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Neurocontrol of a Binary Distillation Column

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Abstract. This paper deals with the control of a methanol-water distillation column using neural networks, setting up a multiloop system. The neural network used is a multi-layer perceptron type, trained off line by a gradient descent algorithm. Results show an improvement on the use of an algorithm based on a classic controller such as PID

1. Introduction

Neural networks, due to their ability to learn and approximate any nonlinear function defined on a compact set, may be a powerful tool in the development of control systems [1]. In some applications conventional controllers, such as the PID, have been widely used and perform well, but when the process to be controlled is complex or has nonlinearities, neural networks might be used to improve the effectiveness of the control process.

The aim of a plant control system is to act on the inputs in such a way as to bring the output to certain desired values. The use of neural networks in control has been the subject of several reports, for example [2] and [3].

In this paper a neurocontrol system is set up to control product concentrations in the upper and lower parts of a methanol-water distillation column. A comparison is made between the results obtained with neurocontrol of the column and with PI type regulators using different behaviour indices such as the ITAE (integral time absolute error) and the establishment time.

2. Brief description of the distillation column

The distillation column is a strong-interaction multivariable system where the load perturbations (feed flow) have a significant influence on system response. This distillation column separates a mixture of methanol and water into two relatively pure products; it is fitted with a partial condenser and reboiler as shown in figure l. The aim

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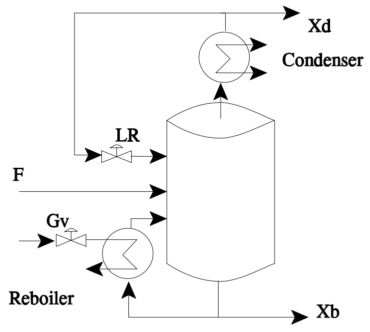

Figure 1. Distillation column

of the control operation is to maintain concentrations in the upper part (Xd) and lower part (Xb) at certain desired values, despite the strong perturbations, mainly brought about by the loading of the product (F) with which the column is fed. Achieving this aim involves operating on the return flow of the distilled product to the column (LR) and also the steam flow (Gv) produced in the lower part of the column. Wood and Berry [4] obtained the following behavioural model for the system:

$$\begin{bmatrix} Xd(s) \\ Xb(s) \end{bmatrix} = \begin{bmatrix} \dfrac{12.8e^{-s}}{1+16.7s} & \dfrac{-18.9e^{-3s}}{1+21s} \\ \dfrac{6.6e^{-7s}}{1+10.9s} & \dfrac{-19.4e^{-3s}}{1+14.4s} \end{bmatrix} . \begin{bmatrix} LR(s) \\ Gv(s) \end{bmatrix} + \begin{bmatrix} \dfrac{3.8e^{-8.1s}}{1+14.9s} \\ \dfrac{4.9e^{-3.4s}}{1+13.2s} \end{bmatrix} . F(s)$$

The rated values of the variables involved in the model are: Xd= 96.25 % mol, Xb=0.5% mol; LR=1.95 lib/min. Gv=1.71 lib/min. and F=2.45 lib/min.

A similar work was made for Uria del Castillo, Brizuela and Lamana [5] that show a predictive scheme for controlling the compositions of the top and bottom product of a three-component distillation column. They present a nonlinear model of the process for the prediction of future outputs, set up with a feedforward neural network. An analysis is made of the column performance under different perturbations using various alternatives of predictive control strategy. The behaviour of the system is compared to that of a plant controlled by a PI regulator.

3. Control architecture

Connectionist systems are widely used for the identification and control of dynamic systems due to their ability to approximate any non-linear function to a predetermined error, this learning being effected on the basis of input-output examples.

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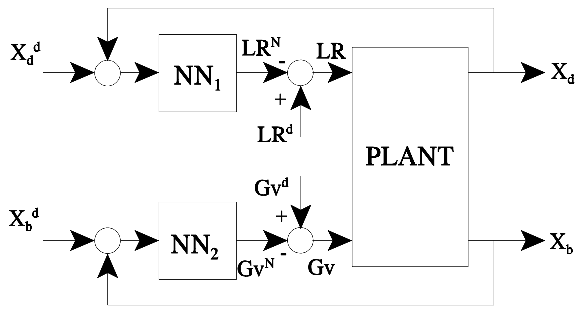

Figure 2. Control architecture

When training a neural network, within a control architecture, the main question is how to adjust network coefficients so that the control error (difference between real and desired outputs) is brought down to acceptable levels. The most widely used of all the main neural control architectures, is perhaps the inverse control scheme: a neural network is set up in series with the plant to be controlled, the aim being to make the transfer function the inverse of the physical system. To achieve this objective the model of Psaltis *et al*. can be used [6] -Indirect Learning Architecture-. In this model a neural network identifies the plant inverse model and the network itself is copied so that it acts as neurocontroller. This same idea is used by [7] but using a single network (half the number of neurons and synaptic connections). Other possibilities might be to set up a neural network in parallel with the plant (neuroidentifier) and use it as a path to propagate the control error to the neurocontroller [8][9]. Variants of this idea might be to use weight perturbation [10], or the fact that the Jacobian of the plant to be controlled can be found out [11][12].

In this work the architecture of figure 2 is used. It is also an inverse control neural model in which the neural network inputs are the desired output ($Xd^d(k)$ and $Xb^d(k)$) and the errors e(k) and e(k-1) (it is therefore a recurrent network type Tapped Delay Line).

If we consider for example the control loop of the concentration in the upper part of the column, the neurocontroller output has to generate the control signal (LR(k)). To enable it to carry out this function, a random set of training data is generated (250 points) for values of the signal $LR^d(k)$ together with another random set of desired values ($Xd^d(k)$), all falling within the plant's operational range, of course. This static set serves for off-line training of the network, the error function to be minimised being:

$$E_1(k) = \frac{1}{2}\left(LR^d(k) - LR^N(k)\right)^2$$

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Being $LR^N(k)$ the output of the upper neural network (NN_1). In the ideal case in which $E_1 = 0$, then the network sets up the system controller perfectly, providing that the set of learning data covers the whole dynamic operational range of the distillation column. The same process is applied to the control loop of the lower part of the distillation column.

For each control loop a multi-layer perceptron network has been used, with hyperbolic tangent type functions, in a 3 input architecture, 30 neurons in the hidden layer and 1 output neuron, the synaptic connections being adjusted by the gradient descent algorithm

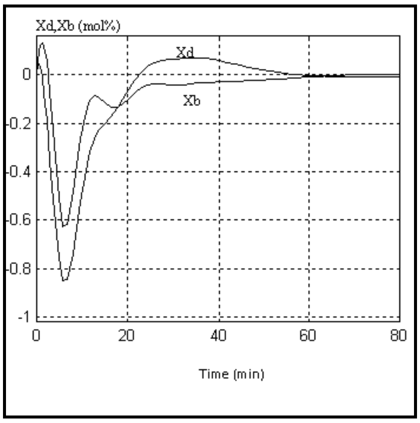

Figure 3. Neural control response

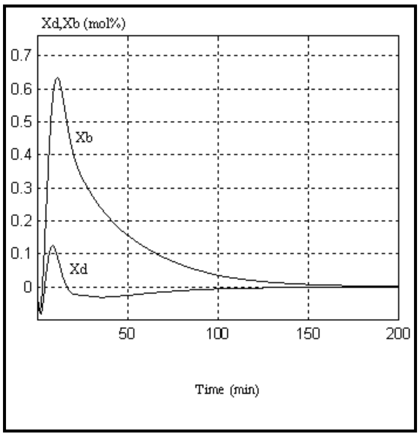

Figure 4. PI response

4. Results

The control system has been tested on the assumption that the flow of the product feeding the column (F) varies at the ratio of 0.34 lib/min, and with this change, the aim is to keep concentrations in the upper part (Xd) and lower part (Xb) within the rated values. Figure (3) shows the percentage variation of said concentrations with respect to the rated value. It can be seen that after a transient, a steady state condition is reached in a time of about 60 minutes.

5. Comparison of results

In this section a comparison is made of the results obtained from the neurocontrol control system as described above and those obtained with PID type regulators. A multiloop control system using PI type controllers has also been set up for the distillation column, the best results being those shown in figure 4. The following

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parameters are used for comparing both methods: ITAE, establishment time (ts), maximum absolute deviation (dma) and the error. Table I shows the results.

The table below shows the results of the behaviour indices ITAE(Integral Time Absolute Error), establishment time (ts) (min) and maximum absolute deviation (dma) (mol %) for the regulators studied. All the values of these indicators were obtained by considering each response to be transitory from its start until entering the area of 0.05 mol % for each variable controlled. The ITAE value shown in the table is the sum of the Xd variable and Xb variable(total area under the curve for each variable controlled)

Table I. Comparison of results

Indices	PI	Neural Control
ITAE	908.8	157.69
Error Xd Xb	 0 0	 0.00993 -0.0024
ts	104	40
dma(Xd)	0.1036	0.85
dma(Xb)	0.62	0.6368

It can be seen that a multiloop PI regulator shows very high establishment times and also high values for the ITAE criterion for load changes. The neural regulator shows very small errors in a steady state; the ITAE value and the establishment time for load changes are the best of all results obtained; the absolute maximum deviation, however, is relatively high.

6. Conclusions

A neurocontrol system has been set up for a binary distillation column using neural networks trained off line. A comparison of the results with a PI-based controller of otherwise similar characteristics shows that the plant response is improved, particulary in terms of the ITAE parameter and the establishment time. Work is currently underway on setting up an adaptive control system with a single RBF type neural network (Radial Basis Function) to compare both neural control techniques and put into practice the one showing the best results.

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References

1. K. S. Narendra, “Neural networks for control: theory and practice”. Proceedings of the IEEE, Vol. 84, nº 10, 1996.
2. K. K. Hunt and D. Sbarbaro, “Neural networks for non linear internal model control”, IEE Proceedings-d, Vol. 138, nº 5, 1991.
3. K. S. Narendra, and K. Parthasarathy "Identification and control of dynamical systems using neural networks". IEEE Transactions on Neural Networks. Vol 1. No.1. 1990.
4. Wood, R. K and Berry M. W. “Terminal composition control of binary distillation column” Chemical Engineering Science. Vol. 28
5. M. Uria del Castillo, E. Brizuela, and R.Lamanna, " Predictive control of a multicomponent distillation column based on neural networks". V. Jornada beroamericana de Automática. Santa Cruz de la Sierra. Bolivia. 1996.
6. D. Psaltis, A. Sideris and A. A. Yamamura, “A multilayered neural network controller”, IEEE Contr. Syst. Mag. Vol. 8, Nº 2, 1988.
7. H. C. Andersen, F. C. Teng and A. C. Tsoi, “Single net indirect learning architecture”, IEEE Trans. on Neural Networks, Vol. 5, Nº 6, 1994.
8. C. C. Ku and K. Y. Lee, “Diagonal recurrent neural networks for dynamic systems control”. IEEE Transactions on Neural Networks, Vol. 6, Nº 1, 1995.
9. L. Boquete, R. Barea, R. García, M. Mazo, “Identification and control of a wheelchair using recurrent neural networks”, Eng. Appl. of Artif. Intell., Vol. 12, 1999.
10. Y. Maeda and R. J. P. Figueiredo, “Learning rules for neuro-controller via simultaneous perturbation”, IEEE Transactions on Neural Networks, Vol. 8, Nº 5, 1997.
11. Y. Zhang, G. E. Hearn and P. Sen, “A multivariable neural controller for automatic ship berthing”, Control Systems, Vol. 17, Nº 4, 1997.
12. L. Boquete, R. García, R. Barea and M. Mazo, “Neural control of the movements of a wheelchair”, Journal of Intelligence and Robotic Systems, Vol. 25, Nº 3, 1999