distillation column modeled also in SIMULINK including non linear hydrodynamic effects. 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, where the front panel has been designed mimicking the distillation column control scheme .

SIMULINK neural

SIMULINK neural control tool

LabVIEW front panel

Results

Pilot-scale distillation column
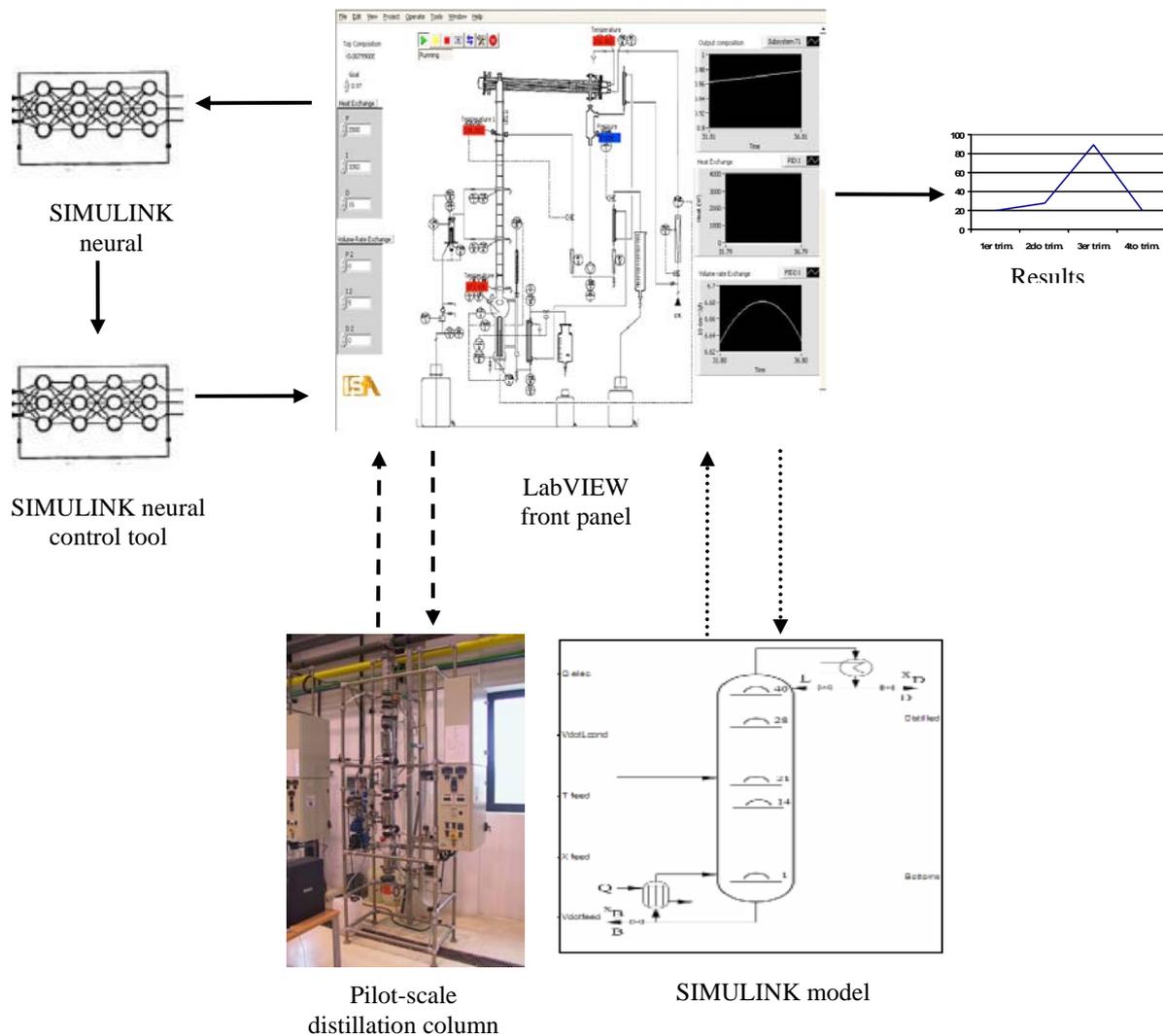
SIMULINK model

Fig. 1. Scheme for monitoring and control of the distillation column

In section II we describe the overall structure of neurocontrolled system while the distillation column model programmed in SIMULINK is summarized in section III. In section IV we present the tool for analysis and design of multivariable neural based control systems. The design of the monitoring system under LabVIEW is described in section V, and computer simulation results for a 9 plates neurocontrolled column are also shown in section VI. Finally, conclusions and future works are also discussed in section VII.

2. Description of the Control System

The proposed architecture for neural control of the distillation column is shown (Fig. 1).

The system is composed by a) A SIMULINK model of the distillation column, based on mass and enthalpy balances; b) An interactive tool running under SIMULINK for identification and control based on neural networks, using I/O data form the distillation plant and c) A graphical user interface for monitoring the neurocontrolled distillation column based on LabVIEW.

The data taken from the SIMULINK distillation column model will be used to train both the neural network model and controller, which in turns once trained will feed the distillation plant to operate under working specifications. The outcome of both modules will be displayed at front panel of LabVIEW to show the user the state of the plant at any time.

The overall system allows also the controlling of a experimental system instead of the simulation model, using instead the measures form the sensors of the column in order to train both the neural model and controller under LabVIEW interface.

3. Distillation Column Model

The distillation column is used for the separation of a binary mixture of methanol and n-propanol which enters as a feed stream with flow rate F, composition X_F and enthalpy q between two sections (a rectifying section and a stripping section). Mass transfer occurs between the vapour flowing up and the liquid flowing down the column. The vapour exiting at the top of the column is condensed, and part of the resulting liquid flow is returned at the column at the top (reflux), while

the remainder is taken as the distillate product D. Part of the liquid flow out of the bottom of the column is vaporized in a reboiler and sent back to the bottom of the column, while the remainder is taken as the bottom product B.

The column consists of a N bubble cap trays. The overhead vapour is totally condensed in a water cooled condenser (tray $N+1$) which is open at atmospheric pressure. The reboiler (tray 0) is heated electrically, and the preheated feed stream enters the column at the feed tray as saturated liquid. The process inputs that are available for control purposes are the heat input to the reboiler Q and the reflux flowrate L_{N+1} (Fig. 2).
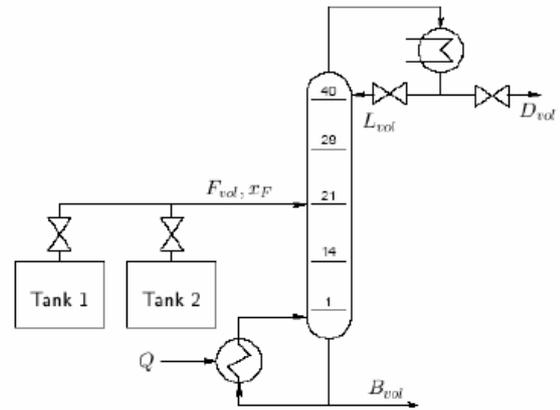
Fig. 2. Scheme of the binary distillation column

In this section we will describe the model of the distillation column developed by [9], composed by the mass, component mass and enthalpy balance equations used as basis to implement the SIMULINK diagram.

3.1. Mass Balance

The differential equations that determine the change of the molar holdup n_l of the trays are given by

$$\dot{n}_l = V_{l-1} - V_l + L_{l+1} - L_l$$

Only valid for $l = 1,....., NF - 1, NF + 1,......, N$ trays, where V_l is the molar vapour flux leaving the l-th tray and L_l is the liquid flux leaving the l-th tray. For the feed tray NF the equation is given by

$$\dot{n}_{NF} = V_{NF-1} - V_{NF} + L_{NF+1} - L_{NF} + F$$

and the corresponding for the condenser and reboiler are

$$\dot{n}_{N+1} = V_N - L_{N+1} - D$$

$$\dot{n}_0 = L_1 - V_0 - B$$

3.2. Component Mass Balance

For the most volatile component, the composition balance will follow the equation

$$(n_l \dot{X}_l) = V_{l-1}Y_{l-1} - V_l Y_l + L_{l+1}X_{l+1} - L_l X_l$$

valid for $l = 1,.....,NF-1, NF+1,......,N$ where X_L is the liquid concentration of the most volatile component and Y_L is the composition of the vapour flow out of the *l-th* tray.

For the feed tray we will have

$$(n_{NF}\dot{X}_{NF}) = V_{NF-1}Y_{NF-1} - V_{NF}Y_{NF} + L_{NF+1}X_{NF+1} - L_{NF}X_{NF} + FX_F$$

while for the reboiler and condenser we have

$$(n_0 \dot{X}_0) = -V_0 Y_0 + L_1 X_1 - BX_0$$

$$(n_{N+1}\dot{X}_{N+1}) = V_N Y_N - L_{N+1}X_{N+1} - DX_{N+1}$$

3.3. Enthalpy Balance

We will assume that the condenser pressure is fixed to the outside atmospheric pressure, and that the pressure in the trays can be calculated under the assumption of constant pressure drop from tray to tray $P_l = P_{l+1} + \Delta P_l$, and the tray temperatures are implicitly defined by the assumption that the total pressure is equal to the sum of the partial pressures, $P_l = X_l P_1^s(T_l) + (1-X_l)P_2^s(T_l)$, with T_l holds for the temperature of the *l-th* tray, and where the partial pressures P_k^S can be evaluated as

$$P_k^s(T) = \exp\left(A_k - \frac{B_k}{T + C_k} \right)$$

with different values of the constants according to the liquid we are evaluating.

The non-ideality of the trays and other unmodelled effects are accounted in the tray efficiencies α_L. With these tray efficiencies we can calculate the composition of the vapour flow out of the *l-th* tray as a linear combination of the ideal vapour composition on the tray and the incoming vapour composition of the tray below by

$$Y_l = \alpha_l \frac{P_1^s(T_l)}{P_l} X_l + (1-\alpha_l)Y_{l-1}$$

starting with $Y_0 = \dfrac{P_0^s(T_0)}{P_0} X_0$.

We will formulate then the enthalpy balances in order to determine the vapour streams that leave each tray as follows

$$\dot{n}_l h_l^L + n_l\left(\frac{\partial h_l^L}{\partial X_l}\dot{X}_l + \frac{\partial h_l^L}{\partial T_l}\dot{T}_l\right) =$$
$$V_{l-1}h_{l-1}^V - V_l h_l^V + L_{l+1}h_{l+1}^l - L_l h_l^l$$

valid for $l = 1,.....,NF-1, NF+1,......,N$, where h_l^k is the enthalpy with k indexing to the phase (L refers to liquid and V to vapour).

For the feed tray and the condenser we will have

$$\dot{n}_{NF} h_{NF}^L + n_{NF}\left(\frac{\partial h_{NF}^L}{\partial X_{NF}}\dot{X}_{NF} + \frac{\partial h_{NF}^L}{\partial T_{NF}}\dot{T}_{NF}\right) =$$
$$V_{NF-1}h_{NF-1}^V - V_{NF}h_{NF}^V + L_{NF+1}h_{NF+1}^l - L_{NF}h_{NF}^l + Fh_F^L$$

and

$$\dot{n}_0 h_l^L + n_0\left(\frac{\partial h_0^L}{\partial X_0}\dot{X}_0 + \frac{\partial h_0^L}{\partial T_0}\dot{T}_0\right) =$$
$$Q - Q_{loss} - V_0 h_0^V + L_1 h_1^l - Bh_0^l$$

The enthalpies h_l^L and h_l^V are given by

$$h_l^L = X_1 h_{l1}^L(T) + (1 - X_1) h_{l2}^L(T)$$

$$h_l^V = Y h_{l1}^V(T, P) + (1 - Y) h_{l2}^V(T, P)$$

where h_{lk}^L can be evaluated as

$$h_k^L = C\left(h_{1,k}(T - T_0) + h_{2,k}(T - T_0)^2 + h_{3,k}(T - T_0)^3\right)$$

with different values for the constants according the liquid were referring to, and the vapour enthalpies can be evaluated as

$$h_k^V = h_k^L + RT_k^c \sqrt{1 - \frac{P}{P_k^c}\left(\frac{T}{T_k^c}\right)^{-3}}$$

$$\left[a - b\frac{T}{T_k^c} + c\left(\frac{T}{T_k^c}\right)^7 + \Omega_k\left(d - e\frac{T}{T_k^c} + f\left(\frac{T}{T_k^c}\right)^7\right)\right]$$

with coefficients according to the liquid or vapour we are considering in each case.

The SIMULINK model corresponding to these equations is depicted in Fig. 3 showing the top level modelling description.
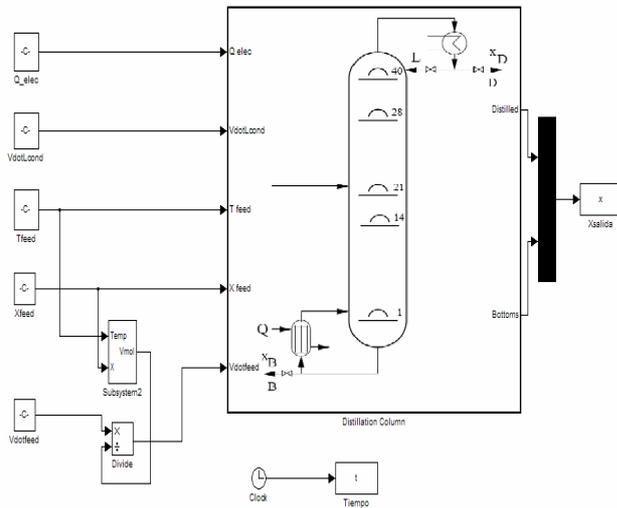
4. Neural Modeling and Control Tool

Neural networks have become a popular tool for identification and control of unknown nonlinear systems. The Neural Network Toolbox commercialised with MATLAB [4] is intended to serve as a general-purpose package for this task, but the efficient exploitation of these services drastically depends on the programming skills and experience of the users.

In this context, the design of MIMO Control Tool running under SIMULINK and specially conceived for building neural-network-type models becomes a more attractive perspective for developing applications than writing laborious MATLAB codes in a classical manner.

In the context of this paper, we present a design tool for neural based modelling and control of nonlinear systems, built also to analyze the stability control problems associated (Fig. 4). We have applied this methodology for a high purity distillation plant, which is clearly a MIMO nonlinear system.

Fig. 3. SIMULINK model of the distillation column
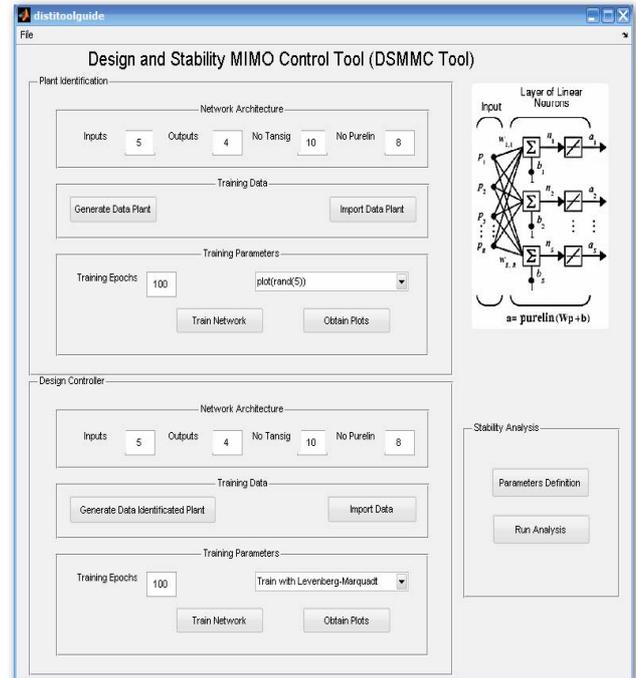
Fig. 4. Scheme of the neural network design control tool

4.1. Neural Identification Tool

The data for training both the neural network model and controller were obtained from dynamic simulations using the SIMULINK model already developed in section III. The reflux rate L_{Vol} and heat flow Q were used as plant inputs together with top and bottom compositions X_D and X_B, while feed variables (F, X_F, q) have been treated as process disturbances.

The training set for identification comprised 200 data points belonging to the open loop operating range for plant inputs reflux flowrate L_{Vol} (0-5E-06 m^3/h) and heat flow Q (0-2000 J/s) for fixed feed rate conditions $F = 1$ E-06 m^3/h, $X_F = 0.3$, and $q = 1$. An additional data set consisting of 150 data points was used to test the neural network model afterwards. For training pattern generation we assume an initial steady state for the column after a start-up process.

The identification task was made using the Levenberg-Marquardt algorithm for a neural network with two layers in a *tansig - purelin* activation function scheme, by using automatic target vector generation with the plant outputs. With these results we obtained an optimum 2-10-2 network SIMULINK block that can be used for running several experiences (Fig. 5).
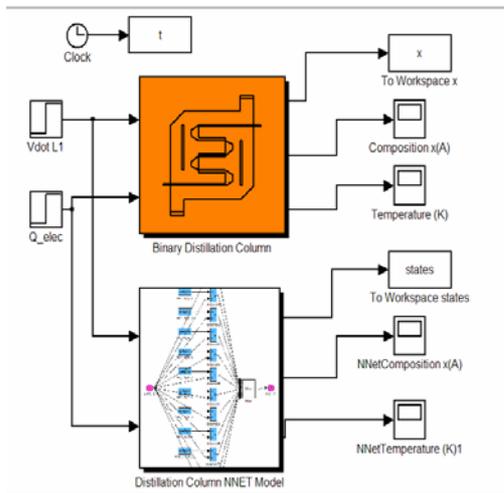
Fig. 5. SIMULINK structure for training the neural network model

Figure 6 shows the comparison between the actual (SIMULINK) and the neural network predicted values of distillate composition for reflux and heating flows signals selected in the operating ranges.
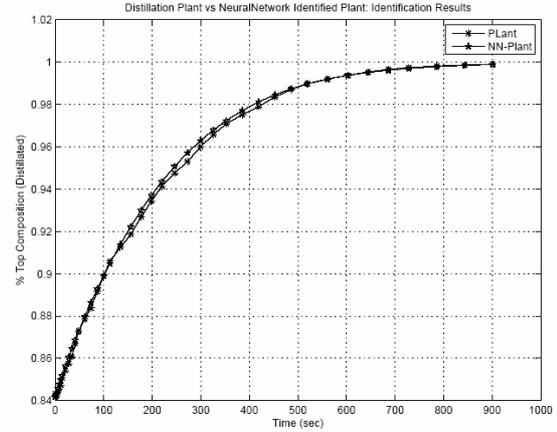
Fig. 6. Prediction for distillate composition of the neural model for L_{Vol} = 3E-06 m^3/h, Q = 1200 J/s

4.2. Neural ControlTool

This tool has been implemented using two approaches, direct design and indirect design [5]. In the direct design method the controller is in itself a neural network, while in the indirect design the controller is not a neural network at all, but the design is based on a neural network model of the plant to be controlled. Besides, the system can be specified either as SIMULINK model, a MATLAB file containing the algebraic differential equations or a neural network model of the system.

The training set for control comprised 150 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 120 data points was used to test the neural network controller also.

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The control task was made using the Levenberg-Marquardt algorithm for a neural network with two layers in a *tansig - purelin* activation function scheme, coupled with a neural identification network previously trained with the Neural Identification Tool, so as to adjust the network controller parameters using the propagation of the output plant error through the neural network model [10]. We obtained an optimum 2-12-2 network SIMULINK block for the neural controller, with top and bottom composition errors as inputs and reflux rate and heat flow as outputs (Fig. 7).
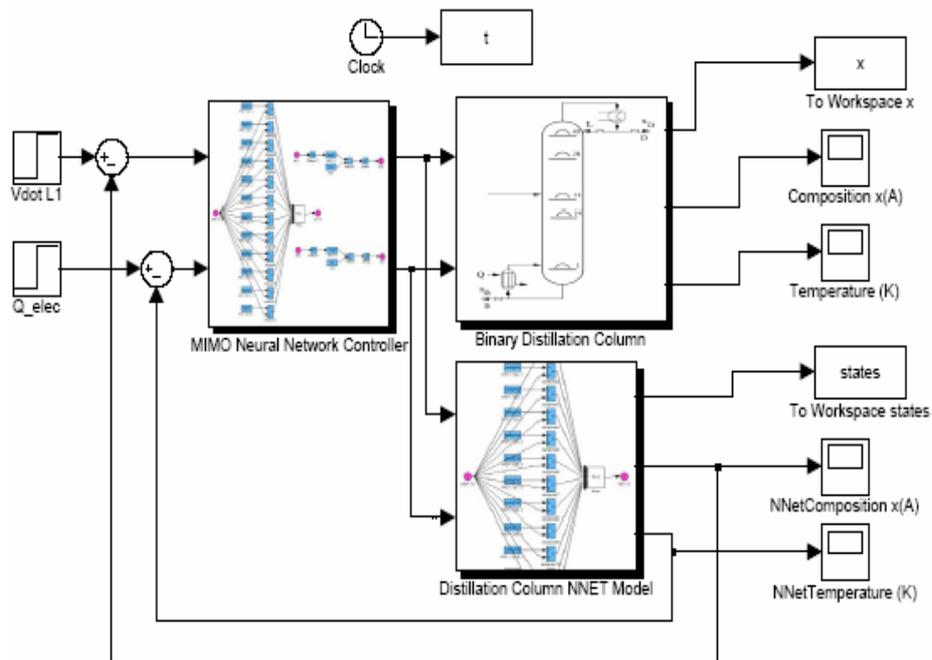
Fig. 7. SIMULINK structure for training the neural network controller

5. Monitoring of the Distillation Column

One of the goals of the present work is to develop a system that allows the monitoring in line and manipulate the variables that take part in the distillation process, as well as to interact with the neuronal tool we have developed in a SIMULINK environment,. Therefore it will be of great interest to develop alternatives to solve this problem in an economic, efficient and reliable way.

The solution we propose is a graphic user interface developed in National Instrument's graphical programming language LabVIEW [6]. In this way, the observation and manipulation of the variables is carried out using virtual instruments while the connection between the virtual instruments and the neural tool is solved using the Simulation User Interface Library, which allows to develop, prototype, and test control systems using models developed in the SIMULINK simulation environment (Fig. 8).
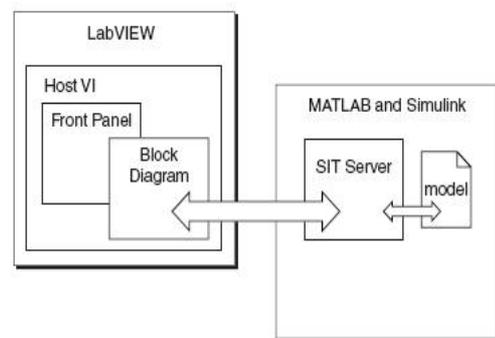
Fig. 8. Interaction between LabVIEW and SIMULINK

In this way, the programming language LabVIEW was used for the tasks of acquisition, analysis and presentation of data in a friendly way to the user and also provides a efficient tool for the communication with the neural tool. So the solution we propose lead us to a flexible and versatile tool, being an efficient, economic and simple way to monitorize a dynamic plant and both to model and control a distillation column by using the neural tool (Fig. 9).

6. Results

In order to show the validity of the proposed control scheme, we have selected a binary high-purity distillation column, for separating a mixture of methanol and n-propanol, which consist in 40 bubble caps trays with heated electrically reboiler and water refrigerated tubular condenser.

In Fig. 10, we show how the neural controller exhibit adequate control action to compensate a dual step change in distillate composition from 99% to 98% and bottom composition from 98.5% to 97.5% in t = 40 s, together with a change in feed composition from 50% to 80%. Changes in the reflux and heat flows are determined by the neural network model-based controller for the column.

Fig. 9. Frontpanel of the monitoring tool
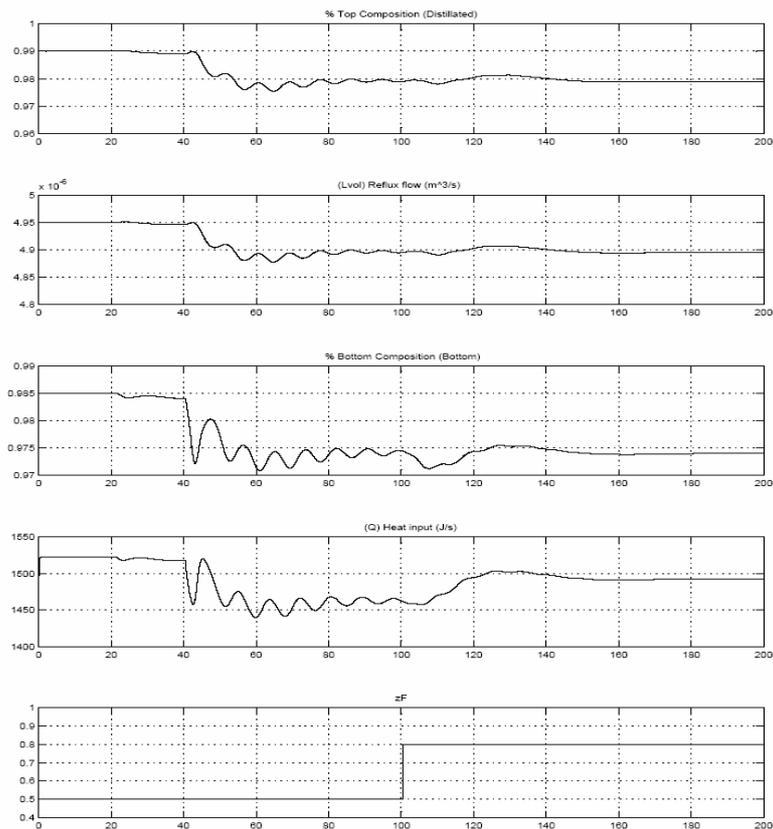
Fig. 10. Response of the distillation control system to step changes in top and bottom compositions and change in feed composition

7. Conclusions and Future Works

A SIMULINK based tool has been developed for analysis and design of multivariable neural based control systems. This tool has been applied to the control of a high purity distillation column also modeled in SIMULINK including non linear

hydrodynamic effects. Also LabVIEW environment has been employed as a graphical user interface for monitoring the neurocontrolled distillation column. The results obtained demonstrate the potential use of this control strategy in this field.
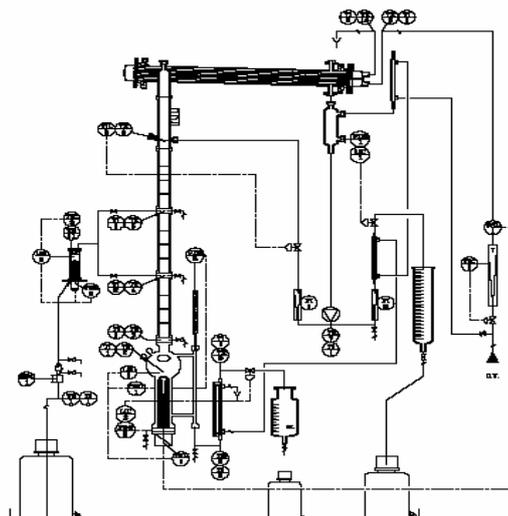
Figure 11. Lab-scale pilot distillation column DELTALAB DC-SP

Future works are directed towards the application of the described toolset to a experimental distillation column as is actually being made by the System Engineering and Automation Group as part of the researching project DPI2005-08344 (fig. 11), which utilizes the same scheme as Fig. 1 but replacing the simulation model by an experimental distillation column DELTALAB DC-SP, whose technical characteristics are displayed at web page below (in Spanish)http://www.isa.uma.es/C4/Control%20Neuroborroso/Document%20Library/index.htm)

At the same time, the stability issued involved in the neural control task are also object of research, since nonlinear and multivariable dynamics are present.

8. References

[1] McMurray, J., Himmelblau, D., "Identification of a packed distillation column for control via artificial neural networks", *Proc. ACC, San Francisco*, CA, pp. 1455-1459, 1993.

[2] Xiong, Q., Jutan, A.,"Grey-box modelling and control of chemical processes", *Chem. Eng. Science*, Vol. 57, pp. 1027-1039, 2002

[3] Hussain, M. A., "Review of the applications of neural networks in chemical process control. Simulation and on-line implementations", *Artificial Intelligence in Eng.*, Vol. 13, pp. 55-68, 1999.

[4] Demuth, H., Beale, M., Hagan, M. *Neural Network Toolbox for use with MATLAB.* The Mathworks, 2006.

[5] Norgaard, M., Ravn, O., Poulsen, N., "NNSYSID and NNCTRL tools for system identification and control with neural networks", *Computing and Control Engineering Journal*, Vol. 23, pp.29-36, 2001.

[6] Bishop, R. *Learning with LabVIEW 7 Express*, New Jersey, Prentice Hall, 2004.

[7] Muhamad, N.A., Ali, S. "LabVIEW with fuzzy logic controller simulation panel for condition monitoring of oil and dry type transformer", *IEEE Trans. on Engineering, Computing and Technology*, Vol. 14, pp. 187-193, 2006.

[8] Luyben, P. *Process modeling, simulation and control for chemical engineers.* McGraw Hill, Chemical Eng. Series, 1990.

[9] Diehl, M., Uslu, I., Findeisen., R.,"Real-time optimization for large scale processes: Nonlinear predictive control of a high purity distillation column", *On Line Optimization of Large Scale System: State of the Art*, Springer-Verlag, 2001.

[10] Norgaard, M, O. Ravn, N.K. Poulsen and L.K. Hansen. *Neural Networks for Modelling and Control of Dynamic Systems*. Springer Verlag, 2000.