International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:2, No:11, 2008

Software Tools for System Identification and Control using Neural Networks in Process Engineering

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Abstract**—**Neural networks offer an alternative approach both for identification and control of nonlinear processes in process engineering. The lack of software tools for the design of controllers based on neural network models is particularly pronounced in this field. SIMULINK is properly a widely used graphical code development environment which allows system-level developers to perform rapid prototyping and testing. Such graphical based programming environment involves block-based code development and offers a more intuitive approach to modeling and control task in a great variety of engineering disciplines. In this paper a SIMULINK based Neural 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 including non linear hydrodynamic effects. 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.

Keywords**—**Distillation, neural networks, software tools, identification, control.

I. Introduction

DISTILLATION columns constitute a major part of most chemical engineering plants and remains as the most important separation technique in chemical process industries around the world. Therefore, improved distillation control can have a significant impact on reducing energy consumption, improving product quality and protecting environmental resources. However, both distillation modelling and control are difficult task because the plant behaviour is usually nonlinear, non stationary, interactive, and is subject to constraints and disturbances [1]. Besides the application of such techniques to real experimental plants are limited by the high cost of distillation equipment.

Neural networks offer an alternative approach to modelling process behaviour as they do not require a priori knowledge of the process phenomena. They learn by extracting pre-existing patterns from data that describe the relationship between the inputs and the outputs in any given process phenomenon. When appropriate inputs are applied to the network, the network acquires knowledge from the environment in a process known as learning. As a result, the network assimilates information that can be recalled later. Neural networks are capable of handling complex and nonlinear problems, process information rapidly and can reduce the engineering effort required in controller model development. 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 [2].

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, such as the MATLAB-SIMULINK neural network toolbox [3] 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, [4] have developed two toolset for use with MATLAB 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 single input single output (SISO) nonlinear systems, being therefore invalid to be extended to general multiple inputs multiple outputs (MIMO) control problems as is frequently usual in high purity distillation units.

Besides SIMULINK [5] is properly a widely used graphical code development environment which allows system-level developers to perform rapid prototyping and testing. Such graphical based programming environment involves block-based code development and offers a more

Manuscript received March 31, 2008. This work was supported by CICYT project DPI05-08344.

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intuitive approach to modelling and control task in a great variety of engineering disciplines, such as process engineering.

In this paper a SIMULINK based Neural 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 including non linear hydrodynamic effects. 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.

II. Neural Identification and Control

Neural networks come in a variety of types, and each has their distinct architectural differences and reasons for their usage. The type of neural network used in this work is known as a feedforward network (Fig. 1) and has been found effective in many applications. It has been shown that a continuous-valued neural network with a continuous differentiable nonlinear transfer function can approximate any continuous function arbitrarily well in a compact set [6].

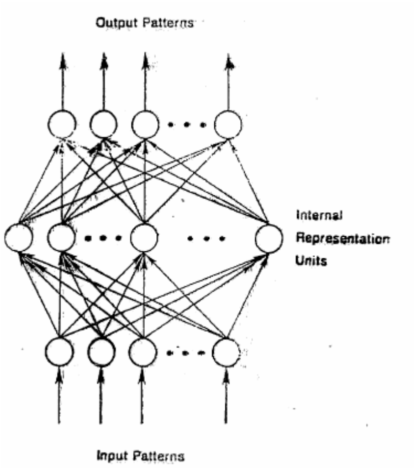

Fig. 1 Feedforward neural network architecture

There are several different approaches to neural network training, the process of determining an appropriate set of weights. Historically, training developed with the backpropagation algorithm, but in practice quite a few simple improvements have been used to speed up convergence and improve the robustness of the backpropagation algorithm [7].

The learning rule used here is common to a standard nonlinear optimization or least-squares technique. The entire set of weights is adjusted at once instead of adjusting them sequentially from the output layer to the input layer. The weight adjustment is done at the end of each epoch and the sum of squares of all errors for all patterns is used as the objective function for the optimization problem. We combined a quickly convergent local method with a globally convergent one: the Marquardt method for solving the nonlinear least squares problem. The Marquardt method switches smoothly between the extremes of the Gauss-Newton method and the steepest descent method [8].

In the system identification stage, it is developed a neural network model of the plant under control using the modeling error. In the control design stage, the neural network controller is coupled with the neural network model, so as to adjust the network controller weights using the propagation of the controlling error through the neural network model [9] (Fig. 2).

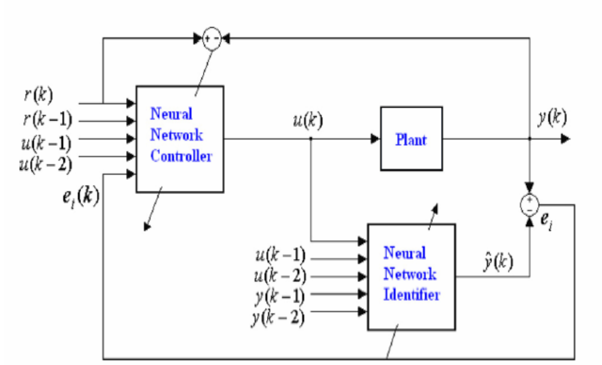

Fig. 2 Structure for neural network modeling and control

It is desired to demonstrate the neural network design tool applied both to the modelling and control of a high purity methanol-water distillation column (Fig. 3).

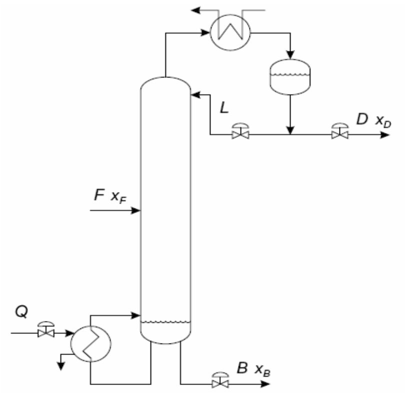

Fig. 3 Distillation column

The binary mixture 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 *L*), while the remainder is taken as the distillate product *D* with composition X_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 with composition X_B. The column consists of a 9 bubble cap trays. The overhead vapour is totally condensed in a water cooled condenser which is open at atmospheric pressure. The reboiler 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.

The model of the distillation column used throughout the paper is developed by [10], composed by the mass, component mass and enthalpy balance equations used as basis to implement the SIMULINK diagram (Fig. 4).

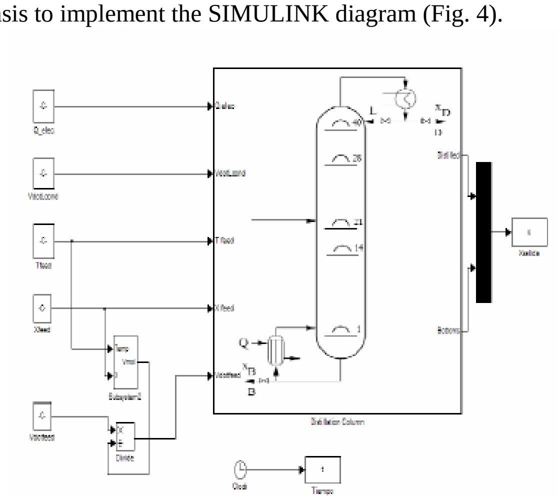

Fig. 4 SIMULINK model of the distillation column

The data for training both the plant's neural network model and controller were obtained from dynamic simulations using the SIMULINK model already described. The reflux rate L and heat flow Q were used as inputs to the neural network model being top and bottom compositions X_D and X_B considered as targets, while feed variables (F, X_F, q) have been treated as process disturbances. The neural controller is obtained with top and bottom composition errors as inputs and reflux rate and heat flow as outputs.

III. Neural Software Tool

Neural networks have become a popular tool for identification and control of unknown nonlinear systems. The Neural Network Toolbox commercialised with MATLAB [3] 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 tools 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.

The lack of tools for design of controllers based on neural network models is particularly pronounced because development of generic software for control system design is relatively difficult as several types of control designs exist.

The Neural Tool here developed offers a useful GUI (Guided User Interface) as front-end for the engineer enabling identification, control and even stability analysis for MIMO systems, throughout the selection of different options (Fig. 5). This tool has been developed for the SIMULINK environment due to its versatility and widespread use in the control engineering community.

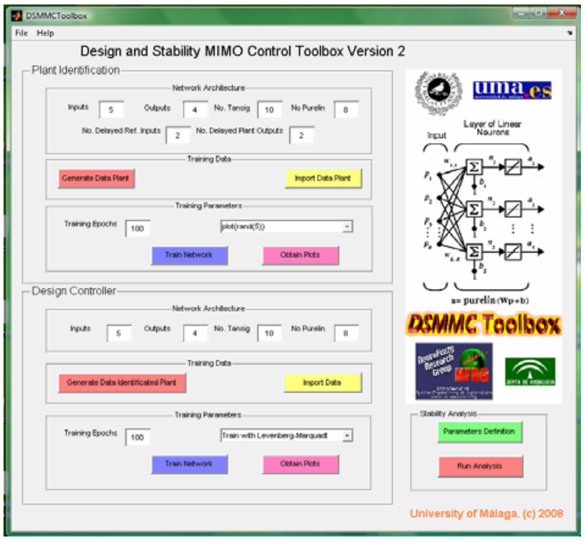

Fig. 5 Main-front screen of the Neural Tool

The neural network basic structure is defined by input layer, two hidden layers, and output layer, and the user can select the internal configuration of the network. Also the external configuration both for the modelling and control neural task can be selected, that is, the number of delayed reference and controller inputs together with the number of delayed plant outputs. Fig. 6 shows details on the neural identification and control architecture as they are implemented in the Neural Tool.

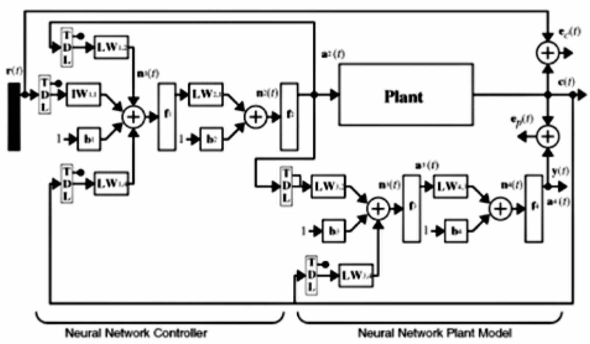

Fig. 6 Neural network structure for modelling and control

During the training stage user must generate or import I/O data using the dynamic system under control, which can be specified as a SIMULINK model. Selecting the training algorithm, we can run the process to obtain the identification neural network. This network is stored in workspace of Matlab as IdentNN variable. Several plots with information about the training process are obtained automatically (Fig. 7).

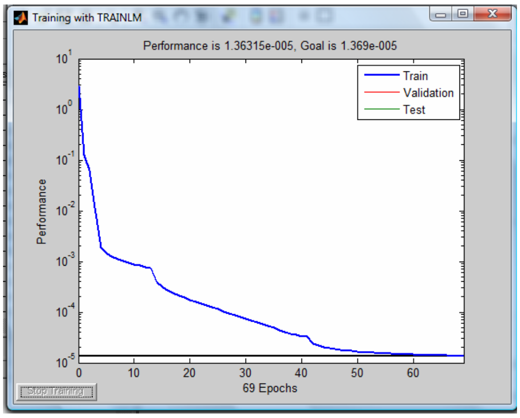

Fig. 7 RMS error plot obtained during training stage

On the other hand, during the training control process we set up several variables to define the neural controller according to the identification neural network already obtained. It is important to highlight that the identification task is previous to the control task, and is necessary to gather I/O generated data files corresponding to plant dynamics to set the neural controller, stored as a ControlNN variable.

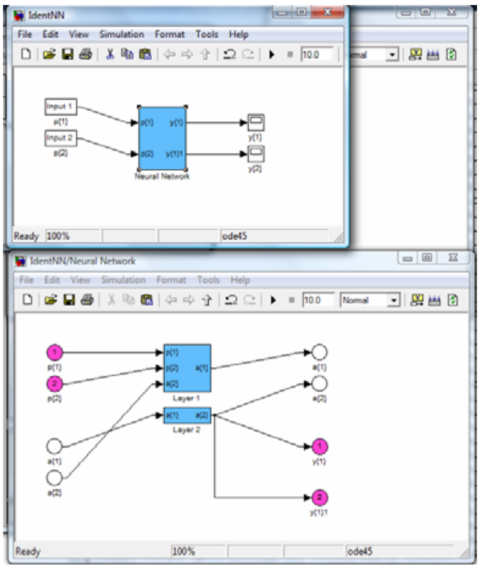

Fig. 8 SIMULINK identification neural network

Finally, two SIMULINK blocks each one corresponding to the neural model and controller are obtained after the training stage which can operate on the dynamic plant (Fig. 8).

IV. Application

To illustrate the application of the proposed Neural Tool on the process engineering field, we have selected a binary high-purity distillation column, for separating a mixture of methanol and water, with 40 bubble caps trays provided with heated electrically reboiler and water refrigerated tubular condenser.

The training set for the neural identification comprised 200 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 = 1 E-06 m3/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 training process was made using the 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.

The training set for neural 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. The control task was made using the Marquardt algorithm for a neural network with two layers in a *tansig* - *purelin* activation function scheme, coupled with the neural identification network previously trained. 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. 9).

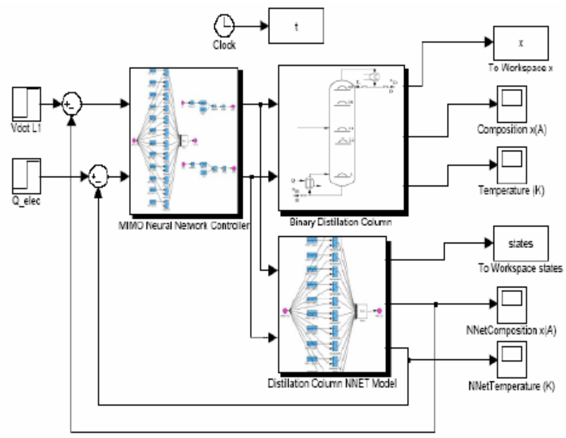

Fig. 9 SIMULINK structure for neural distillation control

In Fig. 10, 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 99% to 98% and bottom composition from 0.975% to 0.98% both in t =40 s, together with a change in feed flow of 30%. Changes in the reflux and heat flows are determined by the neural network model-based controller for the column remaining inside the operating range.

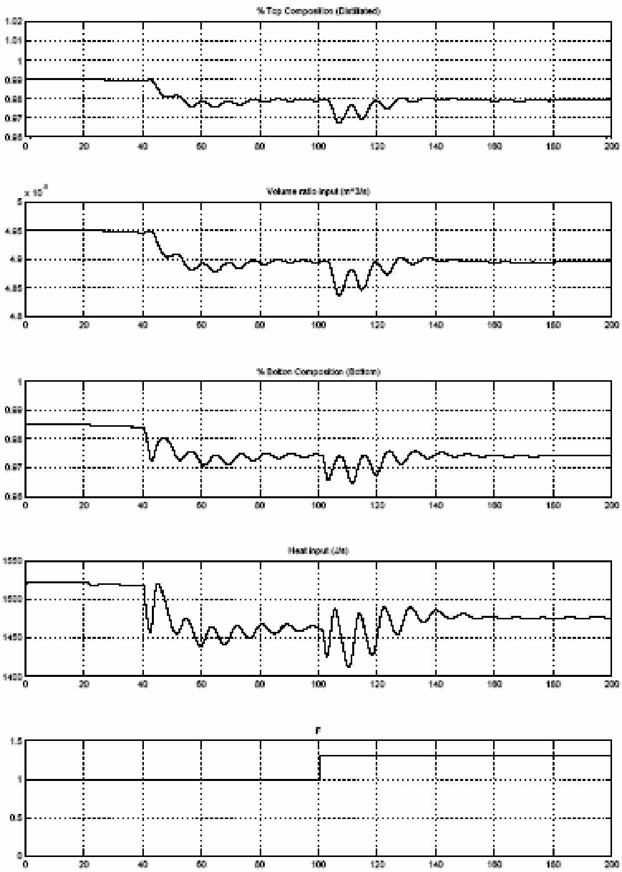

Fig. 10 Response of the distillation control system to step changes in top and bottom compositions and change in feed composition

V. Conclusion

A Neural Tool based in SIMULINK 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 including non linear hydrodynamic effects. The results obtained demonstrate the potential use of this control strategy in this field. Future works are directed towards the application of the described toolset to a experimental distillation column DELTALAB DC-SP as is actually being made by the System Engineering and Automation Group as part of the researching project DPI2005-08344 (Fig. 11), 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.

Fig. 11 Distillation column DELTALAB DC-SP

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