PROCESS IDENTIFICATION WITH ARTIFICIAL NEURAL NETWORK APPLIED TO EXPERIMENTAL DATA FROM A CONTINUOUS DISTILLATION COLUMN

W. G. Vieira, C. H. Sodré, K. B. Barcellos, L. C. Dantas
DEQ/CTEC - Universidade Federal de Alagoas
E-Mail: wvieira@ctec.ufal.br

Abstract

This paper describes an identification procedure, based on Artificial Neural Network (ANN) to study the dynamic behavior of the continuous distillation column. The study was focused on an existing 10 trays, 12cm diameter pilot scale distillation column. The column was used to distillate methanol and water mixture. The dynamic model was developed and validated against pilot distillation column data and used to generate a large data set of operational variables. Open-loop responses were used to generate data. A multilayer feed forward network was chosen for the distillation column representation. Based on the theorectical results, the following strategy was adopted for the network architecture: the input layer was composed by four variables and the output layer was formed by the two variables. The number of nodes in the hidden layer was obtained from a trial-and-error procedure. The backpropagation method was used to the process training. It was observed that the network generalization capacity and the training time increased with the number of hidden neurons. This study can be able to develop a Multivariable Predictive Control (MPC) to be implemented in the column control system, using the ANN as internal model. The obtained ANN model agrees very well with the experimental and theorectical data then it could be used to simulate the real process with the control strategy.

Keywords: Process Identification, Artificial Neural Networks, Distillation Column.

1. Introduction

The use of complex and more precise mathematical methods in systems engineering has been extensively encouraged by the introduction of low cost digital computers and high-speed processing. This new technology allows the Artificial Neural Networks methodology to be used for the identification and control of chemical systems. Any linear or non-linear chemical process can be simulated through a neural network modeling, even when the first principles of the process are unknown. Just input/output operational data are needed [1].

Several researches were already made based on ANN: Narendra, [2] summarizes the application of ANN in Process Control and describes the last advances in this area. This author compares ANN's mathematical bases and some successful industrial applications are mentioned. In the processes identification area, Nikravesh et al. [3] applied the backpropagation training procedure to a CSTR reactor. De Souza Jr. [4] employed an ANN for process classification, where the network was used to predict the properties of a catalyst in function of the conditions of the manufacture process. The author also used the network for the identification of nonlinear reactors within a predictive control loop.

1.1. Process Description

The data used to train the ANN were obtained from the dynamic model from a continous distillation column in pilot scale. The dynamic model was validated against practical data [5]. The column scheme is showed in Figure 1. The distillation column has ten trays. Each tray has two bubble caps. The rig is well equipped with liquid sample points, rotameters and thermowells on the top and the bottom trays and feed stream. Numbering the column trays from top to bottom, the feed is on tray six. The column has a total condenser, reflux drum and a kettle reboiler. The column is lagged with glass wool to minimize heat loss. The mixture used was methanol and water.

1.2. Artificial Neural Network

The ANN is formed by processors elements denominated of neurons or nodes, interconnected by channels called of connections, forming a dense net [4]; [6]. The nodes are arranged in layers linking the input with the output. The connections tie the nodes of one layer with the nodes of another one. The way as the nodes are connected and its dispositions determine the architecture of the net. In the present study the net was configured as multilayer feedforward fully connected, with one hidden layer and without feedback connections. Hidden layers are used to extract, from the network, statistical results of high order [6].

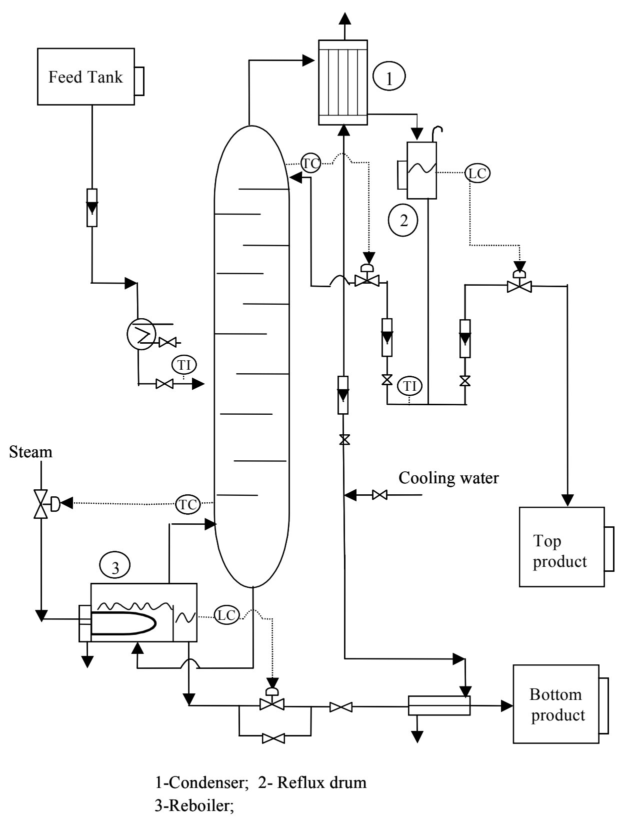

Fig.1. Continuous Distillation Column Scheme

Mathematically, the behavior of a neuron in a generic layer can be represented by:

$$\lambda_{pj,k+1} = \left[\sum_{i=1}^{n_k} w_{jik} . S_{pi,k} \right] + \theta_{j,k+1} , \tag{1}$$

where: λ represents the output of the neuron ' j ', in the layer ' $k+1$ ';

S corresponds to the outputs or activation of all neurons of the layer ' k ';

w is the weight of the connections;

θ is the internal limit of activation of the corresponding neuron ' j ' (bias).

An activation function, called Transfer Function of neuron, is applied to λ. In the present study was used the Sigmoid function, defined by [7]:

$$f\left(\lambda_{pj,k+1}\right) = \left[1 + \exp\left(-\lambda_{pj,k+1}\right)\right]^{-1} . \tag{2}$$

The learning procedure is the process where the weights and biases are modified [8]. The supervised training was used in this work. Known input and output data (patterns) are presented to the network. The network is then adjusted by changing the weights and bias with predefined rules. The patterns are initially normalized to avoid differences in the magnitude order of the input and output [9]. Due to the use of the sigmoid as transfer function, the normalization was made to obtain the patterns in the positive interval between 0.0 and 1.0. Indeed it was chosen a limit interval among 0.1 to 0.9 to allow, if necessary, small extrapolations [10]; [7]. The following relationship is used for the normalization procedure:

$$P_{nor} = 0.1 + \left(\frac{P_{real} - P_{\min}}{P_{\max} - P_{\min}} \right) \times 0.8 ,$$

where: P_{nor} represents the normalized pattern;

P_{real} is pattern in the units of input/output and is obtained from the phenomenological model;

P_{min} is the lower bound of the variable;

P_{max} is the upper bound of the variable.

The initial weights and biases were selected through a random routine that generates numbers between -1.0 and +1.0. The Training Algorithm used was Backpropagation, based on the error correction technique. In the optimization process, the strategy of the steepest descent was used [4]; [6].

2. Methodology

This section describes the Dynamic Model used to generate data to train and test the network and the ANN architecture.

2.1. The Dynamic Model

A dynamic model used to generate the data used in the ANN training was such that the overall and component balance was solved for each tray. Additional algebraic model equations were needed for the steady-state energy balance, vapour-liquid equilibrium relationships and Francis weir formula for liquid flow in the reboiler and liquid flow relationship for each tray. The column has ten real trays, Murphree efficiency of 85%, total condenser and a kettle reboiler. A single feed stream, methanol and water mixture, is fed as a sub-cooled liquid. The model assumptions are: constant pressure, constant molal overflow, negligible vapour hold-up, fast vapour flow dynamics and non-ideal equilibrium vapour-liquid. To describe the vapour-liquid equilibrium relationship for the more volatile component in a binary mixture, Dalton's law is applied to the vapour phase and the liquid non-ideal deviation from Raoult's law behaviour is accounted for by an activity coefficient. For a methanol-water mixture the two parameters can be fitted by the van Laar equations and the van Laar parameters used were from Kojima (apud [11]). All model equations are obtained in Sodré [11]. This model was validated against plant data and the results had a very good agreement. When the experiment starts, the column was allowed to reach the steady-state. When the steady-state was reached the column was subjected to a step change. Perturbation in one of the following variables was made: reflux flow or steam flow to the reboiler. The step changes are bounded by the pilot distillation column limitation. Two cases were studied. For the first case, a step changes in the reflux flow was made. This step change was close to (+) 20%, wait until the steady state was reached and then another step change of (-) 20% was made bringing the column back to the initial condition. For the second case, a step change in the vapour flow to the reboiler was made. The step change was around (+) 17%. The temperature was used to inffer the top and bottom compositions products. The choosen variables to represent the process were the Top and Bottom Tray Temperatures.

2.2. The Artificial Neural Network

A multilayer feed forward network was chosen for the distillation column representation. The following strategy was adopted for the network architecture: the input layer is composed by four variables and the output layer was formed by the two variables. The number of nodes in the hidden layer was obtained from a trial-and-error procedure. The backpropagation method was used to the process training. It was observed that the network generalization capacity and the training time increased with the number of hidden neurons. This study can be able to develop a Multivariable Predictive Control (MPC) to be implemented in the column control system, using the ANN as internal model. The results from the Dynamic Model were used for training the ANN. All the simulations were made with open-loop system. The trained ANN was then validated with different values from the training. Once the ANN was trained and tested, it was used to simulate the real process. The ANN results were compared with the results from the dynamic model and the experimental results. The input variables for ANN training were Reflux Flow, Vapour Flow to the Reboiler, Top Tray Temperature and Bottom Tray Temperature in actual time. The output variables were Top Tray Temperature and Bottom Tray Temperature in future time.

3. Results and Conclusions

Some ANN architectures were tested in attempt to describe the dynamic model. The chosen ANN architecture was 4x12x2 (**I**nput x **H**idden x **O**utput layer). The obtained results from this ANN were compared with the dynamic model and practical results. The results are showed from figures 2 to 11. The first case studied was the step change in the reflux flow Figure 2, [5]. When the step change reaches the tray, the composition of the tray starts to change and so the temperature. This will occur from tray to tray until the whole column is in the new steady-state.

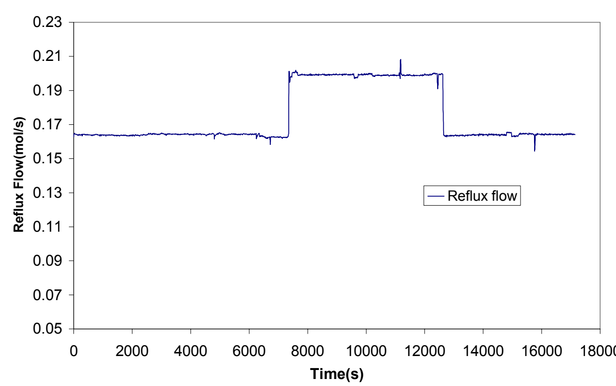

Fig. 2 Step change in the Reflux Flow [5]

Figures 3 and 4 show the comparative results between Dynamic Model and ANN in the choosen architecture. Figure 3 shows the comparison between the results for the Top Tray Temperature for both Dynamic Model and ANN results. Although the Top Tray Temperature change seems small, this represents close to 1% variation in top composition response. There is a very good agreement between the ANN results and the Dynamic Model results.

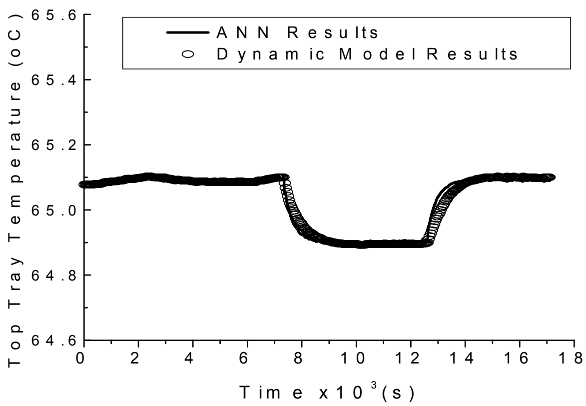

Fig. 3. Comparative Results between Dynamic Model and ANN for the Top tray temperature. Step change in reflux flow

Figure 4 shows the comparison between the results for the Bottom Tray Temperature for both dynamic model and ANN. Again there is a very good agreement between the ANN results and the Dynamic Model.

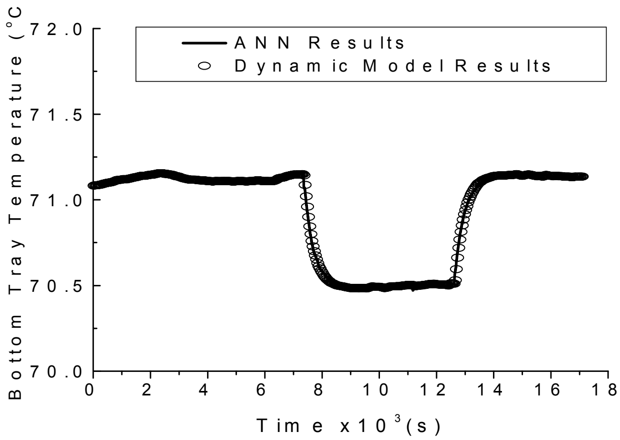

Fig. 4. Comparative Results between Dynamic Model and ANN for the Bottom Tray Temp. Step change in reflux flow

Figure 5 shows the comparison between the experimental data and the ANN data. As can be seen there is a very small shift in the graphic. This could be happened due the thermowell calibration or environment changes during the experiment.

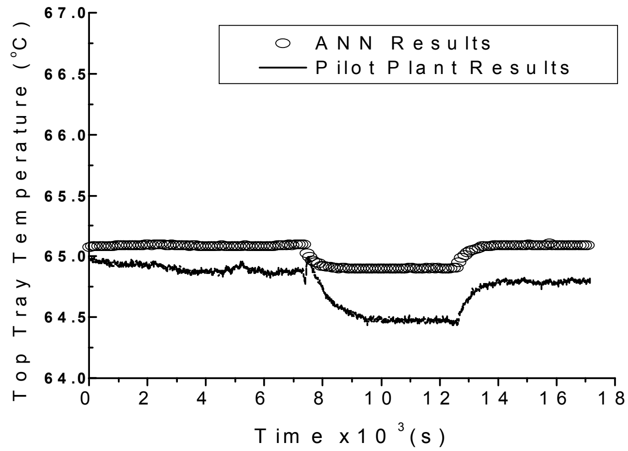

Fig. 5. Comparative Results between Experimental results and ANN with for the Top Tray Temperature. Step change in reflux flow.

The graphic in Figure 6 shows the comparative values between experimental and ANN data for the Bottom Tray Temperature. Again the shift was observed using a different thermowell. This suggests that probably the environmental change, for example atmospheric pressure variation, could be charged by this phenomenon.

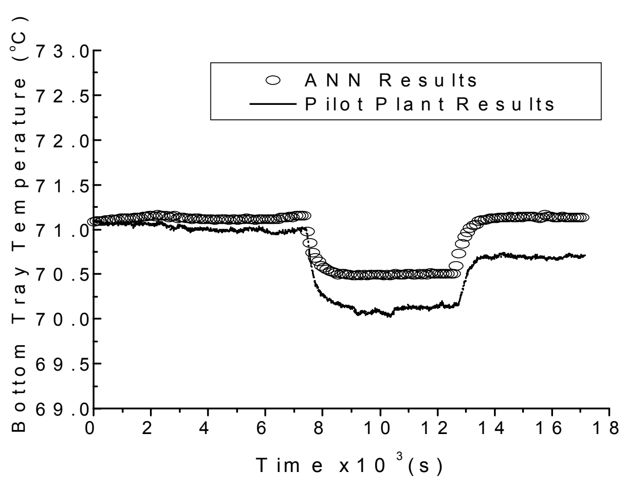

Fig. 6. Comparative Results between Experimental and ANN results for the BottomTray Temperature. Step change in reflux flow

The second case studied was the step change on the vapour flow to the reboiler close to (+) 17%. Figure 7 illustrate this step change. A positive step change in the reboiler heat input acts through the reboiler and a fast first order response is then impressed on all trays nearly simultaneously. The composition on the tray starts to decrease. This gives a higher temperature profile.

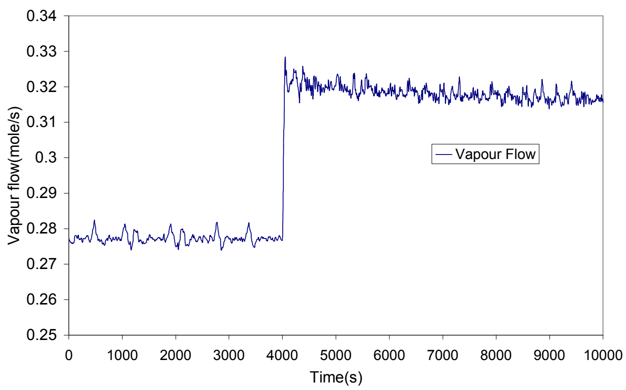

Fig. 7 Step change in the vapour flow [5].

Figure 8 shows the comparison between the results for the Top Tray Temperature for both dynamic model and ANN results when the step change in the vapour flow was made. It can be seen that there is a very good agreement between the ANN results and the Dynamic Model results.

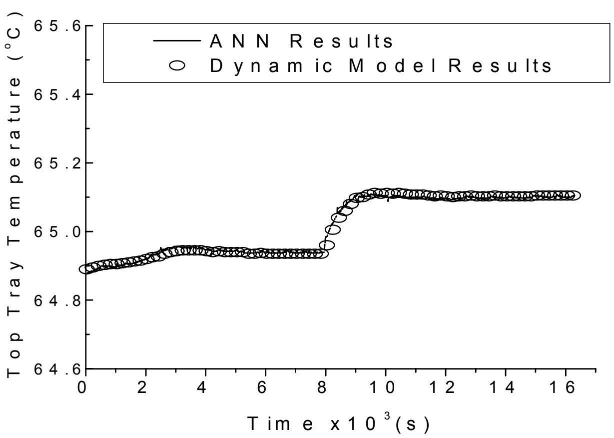

Fig. 8 Comparative results between Dynamic Model and ANN for the Top Tray Temperature. Step change on vapour flow

Figure 9 shows the comparison between the results for the Bottom Tray Temperature for both dynamic model and ANN when the same step change on the vapour flow was made. Again the the dynamic model was well represented by the ANN model.

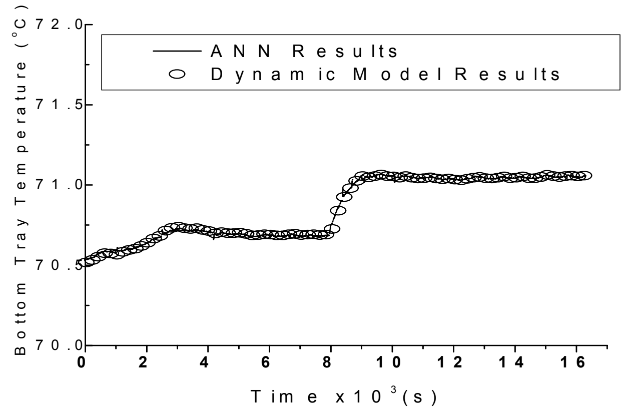

Fig. 9 Comparative results between Dynamic Model and ANN for the Bottom Tray Temperature. Step change on vapour flow.

Figures 10 and 11 show the comparative values between experimental and ANN data for both Top and Bottom Trays temperatures. The network results agree very well with the practical data in both cases.

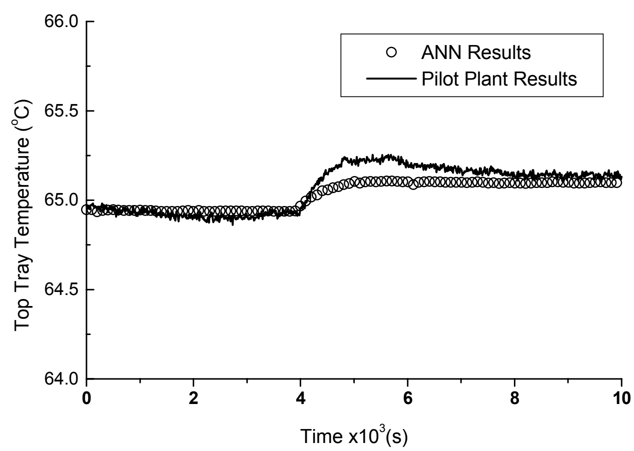

Fig. 10. Comparative Results between Experimental and ANN results for the Top Tray Temperature. Step change in vapour flow.

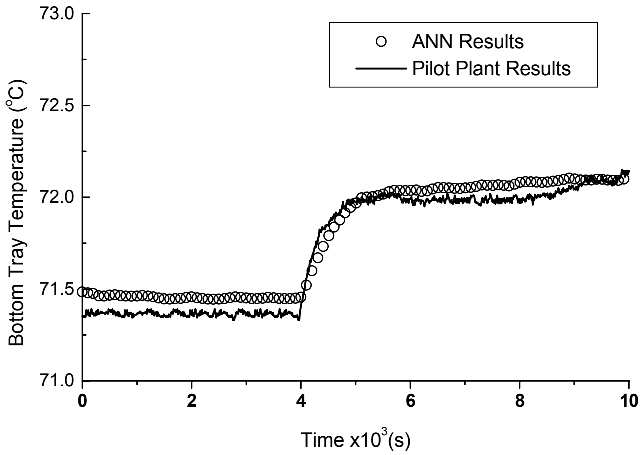

Fig. 11. Comparative Results between Experimental and ANN results for the Top Tray Temperature. Step change in vapour flow.

All the graphics show a very good agreement between the ANN and the compared data. The chosen ANN architecture 4x12x2 (IxHxO) simulates the experimental distillation process in all tested cases and could be used to simulate the real process with the control strategy.

Reference

[1] Narendra, K. S. & Mukhopadhyay, S., 1997, "Adaptive Control Using Neural Networks and Approximate Models". *IEEE Transactions on Neural Networks,* **8(3)**, pp. 475-485.

[2] Narendra, K. S., 1996, "Neural Networks for Control: Theory and Practice". *Proceeding of the IEEE*, vol. **84(10)**, pp. 1385-1406.

[3] Nikravesh, M. Fareli, A. E. And Stanford, T. G., 1996, "Model Identification of Nonlinear Time Variant Process via Artificial Neural Network". *Computers and Chemical Engineering,* **20(11)**, pp. 1277-1290.

[4] De Souza Jr, M. B. (1993) "Redes Neuronais Multicamadas Aplicadas a Modelagem e Controle de Processos Químicos". Dr. Thesis, COPPE/UFRJ, Brazil.

[5] Sodré, C. H., 1999 "Practical Evaluation of Hold-up for Passive Decoupling in Distillation Column" PhD Thesis, University of Nottingham, Available in : George Green Library.

[6] Haykin, S. (1994) "Neural Networks – A Comprehensive Foundation" Macmillan Publishing Co. NJ, 696p.

[7] Vieira, W.G., Santos, V. M. L., Carvalho, F. R., Pereira, J. A. F. R., Fileti, A. M. F. "Identification and predictive control of a FCC unit using a MIMO neural model". *Chemical Engineering and Processing.* Available in: Article in Press.

[8] Simpson, P. K. (1990) "Artificial Neural Systems: Foundations, Paradigms, Applications and Implementations". Pergamon Press, Inc., NY, 203p.

[9] Baughman, D. R. & Liu, Y. A. (1995) "Neural Networks in Bioprocessing and Chemical Engineering". Academic Press, Inc. London, 489p.

[10] Santos, V. M. L., Carvalho, F. R. And De Souza Jr, M. B. (2000) "Predictive Control Based on Neural Networks: An Application to a Fluid Catalytic Cracking Industrial Unit". *Brazilian Journal of Chemical Engineering.* **17(04-07)**, pp. 897.

[11] Sodré, C. H., Wilson, J. A. , Jones, W., 2000 "Practical Evaluation of Hold-up for Passive Decoupling in Distillation Column", *Brazilian Journal of Chemical Engineering.* **17(04-07)**, pp. 1003.

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