

NEURAL MODELING AND CONTROL OF A DISTILLATION COLUMN

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ABSTRACT

Control of a nine stage three component distillation column is considered in this study. The control objective is achieved using a neural estimator and a neural controller. The neural estimator is trained to represent the chemical process accurately, and the neural controller is trained to give an input to the chemical process which will yield the desired output. Training of both the neural networks is accomplished using a recursive least squares training algorithm implemented on an Intel iPSC/2 multicomputer (hypercube). Simulated results are presented for a numerical example.

INTRODUCTION

The success of any attempt to control a physical system is invariably dependent on the ability to model the major features of the system. This is because the design of a controller hinges on the ability to construct an approximation of the real process, so that when a desired output is specified, the process model can be used to solve the inverse problem of finding the input which will yield the desired output.

Obtaining and dealing with a mathematical model for all the subsystems of a distillation column is an extremely difficult task. In fact, a mathematical model for the distillation column can contain several hundred state variables. Furthermore, the distillation column is characterized by highly nonlinear behavior, a wide range of operating conditions, slow dynamic response, significant deadtimes, difficulty in measuring the purity of components on-line, and constraints due to the capacity of the subsystems. In spite of these problems, it is necessary to develop techniques to efficiently control the distillation column because the distillation process is commonly employed in the chemical industry.

Artificial neural networks (ANNs) are attractive for control applications. They can be trained off-line to model the nonlinear inverse dynamics of the process with very high accuracy over a large input space without a priori knowledge of the system equations, and they can continue to learn the nonlinear inverse dynamics during on-line application.

Bhat and McAvoy¹ have modelled chemical process systems using ANNs. Using backpropagation, they trained an ANN to learn the nonlinear relationships to predict the pH value in a stirred tank. The methodology was used later to study a steady-state reactor and interpretation of signals from a light-induced fluorescence spectrum.² The results presented in Refs. 1 and 2 indicate that the backpropagation neural networks can learn the plant dynamics very well and also interpret data from biosensors.

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SYSTEM DESCRIPTION

A schematic of a nine stage three component distillation column is shown in Figure 1. The column has a feed input at the fourth stage, a sidestream product removed at the fifth stage, a heavy product removed at the bottoms, and a light product at the holdup tank at the top. The bottoms has a conventional reboiler with constant holdup, and the top holdup tank also with constant holdup is fed by a partial condenser. The control objective is to produce desired compositions at the bottoms and the holdup tank despite variations in the feed rate and composition. This will be accomplished by manipulating the reboiler heat valve and condenser temperature.

A mathematical model of the distillation column can be obtained by applying mass and energy balance relationships for each stage of the column, reboiler, condenser, and holdup tank. Based on this, Franks³ has presented a computer program which simulates the operation of the distillation column. The program makes available all the state variables at discrete time intervals, and was used in this study to generate training pairs for training the neural controller.

TRAINING RESULTS

As part of the feedforward ANN controller, a neural network is trained as an estimator for the column. The estimator has available to it only a limited number of state variables of the distillation column: flow rate; temperature and compositions of the three components for the bottom and top products; and temperature and three component compositions for the sidestream product. The data for the estimator consists of discrete data sampled once per minute. The input to the estimator consists of the reboiler heat valve setting, condenser temperature, current feedrate, and the limited state vector at two previous sample times. The estimator is trained to give as output a prediction of the limited state vector at the current time. The estimator is a fully connected feedforward network with 31 linear input neurons, 14 linear output neurons, and 157 nonlinear sigmoid neurons distributed over two hidden layers.

Training data is generated by simulating the column during startup, from an initial state to a steady operating state (20 min), and then varying the feedrate, reboiler heat valve setting, and condenser temperature setting sinusoidally about their startup settings. The feedrate is varied at 0.0125 cycles/min with an amplitude of 2.0 moles/min about a mean of 25.0 moles/min. The reboiler valve is varied at 0.0375 cycles/min with an amplitude of 0.05 about a mean of 0.308 both as fractions of the full open position. The condenser temperature is varied at 0.025 cycles/min with an amplitude of 2.0° C about a mean of 75.0° C. These sinusoidal variations are continued for an additional 135 minutes after the 20 minute startup period giving a total of 155 sampled data training pairs for the network. Training is accomplished using a recursive least squares (RLS) training algorithm implemented on an Intel iPSC/2 multicomputer (hypercube) discussed by Steck, *et al.*⁴ Note that training with the RLS algorithm is much faster when compared to gradient descent. This is because of the parallel implementation and higher order nature of the RLS training algorithm. The results of this training are shown in Figures 2 and 3 as time histories of the mass fractions of the heavy (X1) and light (X3) components of the top and bottom products. These figures show that the neural estimator has learned to predict the distillation column almost exactly over the range of data presented to it during training.

Another ANN is trained as a controller for the distillation column. The data for the controller consists of discrete data sampled once per minute, the same sampling rate as the estimator data. The input to the controller consists of the desired compositions of the light component of the bottoms and the heavy component at the holdup tank (the controller reference inputs), the feedrate, and the limited state vector at two previous sample times. The mass fractions of the two components used as reference inputs are generally desired to be small as the goal of the distillation process is to concentrate the heavy component at the bottom and the light component at the top. The controller output consists of a reboiler heat valve setting and condenser temperature at which the distillation column should give the specified reference input compositions. The controller is also a fully connected feedforward network having 31 linear input neurons, 2 linear output neurons, and 157 nonlinear sigmoid neurons distributed over two hidden layers.

Training data for the controller is generated by rearranging the data used to train the estimator. Recall that the estimator inputs are the reboiler heat valve setting, condenser temperature, feedrate, and the state vector at the two previous sample times and that the training output data is the state vector at the current time. The controller is trained by taking as input the two desired composition values from the state vector at the current time, the current feedrate, and the two delayed samples of the state vector. The controller is trained to give as output the reboiler valve setting and condenser temperature which will produce the state vector at the current time. Training is again accomplished using the RLS training algorithm on the Intel iPSC/2 multicomputer.

To investigate the ability of the trained controller to control the distillation column, the neural controller is connected to the neural estimator. The controller outputs, the reboiler valve setting and the condenser temperature, are connected to the inputs of the estimator by neural connections with unity weights. The state vector at two previous samples times is provided to the estimator and controller networks by feedback delay lines from the output of the estimator. The state vector for two sample periods prior to the beginning of the simulation is provided as known initial conditions. The current feedrate and the desired compositions at the bottom and top (the controller reference inputs) are known and specified at each simulation sample time. Figures 4 and 5 show the ability of the trained controller to follow the desired composition reference inputs from startup through step changes in the top and bottom compositions. It is apparent that the controller can manipulate the heavy component (X1) at the top product, and is moderately successful at controlling the light component (X3) at the bottom product. The moderate success is most likely due to the fact that the light component at the bottom is very small even without control and varies only slightly, as evidenced by Figure 3, with the changes in reboiler heat used to train the estimator and controller.

CONCLUSION

Directions for future work in this area are obvious. First the state space over which the estimator and controller are trained needs to be expanded to include a large enough variation in the bottoms product to allow it to be controlled by the reboiler heat. Then the neural controller should be tested by connecting it to the actual program simulating the distillation column as well as the neural estimator. This would allow investigating the ability to train the controller and estimator on-line during simulated operation of the distillation column.

REFERENCES

1. Bhat, N. and McAvoy, T. J., "Use of Neural Nets for Dynamic Modeling and Control of Chemical Process Systems," Proc. of the American Control Conf., pp. 1342 - 1347, 1989.
2. Bhat, N., Minderman, Jr., P. A., McAvoy, T. and Wang, N. S., "Modeling Chemical Process Systems via Neural Computation," IEEE Control Systems Magazine, 10(3), pp. 24-30, April 1990.
3. Franks, R. G. E., Modeling and Simulation in Chemical Engineering, Wiley-Interscience, New York, 1972.
4. Steck, J., McMillin, B., Krishnamurthy, K., Ashouri, M. R. and Leininger, G., "Parallel Implementation of a Recursive Least Squares Neural Network Training Method on the Intel iPSC/2," Proc. of the Int. Joint Conf. on Neural Networks, pp. I-631 - I-636, June 1990.

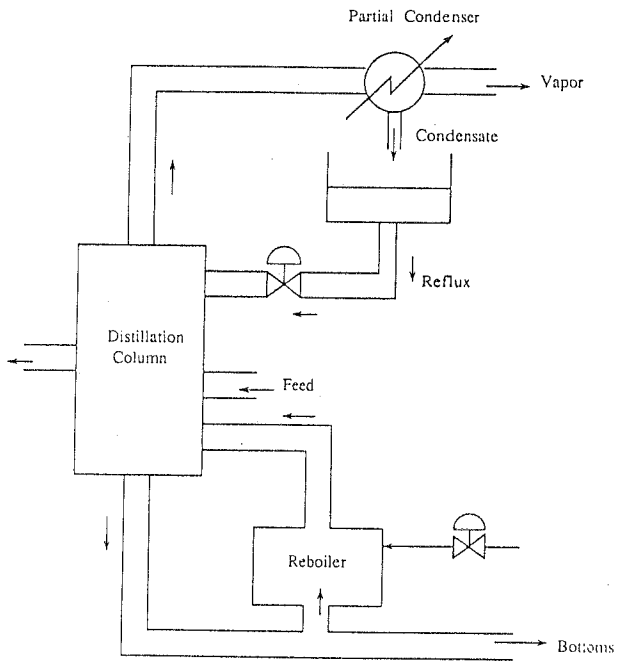


Figure 1. Schematic of a Distillation Column.

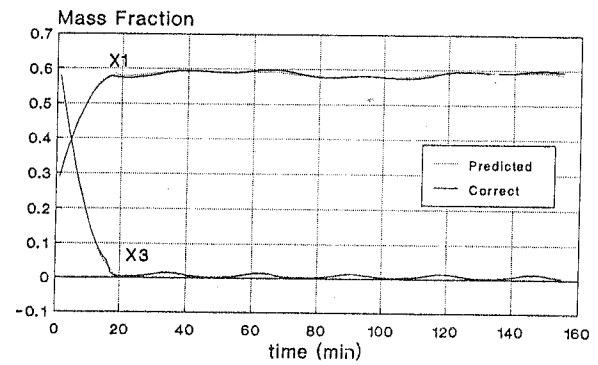


Figure 3. Bottom Product Composition Estimator Training

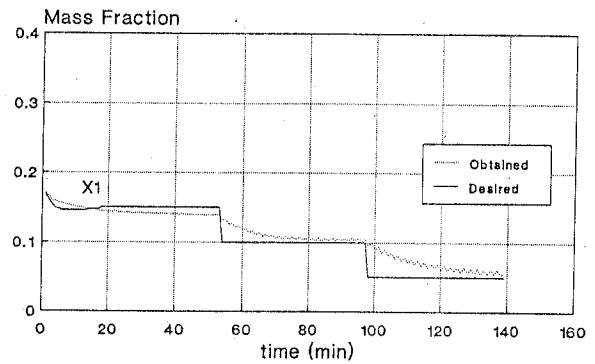


Figure 4. Top Product Composition Controlled Response

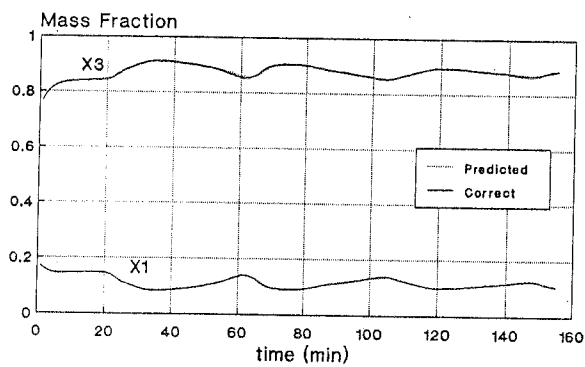


Figure 2. Top Product Composition Estimator Training

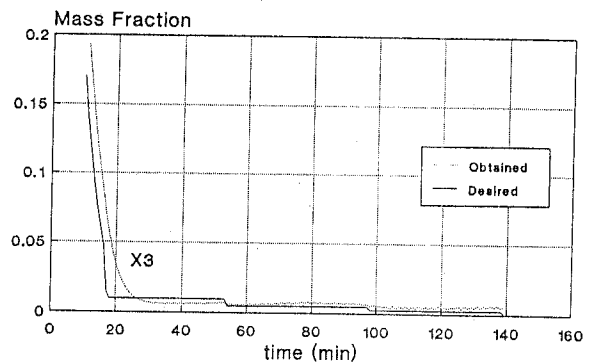


Figure 5. Bottom Product Composition Controlled Response