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NEURO–FUZZY SYSTEM MODELING AND CONTROL APPLICATION FOR A DISTILLATION PLANT

The theory of fuzzy sets and neural networks was applied to the non–linear dynamics of a multicolumn ethanol distillation plant. In order to perform the state prediction necessary for the fuzzy logic controller, a neural net was trained to emulate the behavior of the system based on input output data. The algorithm of the generalized delta rule – GDR was used to train the neural network minimizing the sum of squares of the residual. The backpropagation algorithm was applied to the non–linear relationship between the product composition and reflux flow rates and feeds composition. A fuzzy model reduces the size of the neural network requiring rank to features detected. A fuzzy logic algorithm was generated using production rules processing the corresponding neural networks class. The developed neural–fuzzy model was applied in the multivariable control of the ethanol recovery, distillation plant, after corn starch fermentation. The obtained results show neuro– fuzzy control is better than neural network control or fuzzy control.

There have been several attempts to implement fuzzy logic through neural networks. Many processes are highly non–linear and difficult to define. For these applications neuro–fuzzy modeling has shown promise. Fuzzy logic and neural network based modeling find increasing application in process control in the area of identification and auto controller tuning [1–6].

Fuzzy logic, which was initially developed by Bellmann and Zadeh [7], is a combination of multivalued logic, probability theory and artificial intelligence. Engineering applications of the fuzzy set theory were studied in papers [8–10]

Neural nets have been used in a number of chemical engineering problems for dynamic and process control [11–16]. Neural networks are useful as modules in a larger system interacting with a fuzzy logic generic algorithm. Careful combination of the techniques produces the most useful robust systems. In this work neuro–fuzzy models for an ethanol recovery distillation plant control were investigated. The aim of this investigation was building more robust and accurate process models and improving noise handling.

In this paper a neuro–fuzzy dynamic model was built and applied to product composition and product flow rate control in three modules of the ethanol recovery distillation plant.

A NEURO–FUZZY MODEL

In this model fuzzy logic incorporates the imprecision inherent in many real systems, including human reasoning by allowing linguistic variable classification such as LOW, HIGH and MEDIUM, and the neural network trains to predict the fuzzy output.

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A variety of shapes is possible for the membership function, with triangles and trapezoids being the most popular. Fuzzy systems operate by testing variables with IF–THEN rules which produce appropriate responses. Each rule is then weighted by a membership function or "degree of fulfillment "of the rule invoked (number between 0 and 1) and may be thought of as a probability that a given number is considered to be included in a particular set. A wide variety of shapes possible for membership functions are used. The membership function in this model has the form:

$$\mu_{A_i}(x) = \exp\left[-(|\,x - m\,|)\,/\,s\,\right]^{p_f} \tag{1}$$

where m, s and p_f are user chosen parameters and x is the current value to be tested.

Fuzzy variables present inputs in the neural network and the neuro–fuzzy system output is:

$$y_j^p = f\,[\sum_i \mu_{A_i}(x_j)\, w_{ij} - \theta_j] \tag{2}$$

where w is the weight and can be a positive or negative real number, θ is the threshold of the j*th* neuron and p means the p*th* pattern. The f(x) is a non–linear function of activation that is in the hyperbolic tangent form. Initially the network is trained to predict the fuzzy output variables.

The neuro–fuzzy system must learn the data set: $[(x(t),\, y_{des}(t)]_{i=t}^{l}$ where l is the length of the training set, y_{des} means the desired output. The output obtained from the network output layer, for the p*th* pattern, is $y_{i_{NN}}$ and the neural network is trained by minimizing the error:

$$E = \frac{1}{l} \sum_{p=1} \sum_{i=1} \left(y_{des} - y_i^{NN}\right)^2 \tag{3}$$

Minimizing the sum of the squares of the errors is performed by the gradient descent procedure GDR–algorithm [17]. A simple variation on neuro–fuzzy models is the subclass of processes that can be represented as product models or decompositions.

The neural network dynamic learning model (4 x 2 x 1) was used for the training data base. A Gaussian random signal [18] was added to the scaled measurements. Past and present values of the ethanol distillate composition, reflux flow rate and ethanol feed composition, as well as future values of the ethanol distillate composition, make signals in the neural network at each level.

NEURO–FUZZY CONTROL

A standard fuzzy logic system utilizes the logical functions AND, OR, IF(..), THEN(..). The function operators, LOW, HIGH and MEDIUM are used. A fuzzy controller was generated using production rules. Neural networks can serve as a simulator trained from observed behavior of the process. The learning phase computational function of the neural network has the form:

$$u(k) = f[(y(k+1), y(k), y(k-n+1); u(k-n+1)] \qquad (4)$$

After successful learning, the neural network can be integrated in a feedback control loop. The input unit which coded the future state of the plant $y(k+1),\ldots\ldots, y(k+i)$ during the training phase must now represent the future desired set point $s(k+1),\ldots., s(k+i)$. The computational function of the inverse controller is:

$$u(k) = f(s(k+1), y(k), y(k-n+1), u(k-n+1) \qquad (5)$$

The minimization control function is given as

$$\text{Min } J = \Sigma\,[y_{nn}(k+1) - s(k+1)^2 + (u(k) - u(k-1))] \qquad (6)$$

This approach utilizes inverse neuro–fuzzy models of the plant. The reflux flow rate L is a manipulated variable or u(k), the top product composition Xt1 is a controlled variable or y(k), and s(k+1) is the desired set point value.

Neuro–fuzzy controller design laws are established by Eqs. (4)–(6). Multvariable control handles six process variables and three control outputs. It is decentralized multivariable control that uses different approaches for determining the control efforts.

THE ETHANOL RECOVERY PLANT DESCRIPTION

In order to analyze the training and learning of a neuro–fuzzy system for the process control the multicolumn distillation plant in Fig.1 was investigated. The ethanol is recovered from a mixture of water, carbon dioxide, butanol, acetaldehyde, glycerol, amyl alcohol, acetic acid and lactic acid remaing after the fermentation of corn starchy materials.

The main state variables characterizing the separation process are the feed flow rate F, ethanol composition in the feed Xf1, ethanol composition at the top Xt1, flow rate D, reflux flow rate L, bottom flow rate B, and the pressure drop for three columns: feed column (1), stripper (2) and recovery column (3). The steady state parameters for the examined process units are given in Table 1.

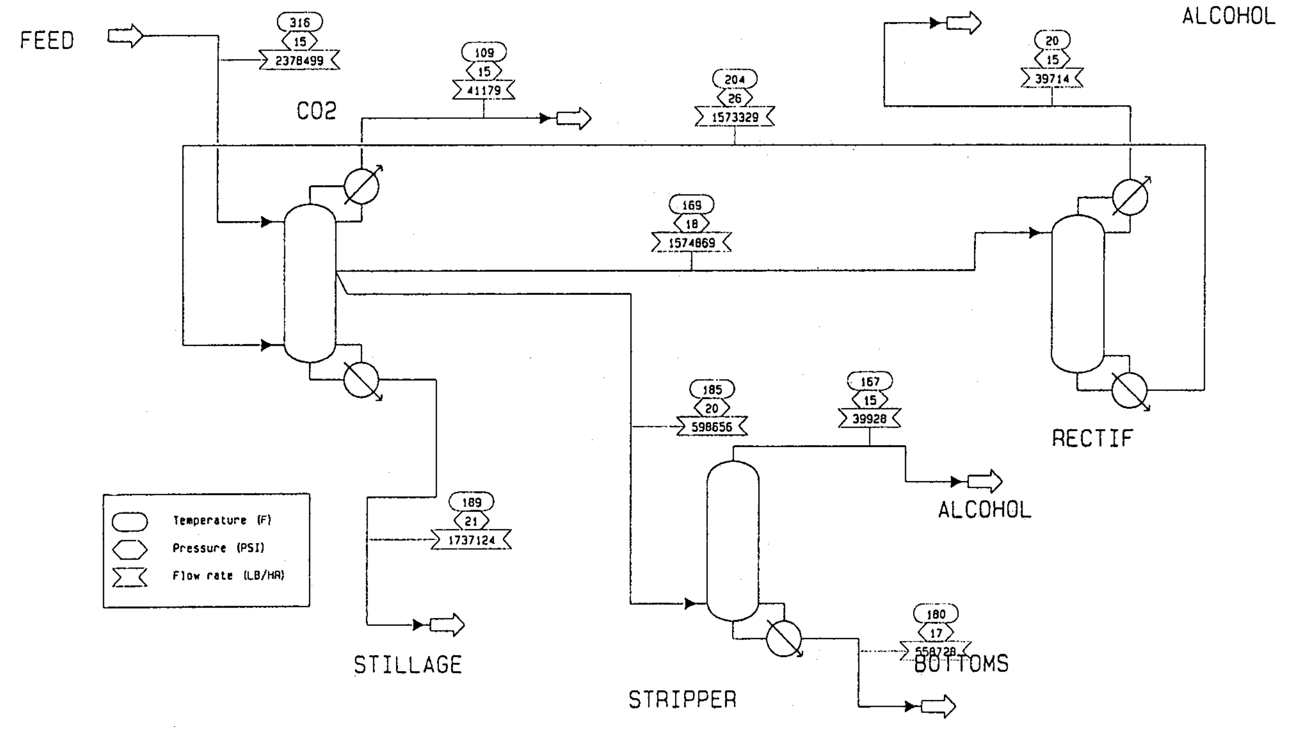

Figure 1. Scheme of the distillation plant

Table 1. The steady state operation parameters

	Unit 1	Unit 2	Unit 3
Feed flow rate F, mole/h	50552	12735	33808
Distillate flow rate D, mole/h	420	381	384
Bottom flow rate, mole/h	40348	5415	33664
Internal reflux flow rate L1, mole/h	1260	–	1152
External reflux flow rate L2, mole/h	33991	–	33808
Feed ethanol composition Xfl	0.034	–	–
Ethanol composition at the top of the column Xtl	0.515	0.715	0.945
Pressure drop Δp, bar	1.0	1.2	1.7

RESULTS AND DISCUSSION

The results obtained for neuro–fuzzy system learning and control are shown in Figures 2–5.

Neuro–fuzzy dynamic learning models use a learning data base. A training data base consisting 2% Gaussian signal added to the scaled variable values was used. The steady state values of ethanol composition in the final product was 94.50 % and the sample time was 60s. The ethanol distillate composition response used for training is shown in Figure 2. A neuro–fuzzy controller based on the process inverse dynamic model was used. Past and present values of ethanol distillate composition and the reflux flow rate are fed to the neural network. A non–linear dynamic relationship requires non–linear properties in the controller realized by hidden nodes with a non–linear activation function in the network. A fuzzy subsystem makes an image recognition and pattern matching. The ethanol composition on the top of the feed column – unit 1 response used for training is shown in Figure 2.

The results of neuro–fuzzy control without time delay for the feed column are shown in Figure 3.

The control results without time delay for the stripper column are shown in Figure 4.

The results of neuro–fuzzy control without time delay of the recovery column are shown in Figure 5.

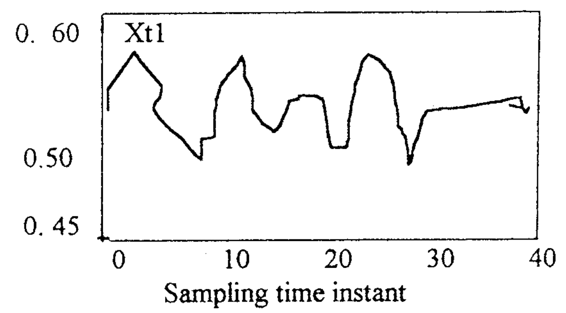

Figure 2. Dynamic response used for the training feed column–unit1

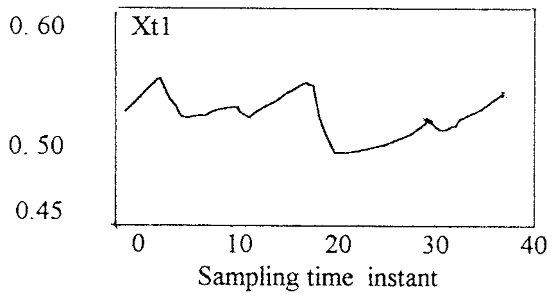

Figure 3. Neuro–fuzzy control without time delay of the feed column–unit 1

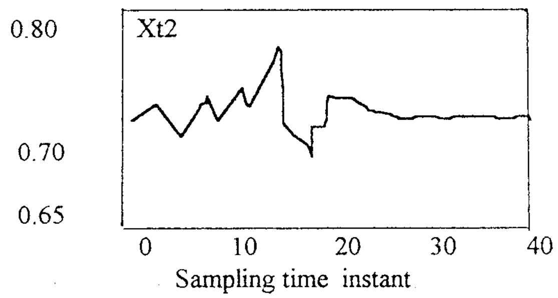

Figure 4. Neuro–fuzzy control without time delay of the stripper column–unit 2

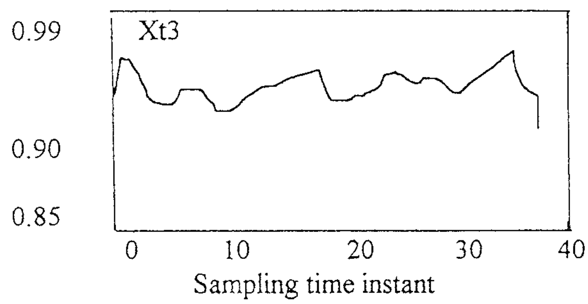

Figure 5. Neuro–fuzzy control without time delay of the recovery column–unit 3

The obtained results show that the recovery column gives the best control performance.

CONCLUSION

A new neuro–fuzzy system model was derived and applied to non–linear control dynamic. Non–linear dynamic relationship requires non–linear properties in the control realized by hidden nodes with a non–linear activation function in the neural network. A fuzzy set makes an image recognition, error correction and pattern matching. Fuzzy logic reduces the size of the neural network. The neuro–fuzzy system integrates qualitative and quantitative information in modeling and control of the distillation plant. Non–stationary characteristics of the process are handled by feeding information on the state variables. Fuzzy logic and neural net systems are very suitable for a precise model and on line modeling possibilities.

NOTATION

B – bottoms flow rate, mole/h
D – distillate flow rate, mole/h
d – desired output
E – minimization error
F – feed flow rate, mole/h
L – reflux flow rate, mole/h
J – control minimization function
m – mean value
p – pattern
s – standard deviation
u – manipulated variables
w – weight
x – input
X – ethanol composition
y – calculated output

Subscript

f – fuzzy
nn – neural network

Greek Symbols

θ – threshold
μ – fuzzy membership

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IZVOD

MODELOVANJE NEURONSKO–FAZI SISTEMA I PRIMENA NA UPRAVLJANJE JEDNOG DESTILACIONOG POSTROJENJA

(Naučni rad)

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Teorija fazi skupova i neuronskih mreža primenjena je na ispitivanje dinamike jednog destilacionog postrojenja za prečišćavanje etanola, koje se sastoji od tri kolone. U cilju predviđanja stanja pri radu fazi regulatora uvedena je neuronska mreža da emulira ponašanje sistema na bazi ulazno/izlaznih podataka. Neuronska mreža se obučava pomoću algoritma opšteg delta pravila minimizirajući sumu kvadrata odstupanja. Iterativni ciklus je primenjen na nelinerane relacije između sastava produkata, refluksnih protoka i sastava napojnih smeša. Fazi model redukuje dimenzije neuronske mreže zahtevajući rangiranje detektovanih karakteristika. Fazi logički algoritam generira produkciona pravila koja aktiviraju odgovarajuće klase neuronskih mreža. Razvijeni neuronsko–fazi model primenjen je na multivarijabilno upravljanje destilacionog procesa za izdvajanje etanola, posle fermentacije kukuruznog skroba. Dobijeni rezultati u ovom radu pokazuju da su neurosko–fazi sistemi efikasniji u regulaciji i upravljanju procesa nego samo neuronski ili samo fazi sistemi.

Ključne reči: Modelovanje neuronsko–fazi sistema • neuronsko–fazi umrežavanje • dinamička simulacija • neuronsko–fazi upravljanje •
Key words: Neuro–fuzzy system • modeling neuro–fuzzy features • neuro–fuzzy networking • dynamic simulation • neuro–fuzzy control •