A neuro-fuzzy artificial intelligence system

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Abstract.- The theory of fuzzy sets and neural networks was aplied to non-linear process dynamics. In order to perform to state prediction necessary for the neuro- fuzzy logic controller, a neural net was trained to emulate the behavior of the system based on input/output data. Fuzzy model reduces size of the neural network requiring rank to features detected. Fuzzy logic algorithm is generated using production rules for processing corresponding neural network. The algorithm of the generalized delta rule was used to train the neural network minimizimg the sum of squares of the residual. As a case study multivariable control of the etanol recovery plant was used.

Keywords: Control, processing, fuzzy, neural network, model, algorithm.

1 Introduction

The decision problems are nearly all concerened with the situation common in scientific inference where the prior distribution is dominated by the likelihood.

There have been several attempts to implement fuzzy logic through neural networks. Neuro-fuzzy system find increasing application in process modeling, control and in the area of identification [1]-[5].

Fuzzy logic is a combination of multivalue logic probability theory and artificial intelligence[6],[7]. Neural network have been used in a number of problems for dynamic and control processes [8]-[9]. Neural nets are useful as modules in a large system interacting with fuzzy logic generic algorithm. The careful combination of techniques produce the most useful robust systems.

In this work neuro-fuzzy system for control and optimization an ethanol recovery distillation plant were examined. The aim of this paper is an integrated neuro-fuzzy system building for reflux flow and product composition control and improving noise handling.

2 A neuro-fuzzy model

In this model fuzzy logic incorporates the imprecision inherent, incuding human reasoning by allowing linguistic variables classification such as LOW, HIGH AND, and neural network trains to predict the fuzzy output.

A variety of shapesis possible for the membership function, with triangle and trapezoid being the most popular. Fuzzy system operates by testing variables with IF-THEN rules which produce appropriate responses (Fig.1 and Fig.2). 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 probability that a given number is considered to be included in a particular set. The membership functions for this study were used in the form:

$$\mu_{A_i}(x,m,ex) = \exp-[(|x-m|)/s]^{ex} \qquad (1)$$

where m, s and m, ex 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:

$$Y_j^P = \sum_i \mu_{A_i}(x_j)w_{ij} - \theta_j \qquad (2)$$

where w is the weight and can be a positive or negative real number, θ is the threshold of the jth neuron and p means

pth pattern. The $f(x)$ is a nonlinear function of activation that is in the hyperbolic tangent form initialy the

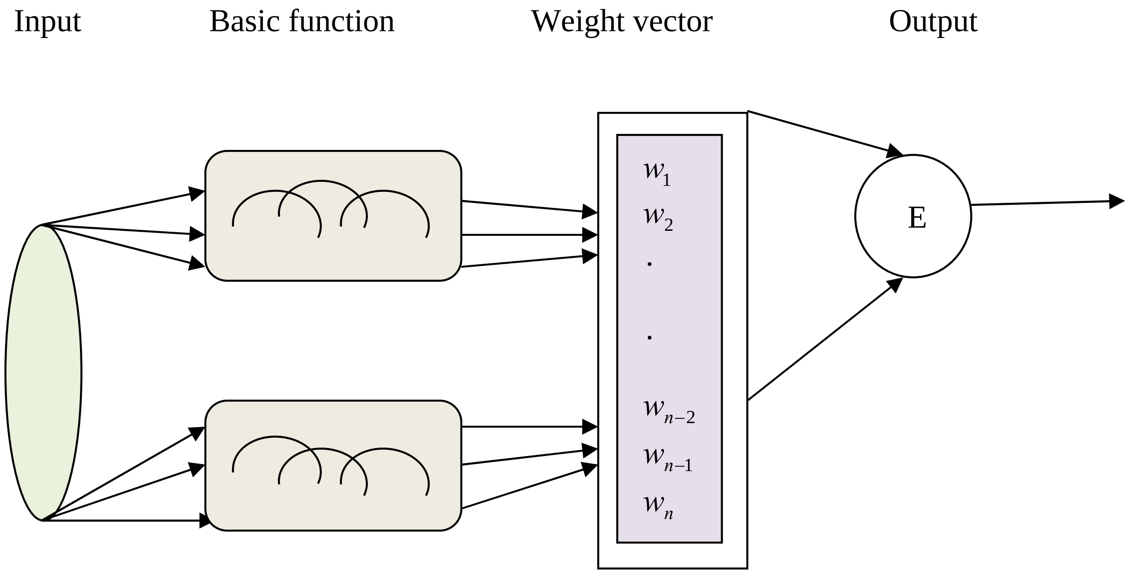

Fig. 1 Neuro-fuzzy unit

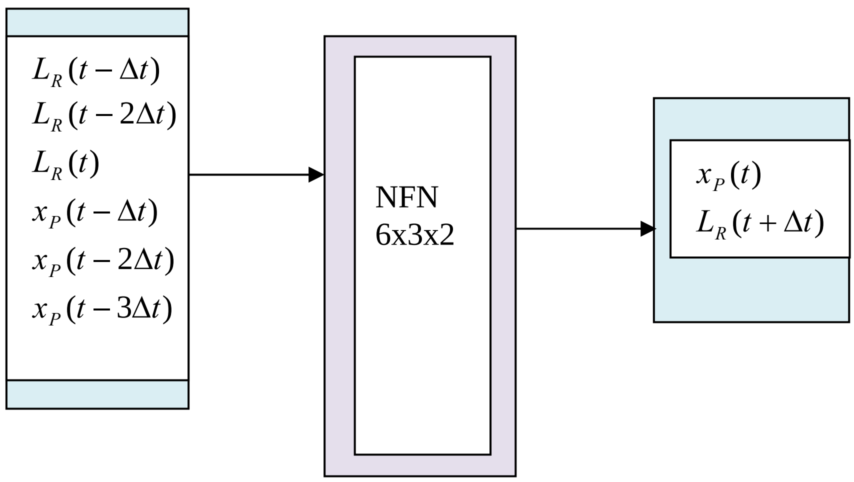

Fig.2 NFN input/output

network is trained to predict the fuzzy output variables.

3 The algorithm

The neuro-fuzzy algorithm has to learn the data set [x(t), y_{des} $]_{i=t}^{l}$ 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 pth pattern is y^{NFN} and the neurl network-NN is trained by minimizing the error:

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

Minimizing the sum squares of errors in eq. (3) is performed by the gradient descant method, gradient descent residual-GDR, algorithm.

Fuzzy logic algorithm is generating using producion rules. The construction of rules and formation of the expertise is based on the fuzzy input/output variables.

The construction generic neuro-fuzzy algorithm-NFG(Fig.3) is a suitable tool for rigorous on line modelling. Neuro-fuzzy network dynamic learning model NFN(6 x 3 x 2) is used for training data base.

These systems can applied for dynamic system on line optimization.

Gaussian random signals added to the scaled measurements. Past and present values of inputs as well as future output values make signals in the network at each level.

4 Neuro-fuzzy modelling and control

Neuro-fuzzy network –NFN for control system involves determining the inverse process control. One could switch the futures outputs with future inputs and develop an inverse control model.

A standard fuzzy logic system utilizes the logical functions AND, OR, IF....THEN. The function operators LOW, HIGH and MEDIUM are used.

Step 1: Input fuzzy variables
Step 2: Assign all neuron thresholds to small random values θ_j .
Step3: Assign all weights to small random values w_{ji}^{p} .
Step 4: Repeat
for $p=1$ to TP (TP is total number of training patterns)
for $j=1$ to n_2 (n_2 is the number of neurons in the hidden layer)
calculate neuron outputs in the hidden layer y_j
endfor
for $k=1$ to n_3 (n_3 is the number of neurons in the output layer)
calculate neuron outputs in the output layer y_k
calculate

$$\delta_k^P = (d_i^P - y_i^P)\sum w_{ji}^P\ y_{i-1}^P + w_{ji}^P\ )$$

adapt θ_k : $\theta_k^P = \theta_k^{(P-1)} + \Delta\theta_{jk}^P$
endfor
for $j=1$ to n_2 and $k=1$ to n_3
adapt w_{jk} : $w_{jk}^P = w_{jk}^{(P-1)} + \Delta w_{jk}^P$
endfor
for $j=1$ to n_2
calculate

$$\delta_j^P = \sum w_{ji}^P y_{i-1}^P + w_{ji}^P\ \sum \delta_k^P w_{ji}^P$$

adapt $\theta_j : \theta_j^P = \theta_j^{(P-1)} + \Delta\theta_{jL}^P$
endfor
for $i=1$ to n_1 and $j=1$ to n_3 (n_1 is the number of neurons in the input layer)
adapt w_{ji} : $w_{ij}^P = w_{ij}^{(P-1)} + \Delta w_{ij}^P$
endfor
endfor
until $\Delta w_{ji} < \varepsilon$ (ε is the convergence criterion)

Fig. 3 The back propagation algorithm

A fuzzy control variables were genereted using production rules and formulation of the expertise is based on fuzzy input and output:

$$IF(x_i in = Ii) \;\; AND \; (x_j out = Ij) \;\; THEN \; (x_k out = Ik) \quad (4)$$

where I an external input.

Neural network serve as a simulator trained from observed behavior of the process. The learning phase computational function of the neural network has the form:

$$u(k) = f[y(k+1), y(k), y(k-n+1); u(k-n+1)] \quad (5)$$

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

$$u(k) = f[s(k+1), y(k), y(k-n+1)); u(k-n+1)] \quad (6)$$

Minimization control function is:

$$Min \;\; J = \sum [y_{NFN}(k+1) - s(k+1)]^2 + [u(k) - u(k-1)]^2 \quad (7)$$

This approach utilize inverse control model of the distillation process. Reflux flow rate, $u(k)$, is manipulated variable, top product composition, $y(k)$, is controlled variable and $s(k+1)$ is desired set point value. Neuro-fuzzy controller design law was established by eqs.(4)-(7).

5 A case study

In order to analyze to training and learning of neural-fuzzy system for the process control, in distillation. The ethanol recovery plant from three distillation column, three process units, was examined.

The main state variables characterizing of the process separation are the feed flow rate , L_F, ethanol composition in the feed, x_F, product ethanol composition at the top, x_P, product flow rate, L_P, reflux flow rate , L_R, bottom flow rate, L_B, bottom ethanol composition, x_B, and pressure drop ΔP. The sudied state parameters for examined process units are given in Table 1.

Table 1.The steady state operation parameters

	Unit1	Unit2	Unit3
Feed flow rate, mol/h	50552	12735	33808
Product flow rate at the top, mol/h	420	381	384
Bottom flow rate, mol/h	40348	5415	33664
Internal reflux flow rate, mol/h	1280	-	1152
External reflux flow rate,mol/h	33991	-	33808
Feed ethanol composition, mol/mol	0.034	-	-
Ethanol composition at the top, mol/mol	0.515	0.715	0.945
Pressure drop,bar	1.0	1.2	1.7

Nonliner dynamic relatioship between composition top product and chosen as:

$$L_R(t) = f[L_R(t-\Delta t), x_{P3}(t), x_{P3}(t+\Delta t), x_{P3}(t+2\Delta t), x_{P3}(t+3\Delta t), x_{P3}(t+4\Delta t) \quad (8)$$

The manipulated variables $L(m), m = k$ to $k + m$, after M time steps are held constant. The input of the networks has the values of the state variables and manipulated variable. The desired output has the values of must be able to compute input to apply to the process from the knowledge of its current state and desired future state. A computer program has written in Basic programming language. The design methodology relies on the ability of the NFN to work input information that differs by nature between the learning phase and control phase.

6 Results and discussion

The obtained results of neuro- fuzzy system learning and control are shown in Fig.4 to Fig.7. Neural-fuzzy dynamic learning models use a learning data base. A training data base the 2% Gaussian signal added to the scaled variable values is used. The steady state values of ethanol composition in the final product is 94.50% and sample time is 60s. The product composition at the top of the column- unit3 used for training and response has shown in Fig.4.

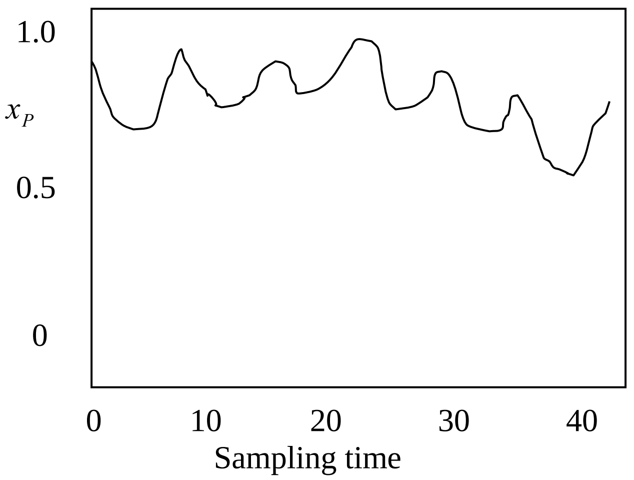

Fig.4 Dynamic response unit3 for the product composition at the top used for training

The neural fuzzy control based on the process inverse dynamic model was used past and present values of the product composition at the top and reflux flow rate to feed the network and future product compositions in output of the network NFN (6x3x2). Nonlinear dynamic relationship requires nonlinear properties in the control realized by hidden nodes with nonlinear activation function in the network.

Fuzzy subsystem makes an image recognition and pattern matching.The product composition at the top unit3 response was used for training. Also, the product composition for unit2 was used for training.

Thr result of the neuro-fuzzy control for unit3 are shown in Fig.5. to Fig.7.

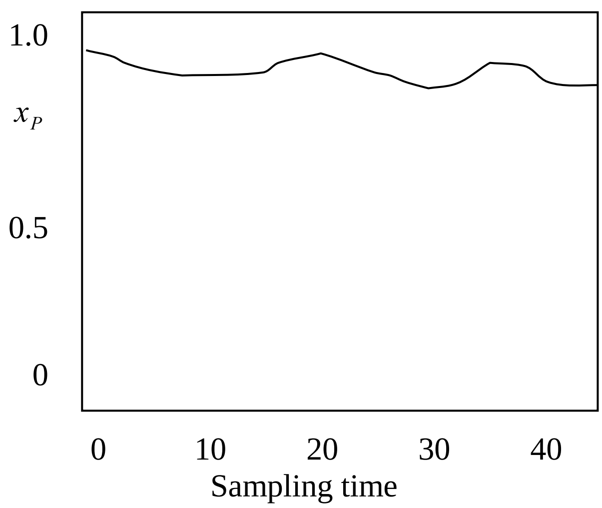

Fig.5 Neuro-fuzzy control for the product composition at the top for unit3

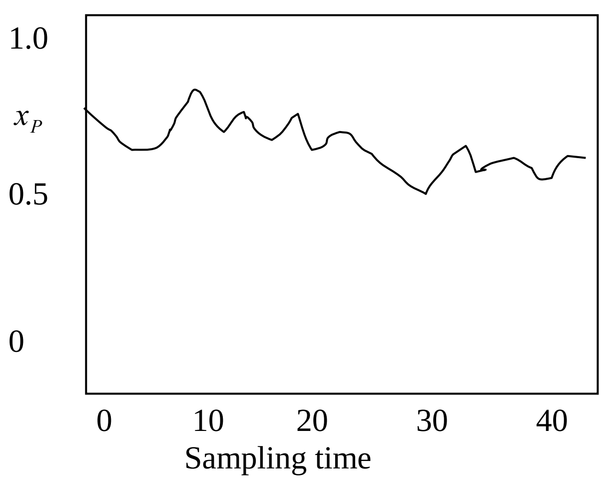

Fig. 6 Neuro- fuzzy control for the product composition at the top unit2

The control results for expected $x_P(t) - x_P(t - \Delta t)$ in addition $x_P(t + \Delta t) - x_P(t)$ and $x_P(t + n\Delta t)$, $n = 1,...4$ as well as one state variables showed the good control performance.

The error un the controlled variable were of the size for different alternative of input state variables but in any case oscillation occured in the control signal. The neuro-fuzzy softver controller must be able to compute input to apply to the proces from the knowledge of the current state and desired future state.

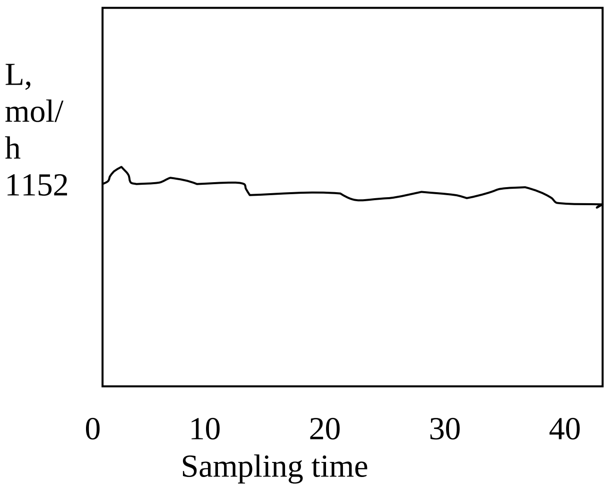

Fig.7 Neuro-fuzzy control of the relux flow for rate at the unit3

Conclusion

In this paper neuro-fuzzy system as computaional cell, trains to emulate the behaior of the system based on input/output data. Nonlinear dynamic relationship requires nonlinear properties in the control realized by hidden nodes with nonlinear activation function in the neural network. Fuzzy set makes an image recognition, error correction and pattern matching. Fuzzy logic and neural network work system have shown very suitable for on-line modelling possibilities.

References

[1] Savkovic Stevanovic J.,A fuzzy- neural network pH controller, *10th International Conference on Mathematical and Computers Modeling and Scientific Computing*, Boston, July 2-8,1995.

[2]C.J. Harris, M. Brown, K.M. Brossley, D.J. Mills, and Feng Ming, Advances in neuro-fuzzy algorithm for real-time modeling and control, *Engng. Applic. Artif. Intell.***9**,1-16, 1996.

[3]J. Savkovic Stevanovic J., S. Prodanovic, Neural-fuzzy controller for a distillation plant, ECCE1-European Congress of Chemical Engineering, Florence, Italy, May 4-7, p.670, 1997.

[4] J. Savkovic Stevanovic, Neuro-fuzzy system modeling and control application for a distillation plant, *Chem. Ind.* Beograd, **54** (9) 2000.

[5] J.Savkovic Stevanovic, Neuro-fuzzy systems development: Modeling and Simulation, *International Journal of Intelligent Games&Simulation*, **3**, 2004.

[6] J.Savkovic Stevanovic, A neural-fuzzy system for ethanol recovery distillation control, Bull.Chemist. Technol. Macedonia,**24**,127,2005.

[7]J. J.Savkovic Stevanovic,Higher order multilevel fuzzy logic controller, *Chemical and Biochemical Engineering,***18**, 345, 2004

[8]K.Klawonn, R. Kruse, Fuzzy set and system, 8,177, 1997.

[8] J.Savkovic Stevanovic, Neural network model for analysis and optimization of processes , *Comput.Chem.Engng.***17**, 411, 1993.

[9] J.Savkovic Stevanovic, Neural network controller by inverse modeling a distillation plant, *Comput.Chem.Engng.,***20**, 925, 1996.