NEURAL NETWORK INFERENTIAL ESTIMATOR FOR PRODUCT COMPOSITION OF A FATTY ACID DISTILLATION COLUMN

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ABSTRACT

This paper discusses the application of a software-based estimator for the measurement of fatty acid composition in a palm oil fractionation process. A typical configuration of a distillation column with appropriate control loops was simulated using Hysys.Plant dynamic process simulator. The simulation model was proved to be a realistic test-bed representing an industrial process since a sufficiently accurate plant/model match was obtained. Using data generated from the simulator, a fatty acid composition estimator was developed using artificial neural networks (ANN). Good estimation of composition was demonstrated.

Keywords: inferential estimator, fatty acid composition, artificial neural networks, soft-sensor, distillation column

INTRODUCTION

Process measurements are important elements of process plants since they are needed for monitoring and control of important process variables. Reliable measurements are required to ensure successful implementation of controls and optimisation tasks in plant operations. Unless reliable and accurate measurements are available at the intended frequency, the performance of control loops cannot be guaranteed. Difficulties in measuring some of the primary variables inevitably lead to poor control. In more serious condition, such weaknesses may even lead to no control at all, resulting in poor process performance or even unwanted shutdown condition due to constraints violation.

The case of product quality is one of the most serious. In practice, most product property variables are analysed off-line in the laboratories. Although online sensors may be available, their usage is often limited due to long measurement delays (e.g. gas chromatographs). Online sensors are also susceptible to factors that affect their reliability such as fouling in the sampling line. As a result, frequent maintenance and calibration are required to ensure the efficiency of the system. This again, limits the use of such devices in industrial process control.

In a typical palm oil fractionation process, the product quality is maintained by controlling the appropriate temperature of the distillation process. This is normally supported by offline laboratory analysis of the product, carried out at one or two hour interval. Although this has almost been the standard practice in the oleochemical industries, it is by no means the best solution. In fact, the main reason for this approach to dominate is the lack of cost effective and reliable online analysers as mentioned in the above. Assuming that the laboratory analysis is reliable and the process is well behaved and not subjected to serious disturbances, the unique relationships between the product composition and temperature as defined by the thermodynamic equilibrium provide the necessary inference. However, this ideal situation does not always transpire. Many processes are exposed to difficulties such as frequent changes in raw materials quality and interruption of utilities. In the event of degrading control performance resulting from serious disturbances, corrective actions are often provided by experienced plant operators or engineers. This leads to inconsistency of action resulting from inconsistencies in human judgement. At times, this can even results in excessive off-specification products, especially when the operation is changing from one operating region to another.

One way to tackle this problem is to apply inferential measurement strategy. Inferential measurement is a powerful methodology that allows difficult to measure primary variables to be inferred from other easily measured secondary variables. An example of application is to use secondary measurements such as pressure, flow or temperature to estimate the product composition in a distillation column. If the model is sufficiently accurate, the estimated values of the product composition can be used directly as the set points for standard industrial feedback controllers. This strategy removes measurement delays, and thus the system delay is then only associated with the secondary measurements. Furthermore, inferential measurement systems mimic what experienced process operators and engineers do in running process plants without subjecting the plants to human inconsistencies. The only concern is the accuracy and robustness of the models being used as the online estimator. In this paper, the use of neural networks in developing an online estimator for the measurement of fatty acid composition and its implementation in the control of top product in a distillation process is described. The case study is a typical industrial column in a fatty acid fractionation plant.

OVERVIEW OF INFERENTIAL ESTIMATION APPROACH

The idea of inferential estimation is not new. Researchers have investigated its usage in inferring product composition of distillation column and product quality variables of reactor such as viscosity, solids moisture and product concentration for quite some time (Joseph, 1999). Some of the earliest works for inferential estimation in distillation processes include the works of Joseph and Brosilow (1978a,b,c) in which they developed methods for construction of optimal and suboptimal estimators using Kalman filter theory and compared the two methods for inferential control of product composition. Choo *et al.* (1987) used tray temperatures to build an inferential estimator to control the top composition of an extractive distillation column. Tham *et al.* (1991) discussed a neural network based estimation procedure for feedback control of the product composition from an industrial distillation tower using measured quantities such as overheads temperatures. Ye *et al.* (1993) reported improved control of both the product flow and compositions with a neural network inferential control approach for the Tennessee Eastman industrial test process. Abdel Jabbar and Alatiqi (1997) presented an inferential feedforward control scheme for a petroleum fractionator with undefined blends of hydrocarbons as the feed. Unmeasured feed composition disturbances were estimated from secondary measurements and the manipulated variables were varied to maintain desired product quality. All these reports highlighted the potentials of inferential estimation approach in providing better process control.

The development of inferential measurement system is essentially the process of developing process model that relates a primary variable to more easily measured secondary variables. Thus any modelling paradigm may be employed. In our study, an ANN model is used. The use of artificial neural networks (ANN) in inferential estimation has been the interest of many researchers since the last decade. ANN has some distinct advantages over other estimation methods (MacMurray, 1995). One of the reasons is that ANN are fairly easy to understand thus easy to implement, yet very computationally efficient. They are also very good at capturing the nonlinearities and complexities that exist in the chemical processes. The availability of process control computers and associated data historians make it easy to generate neural network solutions for process modelling and control. Numerous applications of neural networks in the field of process engineering have been reported in recent years. Surveys on the subject can be found in the work of Azlan Hussain (1999) and Hunt, *et al.* (1992).

PROCESS DESCRIPTION

In this work, the first column, the pre-cut column of a palm oil fractionation plant with five distillation columns serially connected was investigated. A simplified schematic diagram of the plant is provided in Figure 2 below. A typical feed of the plant would be Palm Kernel Oil (PKO), or Palm Hydrogenated Stearine (PST). In the pre-cut column, light products (C8 and C10) are recovered in the overhead. The bottom stream is fed to the light-cut column where C12 is separated from the rest of its constituents. The bottom product then enters the middle-cut column where C14 and C16 are recovered leaving the C18 to be purified from the rest of the oil constituents in the still-cut column. In the residue cut column, C18 is recovered and recycled back to the previous column.

All the distillation columns operate under vacuum condition generated using steam ejectors. The columns are packed with structured packing to provide the desired separation properties. Due to high operating temperatures, thermal oil is used for heating in the reboilers. Top vapours are condensed in a direct contact internal condenser. Cooled fatty acids supplied from the pump around system condensed the vapour. As mentioned in the above, the feed is either PKO or PST. In some cases, unknown mixtures of both PKO and PST supplied from the start-up recovery and rework storage tanks are also used. For cases like these, plant operation will be very challenging and manual supervision and interruptions by the engineers are required.

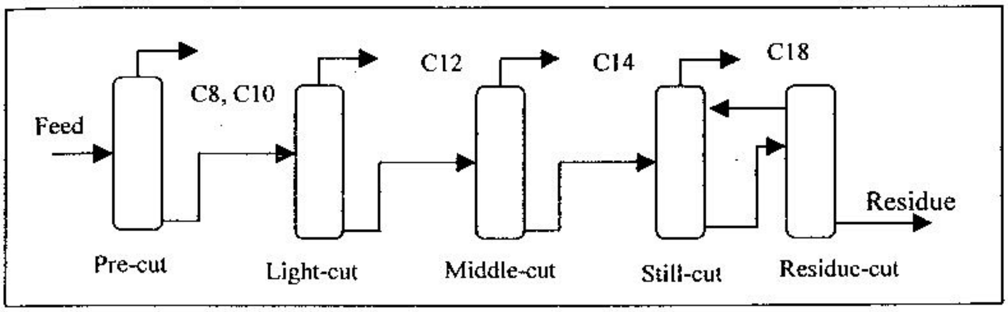

Figure 2: Schematic Diagram of a Fractionation Process

DEVELOPMENT OF INFERENTIAL ESTIMATOR

Dynamic simulation of the column was carried out using Hysys.Plant software. Due to the non-conventional nature of the palm oil distillation system, the development of the flowsheet for the dynamic simulation has not been straightforward. For example, Hysys.Plant does not support packed column and as such, the equivalent tray calculation was used. Similarly, model of a direct contact internal condenser based on packed column is also not available within the standard library and modifications have also been implemented. Despite these difficulties, the column was successfully simulated and excellent match with actual industrial data was obtained. This proposes that the simulation flowsheet is a good representation of the actual process and therefore was used for the simulation test-bed throughout the study.

Neural Network Estimator

The foundation of ANN was inspired by the mechanism of human brain. However, unlike the human brain that consists of between 10^{11} to 10^{14} neurons, the number of artificial neurons in an ANN is relatively very small. The connection within the ANN is also much more simplified than that of the brain. However, despite the simplicity, an ANN designed using only few neurons can be trained to learn information such as patterns and process dynamics. Within each neuron, input signals are summed and transformed using an activation function before being sent to other neurons. This transformation is needed to impart pattern-mapping ability to the networks.

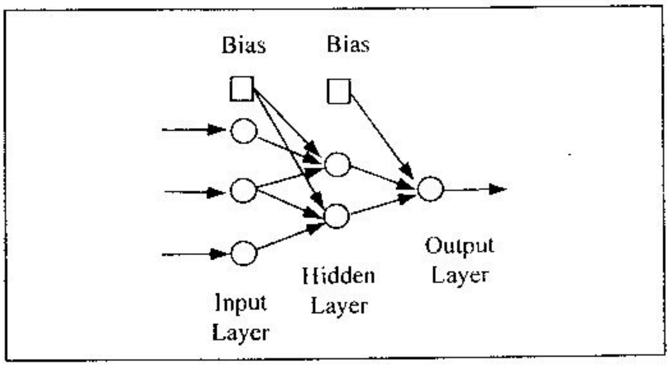

Figure 3: Multilayer Feedforward Network

An example of the network architecture, known as feedforward network is shown in Figure 3. The network consists of neurons connected in layers with flow of information limited only to the forward direction. Associated with each connection are the network weights. From modelling point of view, these weights are analogous to model parameters which regulate the influence of each variable on overall model performance. Thus, network weights serve as a measure for connection strength that controls the influence of each incoming signal to the recipient neuron.

The aim of neural network identification is to compress relationships between process variables into a compact neural network model with its associated weights. A natural way of carrying out this task is to imitate what is traditionally done in black-box identification methods where it is assumed that the output of the process can be reconstructed using a finite number of past values of inputs and outputs. In developing the model, the network weights are adjusted to optimise a pre-set objective function (*e.g.*, mean squares error). Since the ability to predict the dynamics of the "unseen" condition is what we are interested in, validation with different sets of data is then performed. On completion, the model can be applied to represent the process provided the range of the operation is in the region of validity of the model.

In this study, the ANN model development efforts were carried out using the neural network toolbox available within MATLAB software. Data with sufficient excitations were generated from the HYSYS model. The model consists of 12 inputs i.e., the column top temperature, bottom temperature, middle temperature, top pressure, reflux flowrate and distillate flowrate as well as a one sampling interval delayed signals of each these variables. Network trainings were accomplished using the Levenberg-Marquadt algorithm and the optimal topology was decided based on cross validation using a different set of data. The result is shown in Table 1.

Table 1: Selecting optimal topology for neural networks

No. of Hidden Nodes	Training MSE*	Validation MSE*	No. of Hidden Nodes	Training MSE*	Validation MSE*
1	6.649550E-03	1.186301E-02	8	6.447567E-04	8.208794E-03
2	1.028493E-02	9.639567E-03	9	6.404759E-04	6.089203E-03
3	6.923057E-03	1.016372E-02	10	3.758382E-04	7.624375E-03
4	4.522178E-02	9.366018E-03	11	1.028575E-03	5.628273E-03
5#	9.097734E-04	5.569399E-03	12	2.480726E-04	6.249930E-03
6	1.073631E-03	7.583562E-03	13	1.569080E-03	9.158477E-03
7	6.600532E-03	8.744358E-03	14	1.249314E-03	7.177801E-03

Note: * Mean square error
Best number of hidden nodes

Figure 4 displays the performance of ANN in tracking the actual process data during the training and validation stages. Good performance in the validation set indicated that the network was able to represent the behaviour of the process in different operating conditions than that of the training set. In other words, the network is capable of estimating the product composition based on "unseen" data.

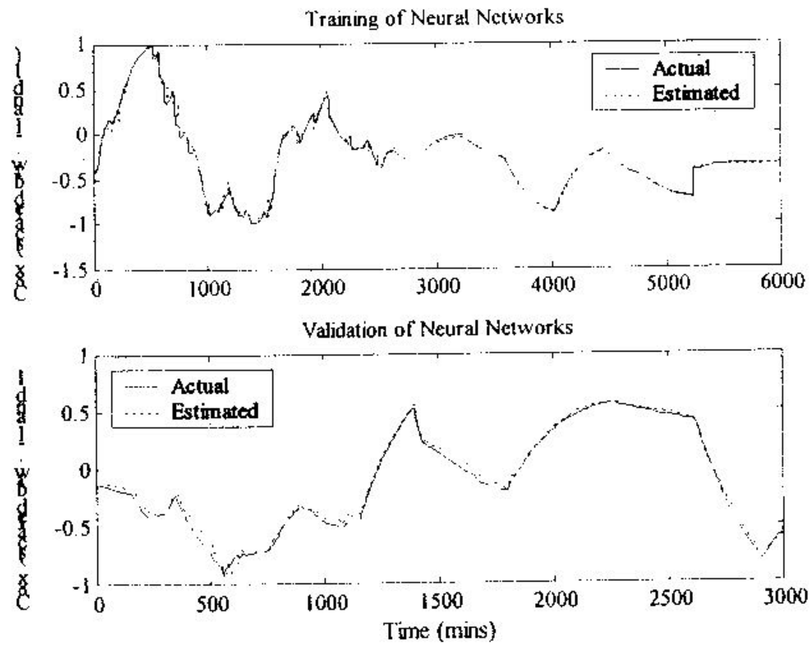

Figure 4: Training and validation of neural network

The accuracy of the constructed model was then tested online within the simulation mode. As exposed in Figure 5, good estimation of the product composition was obtained. As clearly displayed, the neural network model is capable of estimating the product composition accurately and continuously during the operation of the plant.

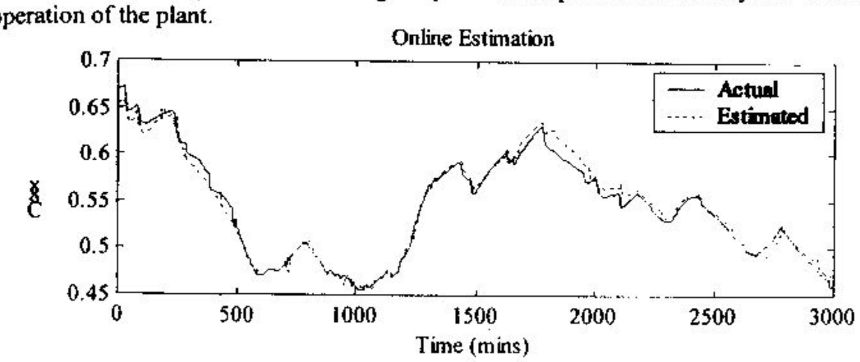

Figure 5: Online Estimation of Product Composition Using ANN Model

A number of possible improvements could also be introduced to the networks to provide better estimation properties. For example, recurrent signals of the estimated composition values can be fed back into the system as one of the inputs. This implies that a network with 13 inputs to be used. However, this will demand the use of training methodologies specifically designed for recurrent networks or modifications of the suitable optimisation algorithms. In this study, exponential filter was used. Better filter design could also be used to further smoothen the estimated values. Alternatively, intermittent addition of information from the laboratory analysis can also be done, but this requires some modification of the present strategy.

CONCLUDING REMARKS

The results presented here have pointed out a number of important conclusions. The dynamic simulation of an industrial oleochemical process has been successfully implemented using a commercial simulator. The use of inferential estimators constructed using ANN has provided efficient estimation of the product composition. It is therefore concluded that the use of inferential estimation is a viable approach when dealing with frequently disturbed processes or in cases where the feed composition is uncertain.

REFERENCES

1. Abdel Jabbar, M. and Alatiqi, I.M. (1997). 'Inferential feedforward petroleum fractionators: a PNA approach.' *Comput. Chem. Engng.*, **21**(3), 255-262
2. Azlan Hussain, M. (1999). 'Review of the applications of neural networks in chemical process control – simulation and online implementation.' *Artificial Intelligence in Engineering*, **13**, 55-68
3. Choo, K.P. and Saxena, A.C. (1987). 'Inferential composition control of an extractive distillation tower.' *Ind. Eng. Chem. Res.*, **26**, 2442-2444
4. Doyle, F.J. III, (1998). 'Nonlinear inferential control for process applications.' J. Process Control, **8**, 339-353
5. Hunt, K.J., Sbarbaro, D., Zbikowski, R. and Gawthrop, P.J. (1992). 'Neural networks for control systems – a survey.' *Automatica*, 1083-1112
6. Joseph, B. (1999). 'A tutorial on inferential control and its applications.' *Proceedings of the American Control Conference*. 3107-3117
7. Joseph, B. and Brosilow, C.B. (1978a). 'Inferential control of processes. I. Steady-state analysis and design.' *AIChE Journal*, **24**(3), 485-492
8. Joseph, B. and Brosilow, C.B. (1978b). 'Inferential control of processes. II. The structure and dynamics of inferential control system.' *AIChE Journal*, **24**(3), 492-500

9. Joseph, B. and Brosilow, C.B. (1978c). 'Inferential control of processes. III. Construction of optimal and subpoptimal dynamic estimators.' *AIChE Journal,* **24**(3), 500-509
10. MacMurray, J.C. and Himmelblau D.M. (1995). 'Modelling and control of a packed distillation column using artificial neural networks.' *Comput. Chem. Engng.*, **19**, 1077-1088
11. Soroush, M. (1998). 'State and parameter estimations and their applications in process control.' *Comput. Chem. Engng.*, **23**, 229-245
12. Tham, M.T., Montague, G.A., Morris, A.J. and Lant, P.A. (1991). 'Soft-sensors for process estimation and inferential control.' *J. Process Control,* **1**, 3-14
13. Ye, N., McAvoy, T.J., Koasnovich, K.A. and Piovoso, M.J. (1993). 'Plant-wide control using an inferential approach.' *Proceedings of the 1993 American Control Conference.* **2**, 1900-1904.