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# ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) APPROACH TO EVALUATE THE DEBUTANIZER TOP PRODUCT

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**Abstract**

*This paper proposed an ANFIS estimator to evaluate the top product from secondary measurements. Real debutanizer column in one of the Iranian refineries has been purchased and the adaptive neuro-fuzzy inference system is trained and validated with real data. According to results, ANFIS can be used with acceptable approximation in replace of costly measurement instruments as gas chromatographs.*

***Keywords: Distillation column; Estimator; ANFIS; Debutanizer Column***

## 1. Introduction

In certain control applications, there are situations when some of the parameters cannot be measured economically online because of either the instrumentation is very expensive or measurement introduces lags, which designing an effective control system will be impossible. In such situations from the secondary measurements, inference is made for the desired parameters, artificial neural network (ANN) and fuzzy logic best suits for this application.

The estimated composition may be used in a control scheme to determine valve position directly, or it may be used to manipulate the set point of a temperature controller as in parallel cascade control. This is the notion behind inferential control developed by Joseph and Brosilow [1]. The inferential control scheme uses measurements of secondary outputs, in this instance, selected tray temperatures, and manipulated variables to estimate the effect of unmeasured disturbances in the feed on product quality. The estimated product compositions are then used in a scheme to achieve improved composition control. The control of many industrial processes is difficult because online measurement of product quality is complicated. This is due to the lack of measurement technology. In 1972, Weber and Brosilow [2] proposed using secondary measurement to control the variables that their measurements are difficult or impossible.

In 2005, Singh et al. [3] estimated composition of distillate in distillation column by using artificial neural network. The structure of neural network has been made by input and output data, which inputs are temperature of trays and outputs are composition of distillate. Artificial neural networks were applied to predict and estimate vapor–liquid equilibrium data for ternary systems saturated with salt by Nguyen et al. [4] (2007).

Since Jang [5] proposed the Adaptive Neural Fuzzy Inference System (ANFIS), its applications are numerous in various fields including engineering, management, health, biology and even social sciences. Specifically, literature has several articles on the application of ANFIS to decision making, medicine, quality control, pattern recognition and inventory control.

Leiviska et. al.[6] (2001) used linguistic equations (fuzzy models) and NN models in prediction of Kappa number in the continuous digester. Actual prediction data was collected from a continuous digester house. It included the extraction flow measurements and reactive index, temperature in the extraction flow, and the measurement of Kappa number from an online device after digester. Then the data was divided into training and testing data. It was used as one of the fuzzy model and gave the best performance in other fuzzy models. Castillo and Melin [7] used an ANFIS methodology in electrochemical process. The problem in battery manufacturing was to find how much the current could be increased without causing battery to explode due to the increase in temperature and at the same time minimizing the time of loading. Since ANFIS can be used to adapt the membership functions and consequents of the rule base according to the historical data of the problem, ANFIS was used as fuzzy controller in this research. Fuzzy logic was used with 5 membership functions and first order Sugeno function in the consequents. ANFIS controller input and output were temperature and electrical current, respectively. They found that, the ANFIS methodology gave better results than manual, conventional and fuzzy control methods.

Kelly et al. [8] designed a neural fuzzy controller that allows for the combination of the qualitative knowledge in fuzzy rules and the learning capabilities of neural networks. This method offered two unique features, namely the ability to eliminate human decision making and enhance the learning capability. The results of this paper show that the neural

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fuzzy controller, developed using ANFIS as part of the control system, successfully learns to control a second order plant autonomously after a short training time, gives better control than the conventional PID, and corresponds with the change made to the original control plant.

In another study of adaptive FNN, Hancheng et. al. [9] used the ANFIS to extract fuzzy rules from experimental data for material property modeling. Prediction of tensile strength based on compositions and microstructure was aimed. Hence, backpropagation NNs used in literature needed large amount of training data in order to acquire high learning precision, and had a poor generalization capability and obtaining experimental data was also expensive, authors tried to use ANFIS. To verify the generation of the model, 38 available patterns were divided into two categories: a training set of 29 cases and a test of 9 cases. All the membership functions of the input variables were of the gaussian type, and parameters sub-spaces were determined by using *K*-means clustering of the training data set, 20 rules being obtained. Inputs to the ANFIS were the carbon equivalent, the graphite flake size, and the microhardness of the matrix, the amount of austenite dendrite and the eutectic cell. Output was the tensile strength. The results were compared with multiple statistical analyses, fuzzy regression and the generalized regression network and ANFIS showed good learning precision and generalization

## 2. Adaptive Neuro-Fuzzy Inference System

Usual approaches to system modeling rely heavily on mathematical tools which emphasizes a precise description of the physical quantities involved. By contrast, modeling approach based on neural networks and fuzzy logic is becoming a viable alternative where the earlier conventional techniques fail to achieve satisfactory results.

Neuro-fuzzy modeling is concerned with the extraction of models from numerical data representing the behavioral dynamics of a system.

This modeling approach has a two-fold purpose:

- It provides a model that can be used to predict the behavior of the underlying system.
- This model may be used for controller design. [10]

The basic idea behind the adaptive neuro-fuzzy learning techniques is very simple. These techniques provide a method for the fuzzy modeling procedure to learn information about data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input-output data. ANFIS constructs an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and simulated input/output data pairs. It serves as a basis for building the set of fuzzy if-then rules with appropriate membership functions to generate the input output pairs.

The parameters associated with the membership functions can be changed through the learning process. The computation of these parameters (or their adjustment) is made possible by a gradient vector, which provides a measure of how well the ANFIS is modeling the input output data for a given parameter set. Once the gradient vector is obtained, backpropagation or hybrid learning algorithm can be applied in order to adjust the parameters. Figure 1 shows the ANFIS structure which consist of five layers.

### 3. Description of the plant

The column is located in the one of the refineries in Iran and it is part of naphtha splitter plant.

In the debutanizer column C3 (propane) and C4 (butane) are removed from heavier composition such as C5 (pentane). The tasks of debutanizer column are as below;

– Preparing sufficient fractionation.

– To maximize the C5 (stabilized gasoline) content in the distillate of debutanizer, while respecting the limit enforced by law.

– To minimize the C4 (butane) content in the debutanizer bottoms.

A detailed scheme of the debutanizer column is shown in Figure 2. A number of sensors are installed on the plant to monitor product quality. The subsets of sensors relevant to the described application together with the corresponding description are listed in Table 1. The gas chromatograph is located in overhead flow and measures the concentration of C3, C4 and C5. The C5 content in overhead depends on the debutanizer operating conditions.

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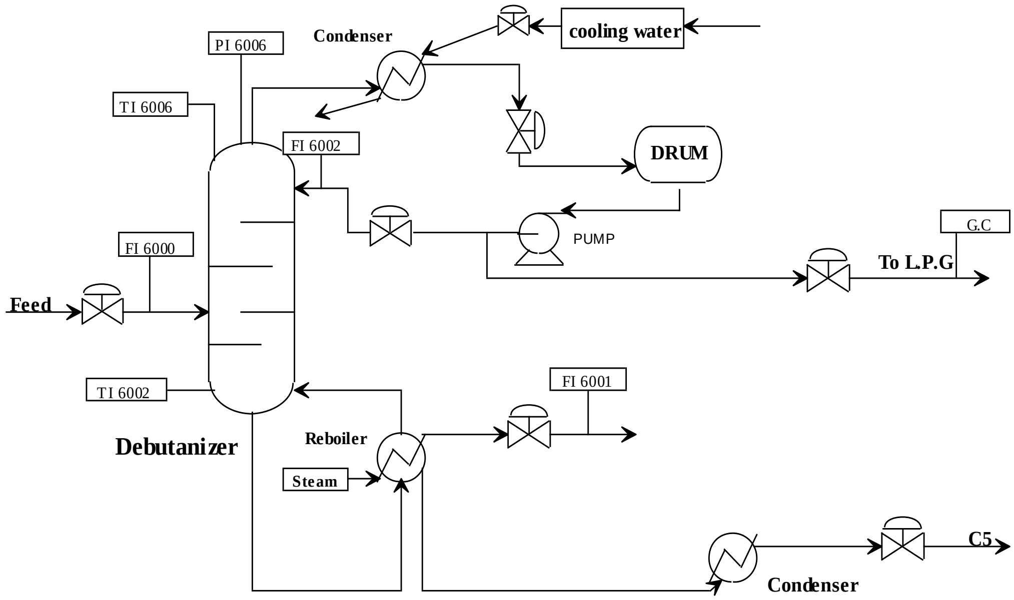


Figure 2. Schematic diagram of debutanizer column

Table 1. Sensors relevant to the describe application and corresponding characteristics.

| Tag | Description | units |
|---|---|---|
| FI 6000 | Feed flow | Kbbl / day |
| TI 6002 | Bottom temperature | $^{o}$ C |
| TI 6006 | Top temperature | $^{o}$ C |
| PI 6006 | Top pressure | bar |
| FI 6002 | Reflux flow | $m^3$ / hr |
| FI 6001 | Steam flow | $m^3$ / hr |
| G.C | Gas Chromatograph | mole fraction |

## 4. Proposed ANFIS estimator

The purpose of the ANFIS is to estimate the top product composition using seven quantities measuring online that are; feed temperature, column bottom temperature, column top temperature, feed flow, reflux flow, existing steam flow from reboiler and column top pressure. Data are real and have been measured online. All these variables can affect the top composition. Selection of input variables is based on their importance and effect in system and that whether they are measurable or no.

For each input variable three membership functions have been taken, consequently there are $3^7$ rules for each ANFIS model. Training is based on hybrid training that described in section 3. The proposed Adaptive Neuro-Fuzzy Inference System (ANFIS) with inputs and outputs is shown in Figure 3.

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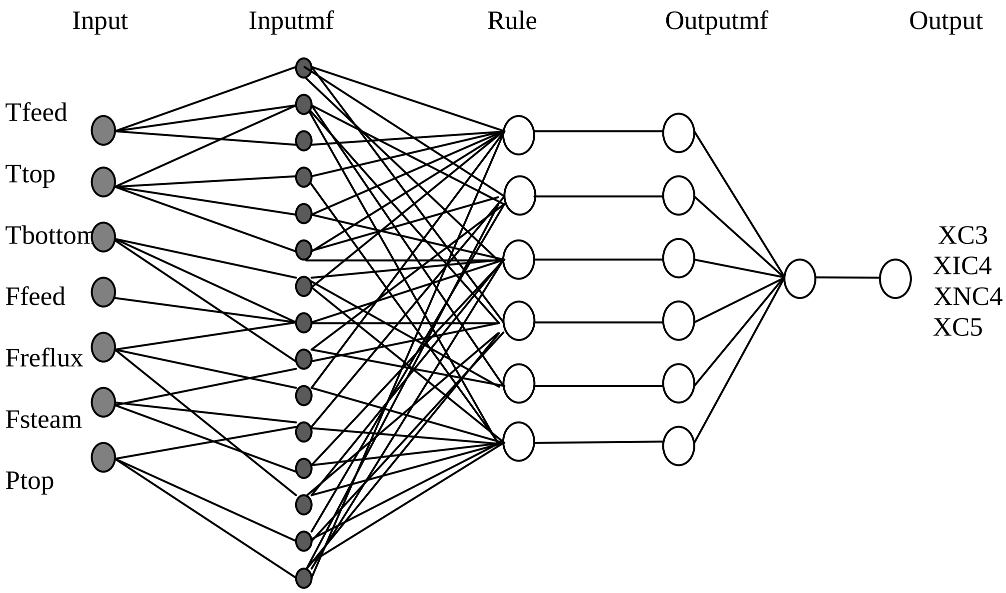


Tfeed = feed temperature Ttop & Tbottom= top and bottom temperature of debutanizer

Ffeed = feed flow Freflux = reflux flow Fsteam = steam flow of reboiler

Ptop = top pressure of debutanizer

X_C3, X_IC4, X_NC4, X_C5 = mole fraction of C3, IC4, NC4, C5( IC5+NC5)

Figure 3. Proposed ANFIS for debutanizer column.

## 5. Simulation Results

132 pairs of data are used that 50% of them are employed for training and others for validation. All data are normalized and put in range of [0, 1]. In this process, some kind of membership functions are tested as triangular, trapezoidal and bell , then number of input MFs and order of sugeno fuzzy inference system are changed. To compare the performances of the different ANFIS configuration with different number of membership functions, there should be a criterion. In most papers with soft computing application subject, root mean square error has been used.

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(A_t - F_t)^2}$$

where $A_t$ and $F_t$ are actual (desired) and fitted (or predicted) values, respectively, and N is the number of training or testing samples. Because there are some outputs and we want to compare the ANFIS with different kind of FIS we use mean of RMSE (MRMSE) in this work. Table 2 shows the RMSE and MRMSE of training and validating data for compositions of top product. As shown in Table 2 the ANFIS with triangular membership function and three MF for each input and zero order sugeno fuzzy inference system has the least MRMSE of training and validating data, so that configuration of ANFIS is selected.

Another criterion to understand that whether the model is acceptable or not is standard deviation (STD) and it is also, a criterion to select most appropriate model. Standard deviation of errors can be calculated from relation (25).

$$STD = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(Er_t - \overline{Er})^2}$$

Where $Er_t$ is error between simulated output and real output values and $\bar{E}r$ is mean of errors. Table 3 shows STD of errors for each composition in each model. MSTD is mean of standard deviations for each model that is basis for comparison between models. Figure 4 shows the

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real and predicted mole fractions of products with training data.

As shown, fittings are very accurate. To get a general model, model tested with validation data.

Figure 5 shows mole fractions of distillate with validation data and Figure 6 plots real data opposite of simulated data for validation data.

Table 2. RMSE & MRMSE of training and validating data

| | | | | RMSE of compositions with training data | | | | |
|---|---|---|---|---|---|---|---|---|
| | Number of MF for each input | order | Type of MF | C3 | IC4 | NC4 | C5 | MRMSE |
| **ANFIS- tri** | **3** | **0** | **Triangular** | **6.876E-06** | **2.041E-06** | **8.231E-06** | **7.282E-07** | **4.469E-06** |
| ANFIS- trap | 3 | 0 | Trapezoidal | 1.000E-04 | 1.000E-04 | 2.000E-04 | 0.000E+00 | 1.000E-04 |
| ANFIS- bell | 3 | 0 | Bell | 9.989E-06 | 1.819E-06 | 1.208E-05 | 9.353E-07 | 6.205E-06 |
| ANFIS- tri2 | 2 | 1 | Triangular | 1.382E-04 | 2.234E-05 | 1.412E-04 | 9.353E-07 | 7.566E-05 |

| | | | | RMSE of compositions with validating data | | | | |
|---|---|---|---|---|---|---|---|---|
| | Number of MF for each input | order | Type of MF | C3 | IC4 | NC4 | C5 | MRMSE |
| **ANFIS- tri** | **3** | **0** | **Triangular** | **0.0221** | **0.0088** | **0.0280** | **0.0019** | **0.015** |
| ANFIS- trap | 3 | 0 | Trapezoidal | 0.0344 | 0.0126 | 0.0653 | 0.0034 | 0.029 |
| ANFIS- bell | 3 | 0 | Bell | 0.0372 | 0.0090 | 0.0387 | 0.0028 | 0.022 |
| ANFIS- tri2 | 2 | 1 | Triangular | 0.0411 | 0.0113 | 0.0412 | 0.0032 | 0.024 |

Table 3. STD & MSTD of validating data

| | | | | STD of compositions with validating data | | | | |
|---|---|---|---|---|---|---|---|---|
| | Number of MF for each input | order | Type of MF | C3 | IC4 | NC4 | C5 | MSTD |
| **ANFIS- tri** | **3** | **0** | **Triangular** | **0.0443** | **0.0155** | **0.0579** | **0.0042** | **0.0305** |
| ANFIS- trap | 3 | 0 | Trapezoidal | 0.0562 | 0.0206 | 0.0630 | 0.0044 | 0.0360 |
| ANFIS- bell | 3 | 0 | Bell | 0.0612 | 0.0175 | 0.0558 | 0.0042 | 0.0347 |
| ANFIS- tri2 | 2 | 1 | Triangular | 0.0745 | 0.0311 | 0.0521 | 0.0043 | 0.0405 |

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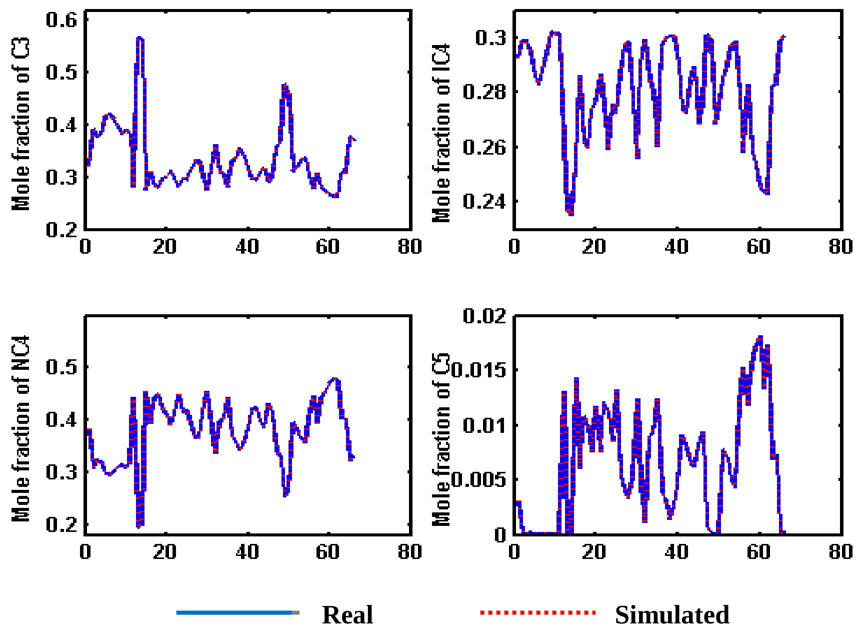


**Figure 4.** Mole fractions of training data (Real and Simulated)

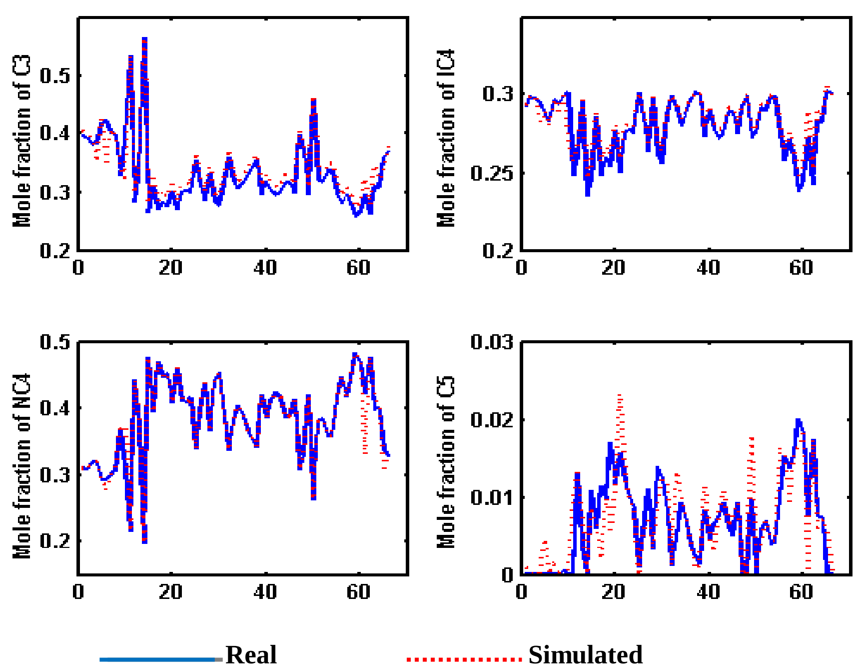


**Figure 5.** Mole fractions of validation data (Real and Simulated)

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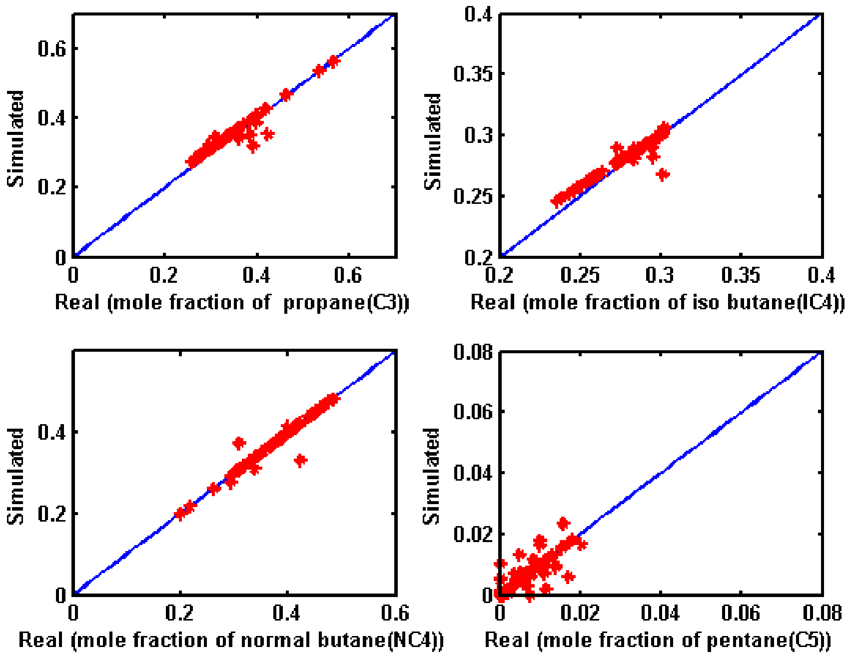


**Figure 6.** Real vs. simulated compositions of C3, IC4, NC4, C5.

## 6. Conclusion

This paper proposes an ANFIS estimator to estimate the top product compositions from secondary measurements. The column of this research is a debutanizer column located in a refinery in Iran that has fifty trays with reboiler and condenser and has five main components. Half of data is used for training and other used for validation. It is clear from Figure 5 and Figure 6, adaptive neuro-fuzzy inference system (ANFIS) has good results and it can be used with acceptable approximation in replace of measurement instruments as gas chromatographs in addition the ANFIS has no delay time and is economical. Generally Soft computing like artificial neural network, fuzzy logic and adaptive neuro-fuzzy inference system could be good, reliable and inexpensive substitution for some expensive devices in refineries, power plants and industrial plants.

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