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Intelligent control system for extractive distillation columns

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Abstract−We developed and implemented an intelligent control system to be used in an extractive distillation column that produces anhydrous ethanol using ethylene glycol as solvent. The concept of artificial neural networks (ANN) was used to predict new setpoints after disturbances, and proved to be a fast and feasible solution. The developed control system receives data from temperature, flowrate and composition measurements of the azeotrope feed, and the ANN estimates the new set-points of the controllers to maintain 99.5 mol% of ethanol at the top and less than 0.1 mol% at the bottom; feed composition was also estimated using an ANN. All ANN were trained to provide output data corresponding to an optimized operating condition. The results showed that the intelligent control system can predict a new operating condition for any disturbance in the column feed and presented superior performance when compared with the control system without ANN.

Keywords: Ethanol, Extractive Distillation, Artificial Neural Networks, Control, Set-points

INTRODUCTION

Control of distillation columns is complex because it is interactive, non-linear, often not stationary, and it is subject to restrictions. One of the major restrictions in the distillation process is related to the mode from which values of the product compositions are obtained, since the composition is generally not directly measurable and hence difficult to control [1].

Mejdell and Skogestad [2] report that one of the greatest difficulties in distillation column control is measuring the composition of the products, with gas chromatography being one of the most used techniques among the alternatives of physical analyzers. However, this technique presents long delays in obtaining measurements and presents high operational costs while used on-line.

Several studies present indirect methods that measure the composition in real time, from a mathematical model built to infer the composition of products (top and bottom) through variables such as temperature, which mainly present low-cost measurers, good accuracy and fast response [3-6].

Model predictive control (MPC) is a widely studied technique that refers to a class of control algorithms that consider the future response of the process from its mathematical model, aiming to keep the process output in well-defined set-points. However, most MPC algorithms are based on a linear process model, and this is their main disadvantage because they may provide low control performance throughout the operating range and large disturbances.

Non-linear controllers based on phenomenological modeling can be developed; however, for practical reasons, they must offer an acceptable response within a short time interval, where it is often not possible. In fact, one of the main difficulties for the widespread use of non-linear models in advanced control techniques in chemical/petrochemical industries is the high computational effort. Furthermore, the high number of equations of a distillation column model increases the number of parameters which are hard to estimate, and could lead to convergence difficulties or produce results with low accuracy [7-10].

Using artificial neural networks (ANN) it is possible to quickly infer important parameters of a system from real data. In this way, the use of ANN presents an option which may result in many control strategies [11-14]. ANN utilizes a type of empirical modeling: it describes the process by mapping the input and output data. Thus, the ANN associates a given input pattern to an output signal, where the size of the input pattern may be different from the output pattern. However, it is necessary to train an ANN, and a data set must be presented containing a representative behavior of the full expected amplitude in which the plant will operate.

Our aim was to develop an intelligent control system based on ANN, capable of maintaining the specifications of the distillate and bottom streams of an extractive distillation column for anhydrous ethanol production using ethylene glycol as solvent. In this work, the developed ANN receives data from process disturbances: temperature, flowrate and composition of the azeotropic feed; then the ANN estimates the new set-points of the controllers present in the plant. The intelligent controller was developed to maintain 99.5 mol% of ethanol at the top, and less than 0.1 mol% at the bottom. The ANN was trained with data obtained from a model implemented in Aspen Plus™ to provide output data corresponding to an optimized operating condition.

PROBLEM STATEMENT

The case-study of this work is the extractive distillation process,

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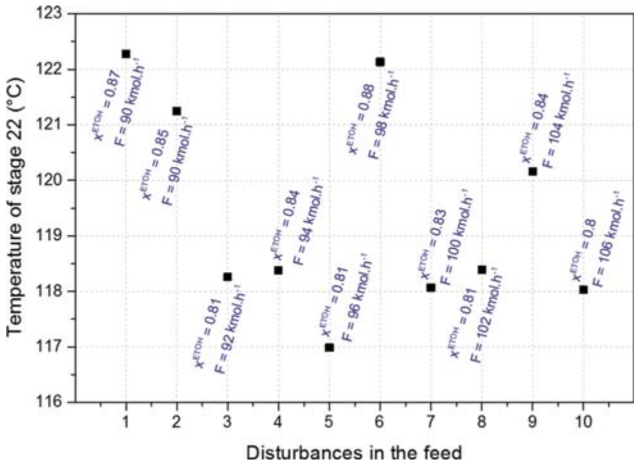

Fig. 1. Stage 22 temperature of an extractive column to maintain product compositions within specifications.

normally used to promote the separation of mixtures that form azeotrope, where a third component named the solvent is used to alter the relative volatility of the initial azeotropic mixture, making separation possible. Gil and Rodríguez [15] studied the conventional extractive distillation process where a control configuration was developed using temperature to control the composition. According to the authors, larger off-sets are observed for disturbances in the azeotrope composition because it implies in a different temperature profile, including the temperature of the sensitive stage, in order to maintain the desired products' specifications. To minimize the off-set, Ramos et al. [16] used dual control for temperature, although this is not recommended by many researchers.

To use temperature, it is necessary to determine the best stage to have this variable controlled, which consists in selecting the tray where considerable temperature variations from tray-to-tray exist. There are several methods for selecting a sensitivity tray; however, all types of disturbances should be considered because the choice is theoretically definitive.

Fig. 1 shows the required temperature value of the sensitive tray to keep product specification for feed disturbances constant (flowrate, temperature and composition) for an extractive distillation column with 24 stages in order to produce high purity anhydrous ethanol using ethylene glycol as solvent. According to Fig. 1, it is possible to infer difficulties to keep the product specification when the option is to control the sensitive stage temperature because of the ongoing need to change the set-point of the controller.

Temperature and flow meters are cheap and accurate; however, some problems arise to measure feed composition. For this case, the ideal tool would be an online analyzer with acceptable response time, reasonable accuracy and low cost, which is hardly found in industrial practice [17,18]. Alternative techniques based on the analysis of refractive index, density and dielectric constant can also be used, but they do not ensure good precision to determine it. Therefore, we developed a soft sensor based on ANN as an option to estimate the feed composition.

A soft sensor could be developed to infer the composition of products, and this way the estimate value would be used in a feedback controller. However, the advantage of inferring the composition in the feed is that it can be used as input information to another model based on ANN, and this can be used to predict the best operating condition of the plant to keep the product compositions constant. In other words, it suppresses deficiency in the feedback control, which implies in the necessity of the existence of an error so that the controller takes some action.

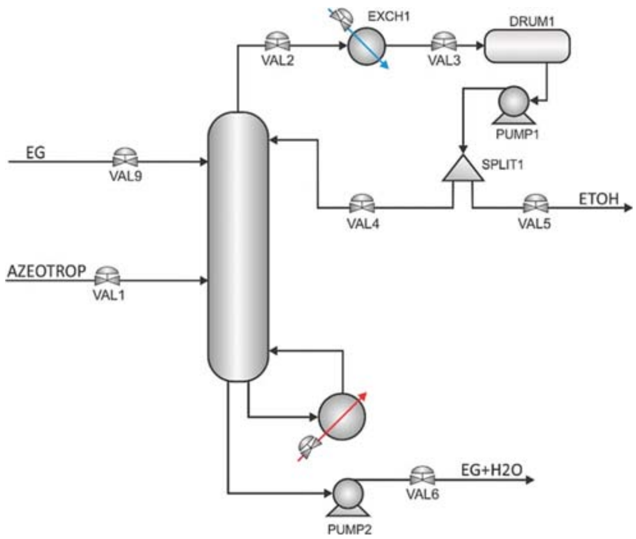

Fig. 2. Flowsheet used for steady-state simulations.

In summary, feeding disturbances (temperature, flowrate and composition of azeotropic) are introduced into the model using the ANN, so that the intelligent controller provides a feedforward response. No article was found with this type of control system in the consulted literature.

STEADY-STATE AND DYNAMIC SIMULATIONS

The performance of the developed intelligent controller was tested using a model implemented in Aspen Plus™, and playing the role of an industrial plant, as shown in Fig. 2. Condensers and reflux vessels were decoupled from the column to obtain a more rigorous and realistic model. The RadFrac™ routine was used for modeling the column, with a fixed Murphree efficiency of 100%. The condenser and reflux vessel was simulated with Heater and Flash2 routines, respectively; moreover, total condensation was assumed in the condenser by setting null vapor fraction, leading to no vapor production in the reflux vessel.

Phase equilibrium (VLE) was represented through a γ-φ procedure with the nonrandom two-liquid (NRTL) model for activity coefficient calculations (γ), and Redlich-Kwong equation of state (EOS) for calculating fugacity values [19,20].

According to Fig. 2, the azeotropic mixture of ethanol/water (AZEOTROP) is fed into the middle region of the extractive column (COL1), while pure ethylene glycol (EG) is fed close to the top. The distillate product from the extractive column is practically pure ethyl alcohol (ETOH), and the bottom product is essentially a water/ethylene glycol binary mixture (EG+H2O). The vapor from the top of the column is condensed in a heat exchanger (EXCH1), and then flows to a reflux vessel (DRUM1). After pumping (PUMP1),

Table 1. Extractive column and stream data

Variable	Stream		
	Azeotrope	Solvent	Distillate
Temperature (°C)	40 [20]	80 [20]	75.3
Mole flowrate ($kmol \cdot h^{-1}$)	100 [15]	76.94	85.4
Mole composition of ethanol	0.85 [19]	-	0.995
Mole composition of ethylene glycol	-	1.0 [20]	113 ppm
	Column		
Number of stages	24 [20]		
Reflux ratio	0.377		
Top pressure (atm)	1.0 [22]		
Bottom pressure (atm)	1.2 [21]		
Solvent feed stage	4 [21]		
Azeotrope feed stage	12 [20]		
Column diameter (m)	0.8		

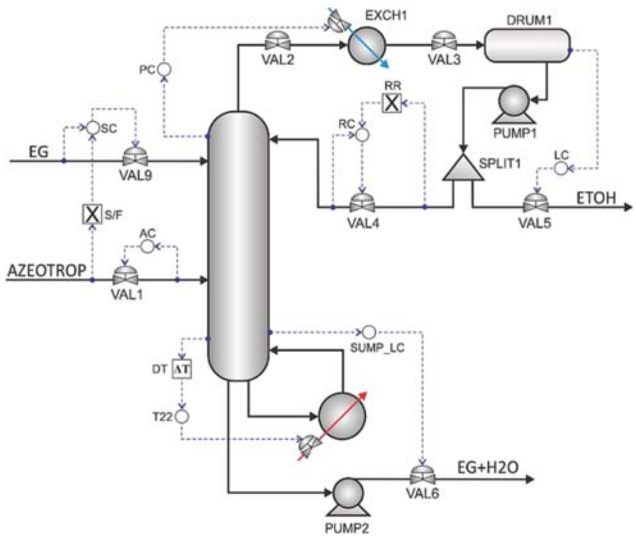

Fig. 3. Flowsheet used in dynamics simulations.

the condensed overhead product is sent to a splitter (SPLIT1), with one fraction being used for reflux and the other is withdrawn as top product (ETOH).

Design and process data to reach the desired specifications are shown in Table 1, and were based on literature reports [15,19-22]. The data not referenced are results of this work.

The top pressure value was chosen to permit using cooling water as utility and medium pressure steam was used in the column reboiler.

The column diameter was calculated using the tray sizing tool from Aspen Plus™, while length and diameter of reflux vessels and sump column height were calculated using the methodology proposed by Luyben [23] for a 5 min hold-up when the vessel or column base is 50% full, as based on the entering or exiting volumetric flowrates.

We decided to use a single temperature control in this work, and selected the sensitive tray based on the following methods [15, 23]: successive stages, sensitivity symmetry, maximum sensitivity and singular value decomposition (SVD). The sensitivity analysis was done in an open loop with disturbances of ±5% in the reboiler heat duty. The two most sensitive stages were determined in each analysis, and according to Table 2, stage 22 showed the best results, thus being chosen as the sensitive stage.

The steady state simulations performed in Aspen Plus™ were exported to Aspen Plus Dynamics™, and a basic control scheme was implemented, including:

- Feed flowrate control;
- Top pressure of the column by manipulating the condenser duty;
- Reflux vessel level by manipulating the distillate flowrate;
- Sump column level by manipulating the bottom product flowrate.

Table 2. Comparison of methods for determining the optimal stage for temperature measurement

Method	Chosen stage
Successive stages	22 or 23
Sensitivity symmetry	Inconclusive
SVD from the sensitivity matrix	22 or 21
Maximum sensitivity	22 or 23

Furthermore, the following controllers were also added:

- Reflux ratio by manipulating the reflux flowrate [24];
- Stage 22 temperature by manipulating the reboiler heat duty;
- Ratio between the solvent and azeotropic feed flowrates (S/F) by manipulating the solvent flowrate [15].

The process flow diagram (PFD) in Aspen Plus Dynamics™ environment, including all controllers, is presented in Fig. 3. Level controllers are only proportional with K_c=2 for reflux vessels, and K_c=10 for sump level [15,25]; pressure controllers are proportional-integral with K_c=20 and τ_I=12 min [15]. Flowrate controllers are proportional-integral with K_c=0.5 and τ_I=0.3 min [25]. To tune the temperature control, an analysis was conducted with disturbances in the reboiler heat duty within the range of ±5% of its nominal value. Next, the parameters were calculated using the Tyreus-Luyben method [25,26] for a Proportional-Integral (PI) type controller, with K_c=3.59 and τ_I=10.56 min.

SOFT-SENSOR AND INTELLIGENT CONTROLLER

The general idea is that the developed ANN receives information about process disturbances and calculates new controller's setpoints, for the new operating condition. The objective of this type of control is to adapt itself to the new situations in order to take the process to a new steady-state with the minimum energy consumption, while keeping the product specifications. To reach this objective, the ANN was developed with the help of neural networks toolbox (NNT) from Matlab® and trained using steady-state data from Aspen Plus™. The software Aspen Plus Dynamics™ was used to reproduce a real plant operation, which environment enables the integration with Matlab® and allows the control system using ANN to be tested in transient regime.

The link between Aspen™ and Matlab® was done using the

Fig. 4. Communication between used software programs.

Elipse Supervisory Control and Data Acquisition (SCADA) software. In this specific application, Aspen Plus Dynamics™ and Matlab® work as the client and Elipse SCADA works as the server. Fig. 4 shows a scheme of the communication between the software and works.

1) Aspen Plus Dynamics™ provides data for Elipse SCADA.

2) Elipse SCADA sends data to Matlab®.

3) Matlab® accesses the ANN (trained using simulations data obtained by Aspen Plus™) from its neural networks toolbox tool (NNT).

4) ANN returns a response (new set-point values) to Matlab®.

5) The value of the ANN output is available on Ellipse SCADA.

6) Aspen Plus Dynamics™ receives new set-point values of the controllers.

As cited before, online analyzers are hardly found in the industry, and an alternative is to use soft sensors, which are commonly developed to infer the composition of products to estimate the value to be used in a feedback controller. However, in this work, we developed a soft sensor based on ANN as an option to estimate the feed composition [27-30].

To obtain the models based on ANN, the first step is to analyze the behavior of the column outside its nominal state. In this way, it is possible to raise historical data of the plant in an operating range at which it is likely to operate. The obtained data to train, validate and test the ANN were obtained from the steady-state simulations using Aspen Plus™ for two different moments: to infer the composition of ethanol in the feed stream, and to predict the set-points of the controllers to keep the product specifications for the process operating at optimum condition.

The first artificial neural network (ANN_1) was created to estimate the composition of ethanol in azeotrope feed stream. For this, disturbances in reboiler heat duty, reflux ratio, distillate flowrate, solvent flowrate and azeotrope feed (flowrate, temperature and composition) were carried out. Disturbances ensure that the historical data is significant and cover the major problem domain. Several and important easy-to-measure variables will be used as ANN_1 input data to relate them to the variable to be inferred (ANN_1 output):

- ANN_1 input - azeotrope feed flowrate (F); Azeotrope feed temperature (T); reboiler heat duty (Q_R) reflux ratio (RR); solvent flowrate (S); Distillate flowrate (D); Temperatures of stages 4 (T4), 8 (T8) and 22 (T22) of the extractive column;
- ANN_1 output: Ethanol composition in the azeotrope feed (x^{ETOH}).

Regarding the choice of variables used as inputs to ANN_1, it is important to emphasize that the cited disturbances change the temperature profile of the column, so it is necessary to modify other variables to define a new temperature profile that maintains product specifications with minimum energy consumption for a new operating condition, and for which their choices as inputs to the network are justified. These variables can be classified into two different types: directly manipulated (solvent flowrate, distillate flowrate, temperature and azeotrope feed flowrate) and indirectly manipulated (reboiler heat duty, reflux ratio and column temperature profile).

Temperatures of all stages of the column were not used because the training set would be very large, resulting in greater computational effort and slow inference by the ANN. The temperatures of stages 4, 8 and 22 were chosen because they present significant variations with disturbances, according to sensitivity analysis performed in the previous item.

The second artificial neural network (ANN_2) was used for the development of an intelligent controller system. The temperature, flowrate and composition of the azeotrope feed were changed in Aspen Plus™.

Optimal values o f the variables to be controlled for operating at minimum energy consumption were observed for different disturbance combinations, thereby maintaining the product specifications. This procedure was possible using the model analysis tool/optimization from Aspen Plus™, which uses the sequential quadratic programming (SQP) method for optimization.

Energy consumption of the distillation column reboiler (Q_R) is defined as the objective function (F_{obj}) to be minimized, Eq. (1), manipulating the following decision variables: reflux ratio, solvent flowrate and distillate flowrate. The model analysis tools/constraint was used to consider the process constraints: mole fraction of ethanol (x^{ETOH}) and recovered mole fraction (FR^{ETOH}) in distillate, according to Eqs. (2) and (3), respectively.

$$F_{obj}=Q_R \tag{1}$$

Subject to

$$x^{ETOH}\geq 0.995 \tag{2}$$

$$FR^{ETOH}\geq 0.999 \tag{3}$$

The two developed ANN work together; the ethanol composition in the azeotrope feed is estimated by ANN_1 and this result is used as input to ANN_2, as shown in Fig. 5.

Using Aspen Plus™, a collection of 8000 input patterns with

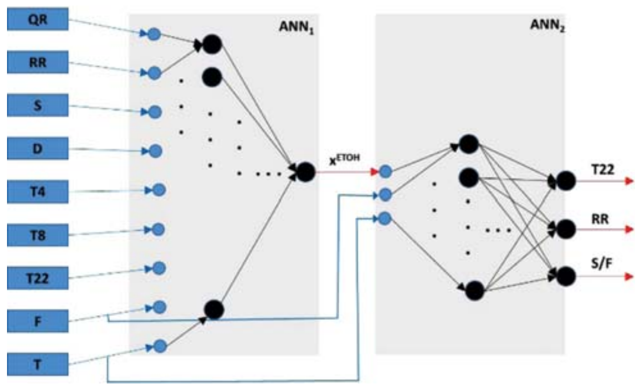

Fig. 5. Two ANN in cascades to predict the best set-points of the controllers.

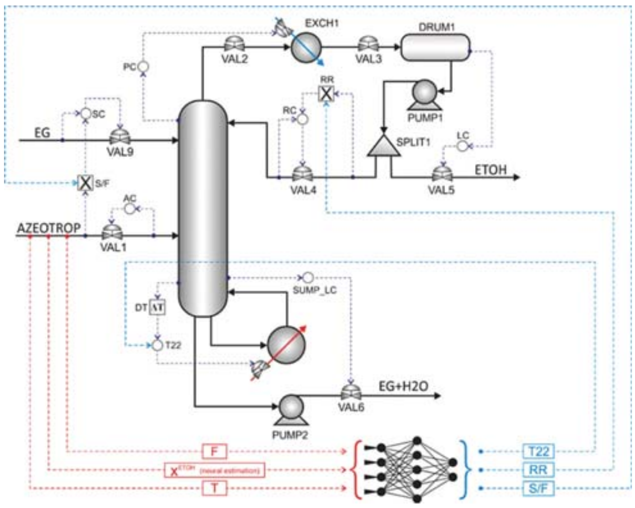

Fig. 6. Diagram of the intelligent control system using ANN.

their desired responses was used to estimate the composition of ethanol in the azeotrope feed; 70% was used for training, 25% for validation and 5% for testing. To develop an intelligent controller, a collection of 5300 input patterns from Aspen Plus™ was used: 50% were used for training, 10% for validation and 40% for testing.

As shown in Fig. 6, it is possible to predict the values of the set-points (output) needed to maintain product specifications from disturbances in azeotrope feed (input) at minimal reboiler heat duty:

• ANN_2 input - ethanol molar composition (x^{ETOH}) estimated by ANN_1, temperature (T) and feed flowrate (F) of azeotrope;

• ANN_2 output - temperature of stage 22 (T22), reflux ratio (RR) and feed ratio between solvent and azeotrope streams (S/F).

CHOOSING THE ANN

The choice of the ANN architecture includes decisions about the number of layers, number of units in each one, type of activation function and the training algorithm. We decided to select two different types of architectures and evaluate them according to their performance related to the problem data. The selected ANNs were:

• Feedforward backpropagation: this is an ANN without feedback, where information is distributed in only one direction [27].

• Elman recurrent: this ANN has an added feedback in its feed

Table 3. Summary of ANN results for soft sensor development

Number of hidden layers	Number of neurons per layer	Feedforward networks			Recurrent elman networks		
		MSE ($\times10^{-8}$)		Maximum error ($\times10^{-3}$)	MSE ($\times10^{-8}$)		Maximum error ($\times10^{-3}$)
		Training	Validation		Training	Validation	
1	“10”	500.66	508.51	20.30	98.85	98.97	20.31
2	“5 5”	20.66	21.1	20.54	20.31	20.88	18.32
2	“10 10”	1.99	1.99	3.64	0.51	1.02	3.25
3	“5 5 5”	1.58	2.10	5.23	0.06	0.07	5.14
3	“10 10 10”	0.88	0.97	1.66	0.11[a]	0.12[a]	0.60[a]
3	“20 20 20”	1.78	2.01	2.48	0.18	2.15	0.14
4	“5 5 5 5”	2.11	2.13	3.55	0.12	0.19	2.36
4	“10 10 10 10”	3.22	3.23	2.39	0.18	0.18	2.36
4	“20 20 20 20”	1.09	1.54	1.71	1.25	1.29	1.22

[a]Best results

Table 4. Summary of ANN results used to develop intelligent controllers

Number of hidden layers	Number of neurons per layer	Feedforward networks			Recurrent elman networks		
		MSE ($\times10^{-6}$)		Maximum error	MSE ($\times10^{-6}$)		Maximum error
		Training	Validation		Training	Validation	
2	“2 3”	3.21	3.24	0.0298	3.05	3.20	0.0277
2	“5 6”	3.13	3.30	0.0193	2.85	2.94	0.0193
2	“10 10”	3.03	3.10	0.0194	2.97	3.21	0.0208
3	“10 5 6”	2.94	2.98	0.0223	3.55	3.78	0.0221
3	“10 6 9”	2.97	3.08	0.0204	2.84	2.99	0.0197
3	“9 8 8”	2.76	2.91	0.0199	2.51	2.70	0.0183
4	“10 4 8 10”	2.44	2.46	0.0185	2.01[a]	2.13[a]	0.0171[a]
4	“5 6 7 2”	2.64	2.55	0.0187	2.5	2.58	0.0190
4	“8 9 10 6”	3.10	3.11	0.0189	3.14	2.19	0.0192

[a]Best results

layer of the outputs of this layer to the input thereof; this makes it capable to store passed information [31].

Tangent sigmoid activation function was used for all layers, since it showed good results with respect to the other one tested. The number of hidden neuron layers was set empirically and takes into account the trade-off between success and computational effort; however, the number of neurons in the input and output layers is determined in accordance with the problem. The ANN training method used in this work was the Levenberg-Marquardt algorithm [32].

Tables 3 and 4 give the best results of some types of feedforward and recurrent Elman ANN [31]. The number of hidden layers and neurons per layer is presented as the name that identifies the neural network. For example, the network "2 3" indicates that the ANN has two neurons in the first hidden layer, and three neurons in the second hidden layer.

According to Table 3, the network chosen as the best option to estimate the ethanol composition in the azeotrope feed was the Elman network "10 10 10" with three hidden layers. According to Table 4, the network chosen as the best option to predict the best set-points was the Elman network "10 4 8 10" with four hidden layers. In fact, the best ANNs have the lowest mean squared error (MSE), which indicates that the networks lead to good results and the largest error obtained in the test set is small compared to the others. Recurrent neural networks can reuse the transformed information, producing dynamic mappings. The presence of feedback information allows for creating internal connections and memory devices capable of processing and storing temporal information and sequential signals [29]. Other networks which are not in the tables presented larger errors, indicating that they converged to local minimums.

A different data set from those used in the training and validation phase was used during the testing phase of the highest ranked neural network. The absolute error (E) for each sample (j) was obtained according to Eq. (5):

$$E=\frac{|d_j-y_j|}{d_j} \tag{5}$$

Fig. 7 presents the errors and the comparison between predicted results (ANN_1 estimation) and expected results (Aspen output) of the ethanol composition in the feed stream of the azeotrope.

It can be concluded from Fig. 7 that the RNA training chosen for the development of the soft sensor presented good convergence, since the difference between the simulator result and the result estimated by the soft sensor is minimal. Consequently, the errors present uniform values, showing that the network has an excellent estimation capacity.

In the tests to predict the new setpoints after the disturbances, it was noticed that for a given set of points, the errors found were quite higher compared to the others; therefore, the network in this region was not sufficiently trained. Thus, a new ANN training was performed with an increase of 500 points around the deficit region to solve this problem. When analyzing the results, it could be noted that the increase in the number of training data reduced the error in the deficit region, but there was considerable loss in the estimation quality of other points, indicating that the condition obtained in the initial training was lost. An alternative was to create and train a new neural network (ANN_3) with the same features of the best network already chosen, acting exclusively in the deficit region and with the addition of new points around this region (Fig. 8).

Fig. 8 shows that retraining using two neural networks can improve the large errors region without damaging the other, and this reflects in better control of product composition (as shown next). To predict the set-points in on-line use, the two ANNs (ANN_2 and ANN_3) never act simultaneously, since each one is programmed to operate in distinct and specific regions where the smallest errors are observed.

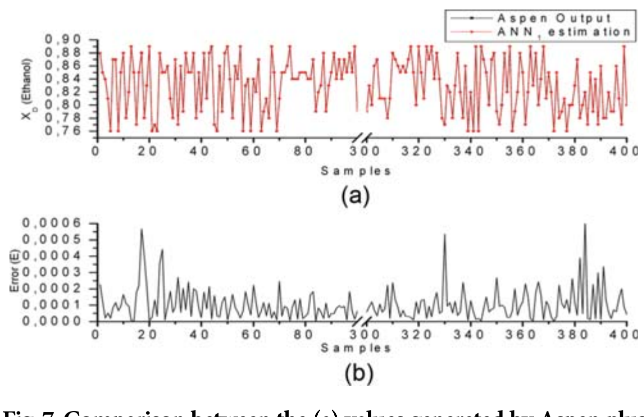

Fig. 7. Comparison between the (a) values generated by Aspen plus and the values estimated by ANN; and (b) the respective absolute errors.

CONTROL SYSTEM PERFORMANCE

The intelligent controller developed was tested with the aim to maintain the ethanol composition at the top at 99.5 mol%, and with

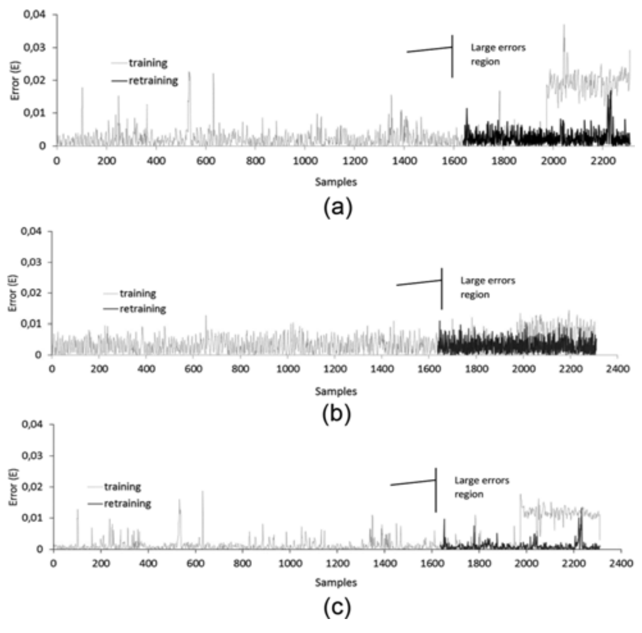

Fig. 8. Absolute errors for the variables (a) reflux ratio, (b) stage 22 temperature and (c) S/F ratio with two ANN in the retraining.

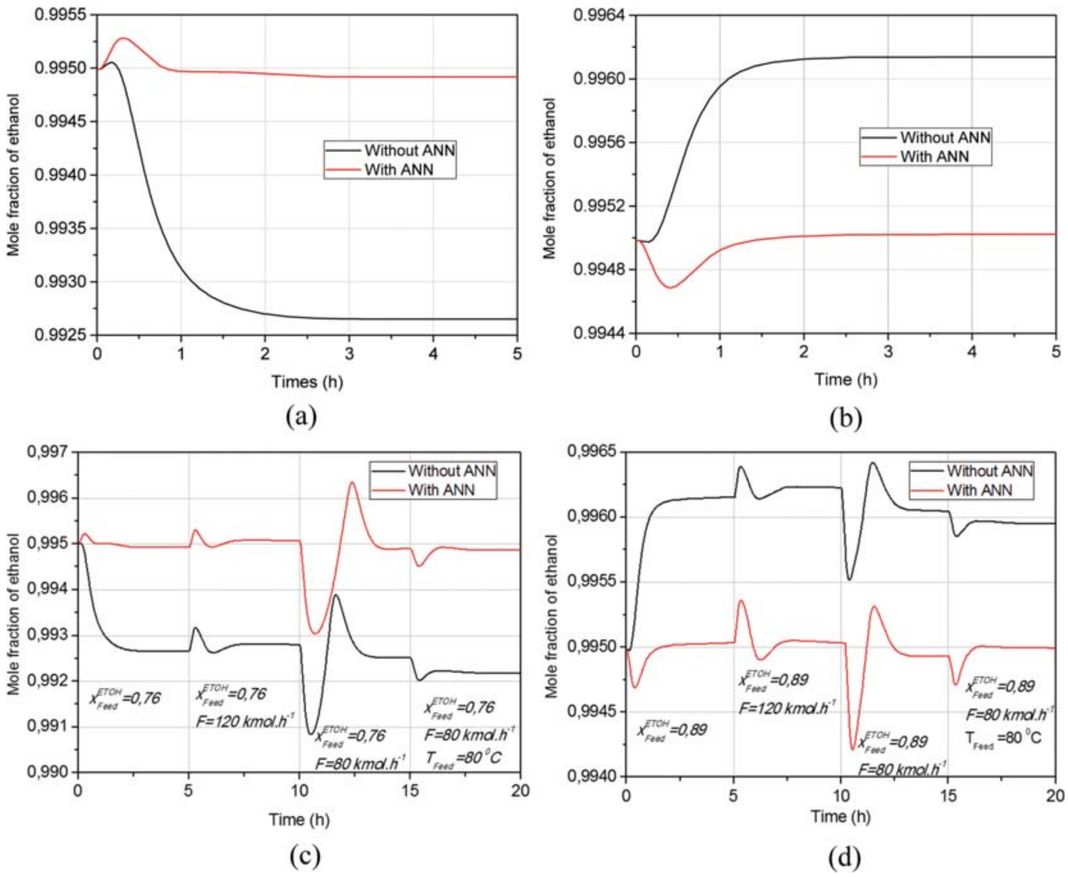

Fig. 9. Dynamic response for disturbance of −10% (a) and +4.7% (b) in the azeotrope feed composition, and simultaneous disturbances in composition, flowrate and temperature of the azeotrope feed (c) and (d).

a loss lower than 0.1 mol% at the bottom stream of the column for disturbances in the azeotropic feed stream.

Fig. 9 shows the ethanol composition behavior at the top product from disturbances in the feed stream by comparing the control system performance with and without the use of the developed intelligent controller.

The control system without ANN only works for feed flowrate disturbance. The ethanol composition behavior had no significant changes to a disturbance of ±20% in the azeotrope feed flowrate and the results were omitted.

On the other hand, the control system with ANN rejected all disturbances well. However, it is important to highlight that the control becomes more difficult when the disturbances are simultaneous, so that product specifications are more difficult to reach. The computational time was approximately 2 min to simulate 20 h of processing. This computational time is relatively short since the

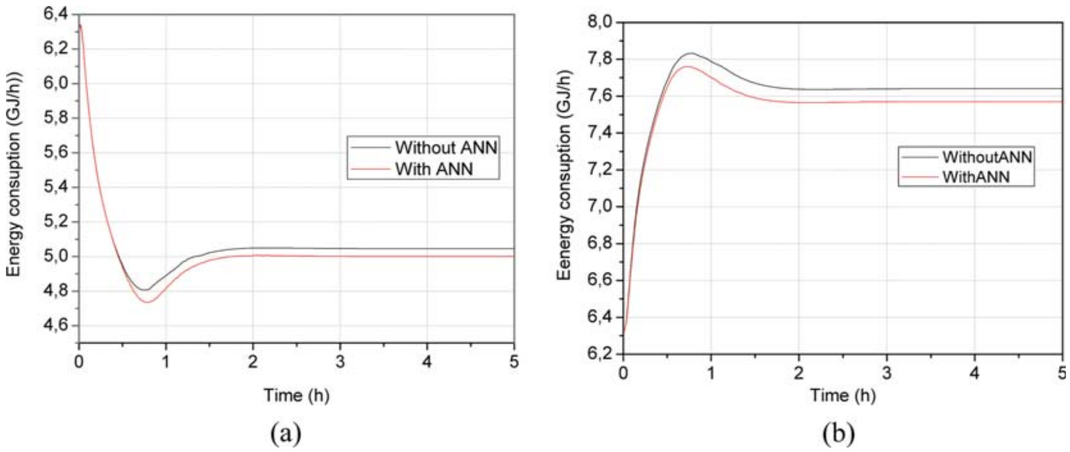

Fig. 10. Dynamic response of reboiler heat duty for disturbances of −20% (a) and +20% (b) in the azeotrope feed flowrate.

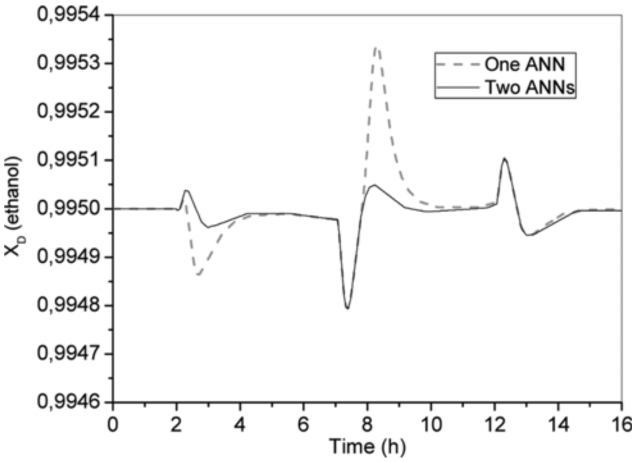

Fig. 11. Comparison of control with set-point change using one ANN and two ANN for different disturbances in the azeotropic feed composition.

use of ANN reduces calculation requirements. The detector is fed in online mode, and may be extremely fast in processing the results since most calculations are performed in the ANN training phase.

It must be emphasized that this type of control not only presented satisfactory performance, but also presented energy efficiency, meaning that it guarantees the quality of the products with minimum heat duty and optimizes the operational conditions during ANN training. For example, the control without ANN can maintain quality of the product within specifications only for disturbances in the feed flowrate, but with greater energy consumption when compared to the intelligent control system, as shown in Fig. 10. Therefore, the control using ANN is the most interesting alternative because the energy consumption in the reboiler presented savings of 0.90% and 0.94% for disturbances of −20% and +20% in the azeotrope feed flowrate, respectively.

Fig. 11 shows that the performance of the intelligent control using two networks (ANN_2 and ANN_3) is better compared to the use of only one network (ANN_2) to predict the best set-points. A performance error stems from the fact that any adjustment promoted by a control system takes a while to complete, and accumulates control errors during that time (desired value - set-point - less measured value). Note that Fig. 11 was constructed using two different intelligent controllers: a control system with one ANN and a control system with two ANN. The computational effort is almost the same because in the final product (control system using two ANN) each ANN will only act depending on the disturbance in the feed composition.

For the transient adjustment, the value of the instantaneous error (ISE), represented by Eq. (6), can also be obtained, resulting in a cumulative overall error, which depends on the values of the controller action constants.

$$\mathrm{ISE} = \int_0^{\infty} [e(t)]^2 dt \tag{6}$$

The value of ISE for the simulation depicted in Fig. 10 using one and two neural networks was 9.02×10^{-8} and 2.4×10^{-8}, respectively. The bottom product composition had no significant changes for all the simulations, with the ethanol composition remaining below 0.1 mol%.

CONCLUDING REMARKS

An intelligent controller using ANN could predict the new condition from disturbances in the azeotropic feed, making changes in the set-points of the controllers to keep specifications of the product at the top and bottom of the column.

The success of an intelligent controller using ANN depends on a consistent analysis of the system to define which topology best meets the needs of the proposed problem and in choosing which data are relevant for processing. The technique used in this study shows that it is possible to obtain good accuracy in estimating the values of new set-points using two ANN without increasing the computational effort.

A third network can be used without increasing the computational effort because the networks used to predict the set-points (ANN_2 and ANN_3) do not act simultaneously, providing good results when one of the input variables is the ethanol composition in the azeotrope feed. Such a variable is inferred by ANN_1, which has proven to be an interesting solution to replace expensive measurers of composition.

This new control approach is conceptually simple and can be easily implemented in the chemical industry, as it improves the performance of the conventional controller when it acquires feedforward characteristics. Furthermore, it is possible to eliminate additional energy costs and additional costs associated with product specifications.

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