NEURAL NETWORK AND GENETIC ALGORITHMS FOR COMPOSITION ESTIMATION AND CONTROL OF A HIGH PURITY DISTILLATION COLUMN

J. Fernandez de Cañete, P. del Saz-Orozco and S. Gonzalez-Perez

System Engineering and Automation Dpt., University of Malaga, Malaga, Spain

Abstract: Many industrial processes are difficult to control because the product quality cannot be measured rapidly and reliably. One solution to this problem is neural network based control, which uses an inferential estimator (software sensor) to infer primary process outputs from secondary measurements, and control these outputs. This paper proposes the use of adaptive neural networks applied both to the prediction of product composition from temperature measurements, and to the dual control of distillate and bottom composition for a continuous high purity distillation column. Genetic algorithms are used to automatically choice of the optimum control law based on the neural network model of the plant. The results obtained have shown the proposed method gives better or equal performances over other methods such fuzzy, or adaptive control.

1 INTRODUCTION

Nowadays, advanced control systems are playing a fundamental role in plant operations because they allow for effective plant management. Typically, advanced control systems rely heavily on real-time process modelling, and this puts strong demands on developing effective process models that, as a prime requirement, have to exhibit real-time responses. Because in many instances detailed process modelling is not viable, efforts have been devoted towards the development of approximate dynamic models.

Approximate process models are based either on first principles, and thus require good understanding of the process physics, or on some sort of black-box modelling. Neural network modelling represents an effective framework to develop models when relying on an incomplete knowledge of the process under examination. Because of the simplicity of neural models, they exhibit great potentials in all those model-based control applications that require real-time solutions of dynamic process models. The better understanding acquired on neural network modelling has driven its exploitation in many chemical engineering applications.

For many reasons, distillation remains 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 it is usually a nonlinear, non-stationary, interactive, and subject to constraints and disturbances process. Nevertheless, process identification and optimization (Bhat and McAvoy 1990) (Bulsari 1995), software sensor development (Zamprogna et al 2001), fault analysis and process control (Hussain 1999) (Xiong and Jutan 2002) works have been successfully reported in this field.

Genetic algorithms (GA) are model machine learning methodologies, which derive their behaviour from a metaphor of the processes of evolution in nature and are able to overcome complex non-linear optimization tasks like non-convex problems, non-continuous objective functions, etc. (Michalewitz 1992). They are based on an initial random population of solutions and an iterative procedure, which improves the characteristics of the population and produces solutions that are closer to the global optimum. This

is achieved by applying a number of genetic operators to the population, in order to produce the next generation of solutions. GAs have been used successfully in combinations with neural and fuzzy systems (Fleming and Purshouse 2002).

In this paper we describe the application of adaptive neural networks to the estimation of the product compositions in a binary methanol-water continuous distillation column from available on-line temperature measurements. This software sensor is then applied to train a neural network model so that a GA performs the searching for the optimal dual control law applied to the distillation column. The performance of the developed neural network based estimator is further tested by observing the performance of the designed neural network based control system for both set point tracking and disturbance rejection cases.

2 PROCESS DESCRIPTION

The distillation column used in this study is designed to separate a binary mixture of methanol and water, which enters as a feed stream with flow rate F_{vol} and composition X_F between the rectifying and the stripping section, obtaining both a distillate product stream D_{vol} with composition X_D and a bottom product stream B_{vol} with composition X_B. The column consists of 40 bubble cap trays. The overhead vapour is totally condensed in a water cooled condenser (tray 41) which is open at atmospheric pressure. The process inputs that are available for control purposes are the heat input to the boiler Q and the reflux flowrate L_{vol}. Liquid heights in the column bottom and the receiver drum (tray 1) dynamics are not considered for control since flow dynamics are significantly faster than composition dynamics and pressure control is not necessary since the condenser is opened to atmospheric pressure.

The model of the distillation column used throughout the paper is developed by (Diehl et al 2001), composed by the mass, component mass and enthalpy balance equations used as basis to implement a SIMULINK model (figure 1) which describes the nonlinear column dynamics as a 2 inputs (Q, L_{vol}) and 2 output (X_D, X_B). Implementations details for the overall column

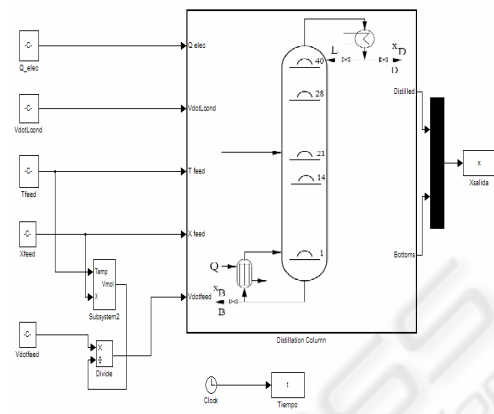dynamics are given in (Fernandez de Canete et al 2007).

Figure 1: Schematic of the SIMULINK model of the distillation.

3 NEURAL ESTIMATOR AND CONTROLLER

The complete neural network based estimation and control system is described below (Figure 2).

3.1 Neural Composition Estimator

In order to infer the composition from temperature a neural network is used. Previously, a sensitivity study is performed in order to choose the correct set of temperatures to infer top and bottom compositions, resulting a three temperature vector $T[k] = [T_{41}[k], T_{21}[k], T_1[k]]$ selected as input to the neural network predictor which outputs the predicted values of composition vector $\hat{y}[k] = [\hat{X}_D[k], \hat{X}_B[k]]$. Normally, in a plant operation, both real values are measured off-line in the laboratory. In this study, the neural network parameter update is made accepting the simulation results as same with the actual plant data. Training set for a 3-layer net (3-15-2 units) is generated by selecting 1200 temperature data points obtained by during column open loop operation with range for L_{Vol} (0-5E-06 m3/h) and heat flow Q (0-2000 J/s) for fixed feed rate conditions $F_{Vol} = 1$ E-06 m3/h, $X_F = 0.3$, where the Levenberg-Marquardt training algorithm has been applied.
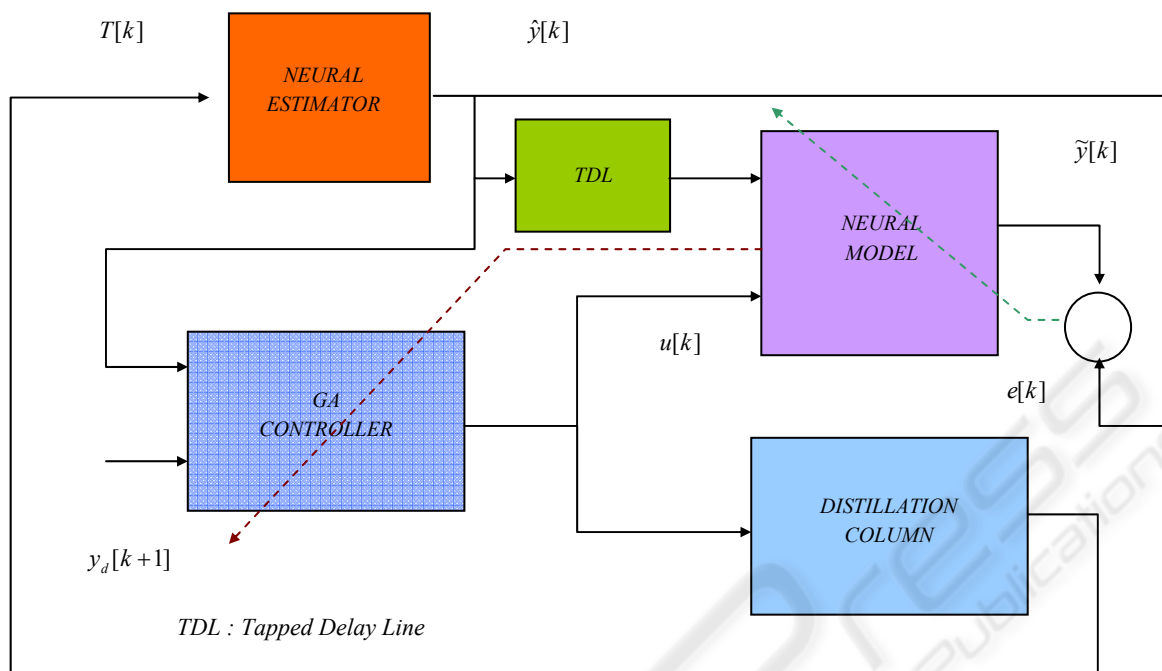
Figure 2: Estimation and control neural network based structure.

An additional temperature data set consisting of 150 data points was used to test the neural predictor afterwards. The error in the training phase is under 0.001% and 0.002% in the validation phase. For training pattern generation we assume an initial steady state for the column after a start-up process.

3.2 Neural Model

Prior to the design of the controller, a neural network has been used as an identification model of the distillation column dynamics. 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 model. The a 3-layer net (4-10-2 units) with vector input $\widetilde{y}[k] = f(\hat{y}[k], \hat{y}[k-1], \hat{y}[k-2], u[k])$ and vector output $u[k] = [L_{Vol}[k], Q[k]]$ with $\hat{y}[k]$ regularly spaced covering the same range as defined in the former. As the model's dynamic will be modified with unknown perturbations, this neural network based model will be updated with the real plant response.

3.3 Neural GA Controller

As the estimation of the composition vector $\widetilde{y}[k]$ in the next simulation step according the present and previous states of $\hat{y}[k]$ and the input to the system $u[k]$ can be achieved using the neural net, the control problem can be implemented as an optimization problem in which the function to minimize is the difference between the desired output $y_d[k]$ and the estimated one $\widetilde{y}[k]$ in the next step. As a result, the optimum control law $u[k]$ is elicited for the distillation control problem.

In order to search for the optimum for the highly non-linear function a genetic algorithm is used with 75 members fixed population, 75 generations and random mutation. If an error under 0.01% is achieved, the algorithm is stopped in order to accelerate the simulations.

4 RESULTS

The aim in the design of the composition neural estimator is to use together with Neural-GA controller for dual composition control of the distillation column. Therefore, the composition

estimator is tested by using the SIMULINK model before it is used for control (Figure 3).

Changes in the reflux and heat flow are determined by the neural network based controller for the column (Figure 4). The performance of the control structure is checked for a 95% to 98% (5% to 7%) pulse change in the distillate (bottom) composition set-point at t = 4600 s together with a 40% to 30% change in feed composition X_F at t = 9050 s, this variable taken as a disturbance (Figure 5). The results obtained demonstrate the potential use of this control strategy in this field.
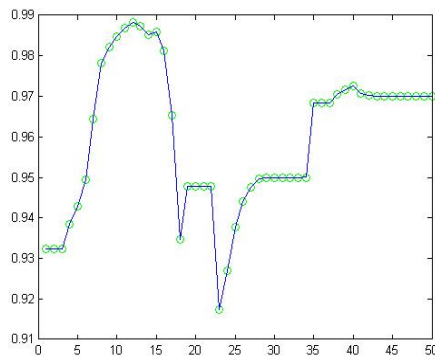

Figure 3: Composition estimation for the neural predictor.

5 CONCLUSIONS

We have proposed a neural network design methodology to dual composition control in a multivariable binary distillation column. A neural network has been employed both for prediction of composition profiles from temperatures and design

of optimum control law using a GA search technique, by using a neural model based fitness function. The results obtained point to the potential
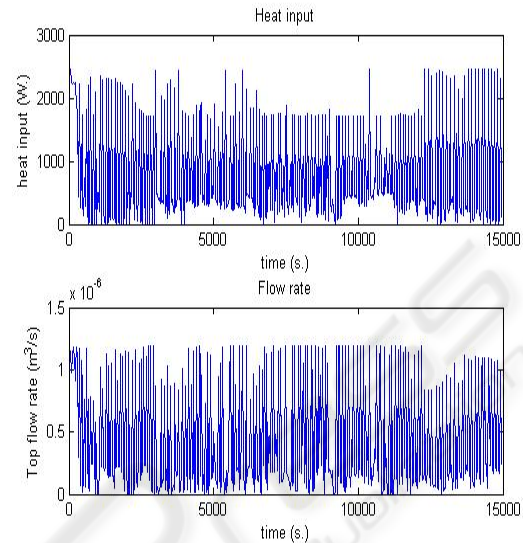

Figure 4: Heat flow and reflux flow rate for a pulse set-point change in top (bottom) product purity and disturbance in X_F.

use of this control strategy in areas of design related to operability and control in process engineering.

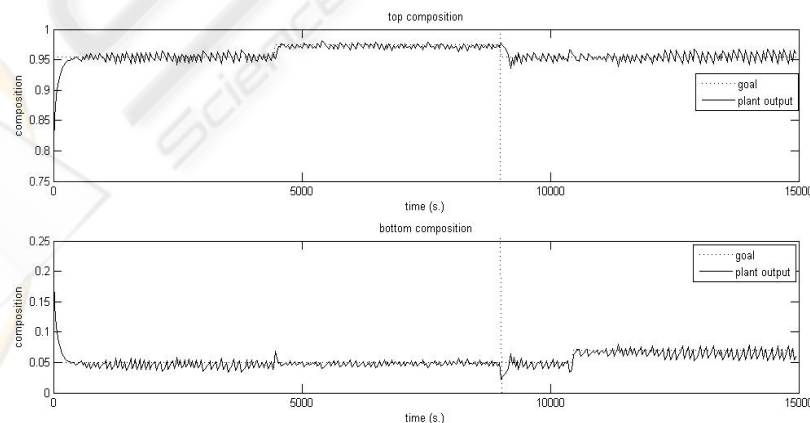Future works are actually directed towards the application of the proposed methodology to a real small scale pilot plant DELTALAB DC-SP (web http//www.isa.uma.es/C4/Control%20Neuroborroso/Document%20Library/index.htm)

Figure 5: Performance of the Neural-GA controller for a pulse set-point change in top (bottom) product purity and disturbance in X_F

REFERENCES

Bhat N, McAvoy T., 1990. Use of neural nets for dynamic modeling and control of chemical process systems. *Computers and Chemical Eng* , v. 14, n. 4, pp. 573–583.

Bulsari A.,1995. *Neural networks for chemical engineers.* Elsevier, Amsterdam.

Zamprogna, E.; Barolo, M.; Seborg, D.E., 2001. Composition estimations in a middle-vessel batch distillation column using artificial neural networks. *Chemical Engineering Research and Design*, v.79, n.6, pp. 689-696.

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

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

Michalewitz, Z., 1992. *Genetic Algorithms + Data Structures = Evolution Programs*, Springer, Berlin, Germany.

Fleming, P., Purshouse, R., 2002. Evolutionary algorithms in control systems engineering: a survey. *Control Engineering Practice*, v. 10, pp. 1223–1241.

Diehl, M., Uslun I., Findeisen, R., 2001. 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

Fernandez de Canete, J., Gonzalez-Perez, S., Del Saz-Orozco, P., 2007. A development of tools for monitoring and control of multivariable neurocontrolled systems with application to distillation columns*, Proeedings of the EANN 2007 International Conference*, Thesaloniki, Greece, pp. 296-305.