Structured Logic Processors Based Self Learning Fuzzy Neural Network

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Abstract: -This paper presents a new and simple fuzzy neural network based on structured fuzzy logic processors. The modifications of the referential fuzzy logic processors provide the equality index. The major advantage of the proposed network is that the learning process is faster and it has the capability of self -determining the relative cardinality. The fast learning is due to incorporating the receptive field injector, which injects the self -learning excitation level. The proposed network has the capability of controlling a nonlinear and uncertain plant even if it is subjected to sever unmeasured disturbances .The simulation was done using Borland C++, version 4.5,and the plant has been simulated as a template.

Key Words: -Fuzzy logic processors; Neural networks; Relative cardinality; Receptive field.

1 Introduction

Unlike the approach which has been introduced in recent literature, namely; the fuzzy neural network, a different and novel approach is proposed in this paper. The designed network is as a result of integrating three theories: possibility theory, fuzzy set theory, and artificial neural network theory.

The motivation behind this effort is to design a fuzzy neural network directly in the frame of fuzzy relational systems [1] [2] [3] has the capability of coping with the difficulties of relational matrix computations.

Mamdani E.H. [4] has introduced knowledge-based systems depending on fuzzy relational equations .The fuzzy relational matrix is based on the fuzzy knowledge using some logical operators. For a given input, the output is deduced using Zadeh's compositional rule of inference [5].

Some researchers, for instance Yager R.R.and his associates[6] have performed some developments of Mamdani's knowledge based systems. It should be noted that the proposed architectures still depend on fuzzy relational knowledge and the qualitative knowledge affects the system performance. Moreover, the architectures do not have the neural learning capabilities.

The researchers in [7] [8] have proposed solutions of the fuzzy relational equations. The proposed techniques for finding solutions of the fuzzy relational systems are not beneficial for real world situations due to the complexity of computations and the difficulties of finding relational equations for all pairs of fuzzy input and output data simultaneously. This is due to the presence of vagueness and uncertainty in the system.

The research in [9] has suggested three layer neural logical processing network for coping with some of difficulties stated above concerning the issue of the fuzzy relational structure and performing the nonlinear mapping. It is worth noting that this network still suffers from the problems of the feed forward neural networks. This issue is of critical importance for achieving the fitness phenomenon.

The effort which has been done has three objectives: The first objective is to overcome the previously mentioned difficulties in the traditional systems and design a novel more generalized self learning fuzzy neural network based on the multidimensional structured possibilistic scheme using modified inferential fuzzy neurons.

The second objective is the enhancement of the capability of carrying out the mapping under high degree of uncertainty conditions as fast as possible with an effective and efficient learning mechanism.

The third objective is to control a nonlinear dynamical plant using the proposed possibilistic fuzzy neural network.

2 Modifications of referential fuzzy logic processors: Multi-dimensional referential fuzzy logic processors providing modified equality index:

In this section we discuss a new type of referential neuron known as the multidimensional referential fuzzy neuron.

Definition 1:

We introduce a new type of referential neurons called referential fuzzy neuron which provides an equality index having a value iff $\left|\vec{x}-\vec{r}\right| \le \beta$ and having zero-value iff $\left|\vec{x}-\vec{r}\right| > \beta$ where β is the neuronal bandwidth.

This equality index in a readable form is provided by:

$$m_i = (x_i \equiv r_i) = \begin{cases} 1 + x_i - r_i & iff(r_i > x_i) \\ 1 - x_i - r_i & iff(r_i < x_i) \\ 1 & iff(r_i = x_i) \\ 0 & iff(\vec{x}-\vec{r}) > \beta \end{cases}$$

$$\forall 1 \le i \le n \;, r_i \in [0,1] \;, x_i \in [0,1]$$

Whereβ is the neuronal bandwidth. (1)

Observation 1:

The above definition is viewed as an adaptive version of Lukasiewicz implication $x_i \to r_i$ = *min (1, 1 +* r_i - x_i*)*.

Adaptation of the above definition is carried out by manipulating M, X, and R as fuzzy sets defined in the unit interval [0, 1]. By using the extension principle we can obtain a normalized measure N as,

$$N = \frac{1}{n}\sum_{i=1}^{n} \sup_{(r_i,x_i):U_i \to [0,1]} \left(\mu_R(r_i)\; t\, \mu_X(x_i)\right)$$

$$\forall 1 \le i \le n \quad , \quad N \in [0,1]$$

where t is the t-norm. (2)

Observation 2:

If the elements r_i (1 ≤ i ≤ n) of the reference fuzzy set R is exactly coincide with the centroid of the referential fuzzy neuron, then equation (2) is modified as,

$$N = \frac{1}{n}\sum_{i=1}^{n} \sup_{x_i:U_i \to [0,1]} \mu_X(x_i) \qquad (3)$$

$$N \in [0,1]$$

With the definition (1) and the observation (1), we introduce a new equality index based on a strong logical background.

W. pedrycz [9] has introduced an equality index (I) given by

$$I = 0.5\left[(x \to r) \wedge (r \to x) + (\bar{x} \to \bar{r}) \wedge (\bar{r} \to \bar{x})\right]$$

$$\bar{x} = 1 - x,$$

"∧" is the logical minimum operator.

Thus, the normalized equality index in more general form is given by:

$$N = z \;\; t \left\{ \mathop{S}_{i=1}^{n}\left[\left(\mu_X(x_i) \to \mu_R(r_i)\right) \; t \; \left(\mu_R(r_i) \to \mu_X(x_i)\right) + \left(\bar{\mu}_X(x_i) \to \bar{\mu}_R(r_i)\right) \; t \; \left(\bar{\mu}_R(r_i) \to \bar{\mu}_X(x_i)\right)\right]\right\} \qquad (4)$$

where *N* ∈ *[0, 1]*, S is an aggregative type of operation, $z = \frac{1}{2n}$

3 Proposed architecture of self-learning fuzzy logic neural network

In this section, we will discuss the different modules of the proposed self-learning fuzzy logic neural network based on structured fuzzy logic processors (FLP_s).The architecture is shown figure 1.

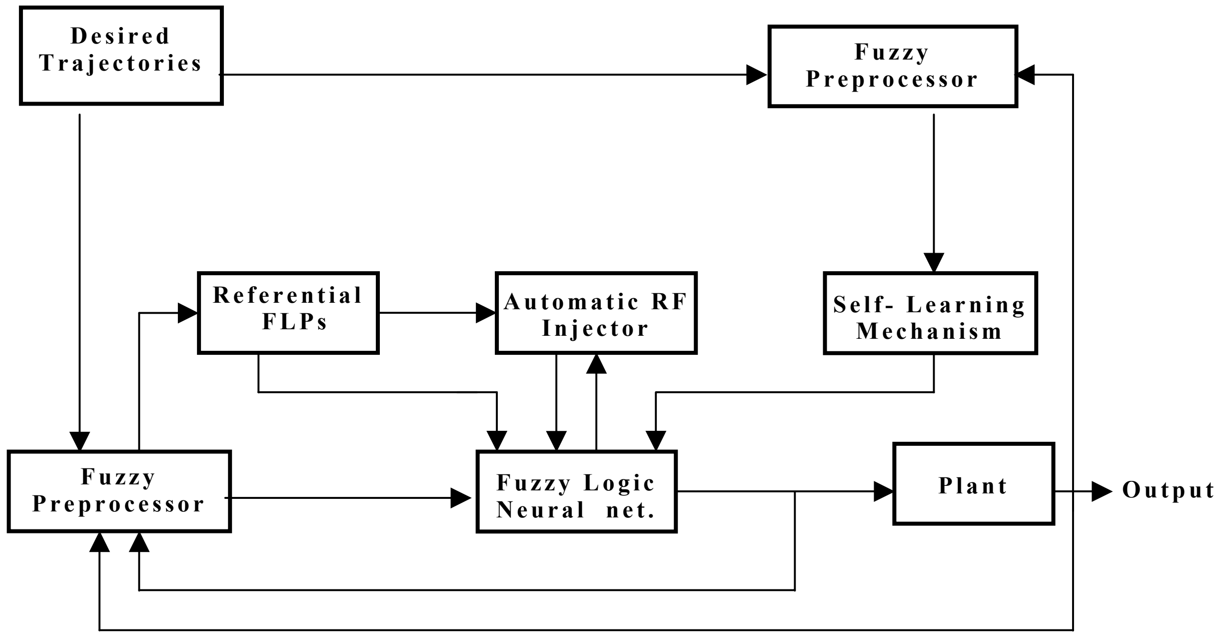

Fig. 1 Architecture of self- learning fuzzy logic neural network controller.

Fuzzy preprocessor:
The 1 × n dimensional preprocessor, with 1 < n, includes delay units in its structure. The inputs of the preprocessor are $\vec{X}_d(k)$, $\vec{X}(k)$, and $\vec{U}(k)$,
where $\vec{X}(k)$ is the actual output vector , $\vec{X}_d(k)$ is the desired system trajectories and $\vec{U}(k)$ is the control input vector .The output of the preprocessor $\vec{V} \in [0,1]^n$ is fed to the multidimensional referential fuzzy neurons $(\vec{\beta},\vec{c})$ where $\vec{\beta}$ is the neuronal bandwidth vector and $\vec{c}$ is the neural controid.

Multidimensional referential fuzzy neurons:
The input vectors,

$$\vec{X}_j \equiv \vec{V}_j \quad (1 \le j \le T) \quad \in [0,1]^n$$

are first processed with respect to a multi-dimensional referential fuzzy neuron $\vec{r} = [r_1, r_2, ..., r_n] \in [0,1]^n$. The induced possibilistic distributions are aggregated using AND or OR fuzzy logical neurons as a multidimensional fuzzy logic processors.

Automatic RF injector:
The automatic receptive field (RF) injector injects the self-learning excitation level vector $\vec{\varepsilon}^{\,l}_{i_1,...,i_n}$ into the localized neuronal field to achieve good fitness and smoothness phenomena and to solve the problems of feed-forward neural networks.

Process:
Consider the process described by the general nonlinear equations:

$$\dot{\vec{X}} = F(\vec{X},\vec{U})$$
$$\vec{Y} = C\vec{X}$$

Where $\vec{X} \in U \subset R^n$ is the state vector, $\vec{U} \in V \subset R^m$ is the input control vector, $\vec{Y} \in R^p$ is the output vector, C is m × n matrix and F is the function vector.

4 Design of a structured fuzzy logic processors based self-learning fuzzy neural network

In this section, we will discuss the design procedures of the multidimensional structured fuzzy logic processors based self-learning fuzzy logic neural network.

Step 1:

Let the fuzzy input vector,

$\vec{X}_j = \left[x_{j_1}, x_{j_2}, \ldots x_{j_n}\right]^T \in [0,1]^n, 1 \le j \le N,$

be applied at the input layer of the proposed inferential network and let $n_k^r \left(1 \le k \le L_n\right)$, where L_n is the total number of the receptive field units, be the inferential fuzzy neuron having the inferential point

$\vec{R} = \left[r_1 r_2, \ldots, r_n\right]^T \in [0,1]^n$.

The normalized equality measure vector

$\vec{N} = \left[N_1, N_2, \ldots, N_{L_n}\right]^T$ and

$N_k = \left(X_i \equiv R_i\right) \quad \left(1 \le k \le L_n ; 1 \le i \le n\right)$

Where X_i and R_i are fuzzy subsets of the input space R^n, *i.e.*, X_i, $Ri \subset R^n$

a. $$y^k = \begin{cases} c^k & \text{iff} \quad N_k \ge \varepsilon_k \\ 0 & \text{otherwise} \end{cases} \qquad (5)$$

$$\forall 1 \le k \le L_n$$

Where y^k is the kth output of the localized receptive field unit.

b. The centroidal vector of the effective receptive field is modified by

$$\vec{c}_k(t) = \frac{\tau - 1}{\tau} \vec{c}_k(t-1) + \frac{1}{\tau} \vec{X}_j(t) \qquad (6)$$

Where $1 \le k \le L_n$, and τ is the time constant of the system.

c. For created neuronal receptive, the new centroidal vector is given as :

$$\vec{c}_k = \vec{X}_j(t) \qquad (7)$$

Step 2:

The joint possibilistic distribution at the localized receptive field can be computed as

$$\mu_{X_i}(x_i) \ o \ \mu_{L_i}(l_i) = \sup_{x_i, l_i \in U_i \to [0,1]} \left(\mu_{X_i}(x_i) \ t \ \mu_{L_i}(l_i)\right)$$

Then, the effective characteristic function of the localized neuronal receptive field is given by:

$$c^k = \mathop{T}_{i=1}^{n} \left(\sup_{x_i, l_i \in U_i \to [0,1]} \left(\mu_{X_i}(x_i) \ t \mu_{L_i}(l_i)\right)\right) \qquad (8)$$

$$\forall \quad 1 \le k \le L_n$$

Step 3:

The power fuzzy sets of the reference output fuzzy neurons r^p $(1 \le p \le m)$ is computed as

$$r^p = \mathop{S}_{k=1}^{L_n} c^k \qquad \forall (1 \le p \le m)$$

Or the reference output characteristic functions of the reference output fuzzy neurons can be viewed as the relative cardinality i.e.

$$r^p = L_n^{-1} t \left(\mathop{S}_{k=1}^{L_n} c^k \right) \qquad \forall (1 \le p \le m) \qquad (9)$$

Step 4:

The field strength f_{kp} $(1 \le k \le L_n \ ; \ 1 \le p \le m)$ control the propagation of the localized receptive field c^k $(1 \le k \le L_n)$ to the pth reference output fuzzy neuron o^p $(1 \le p \le m)$.

Thus the effective characteristic function of the output fuzzy neuron o^p is given by:

$$o^p = \mathop{S}_{k=1}^{L_n} \left(f_{kp} \ \ t \ \ c^k \ t \ \ L_n^{-1} \ \ t \ \left(\mathop{S}_{k=1}^{L_n} c^k \right)\right)$$

$$= \mathop{S}_{k=1}^{L_n} \left(f_{kp} \ \ t \ \ c^k \ \ t \ \ r^p \right), \forall (1 \le p \le m)$$

The normalized output is given dividing o^p by d where ,

$$d = \mathop{S}_{k=1}^{L_n} \left(c^k \ t \ \ r^p \right) \qquad (10)$$

5 Simulation Studies:

The aim of the simulation studies is to test the ability of the self -learning fuzzy neural network based on structured fuzzy logic processors for achieving good performances. The proposed algorithm (steps 1-4) and with incorporating the self learning mechanism exhibit excellent performances, after the first learning epoch, in case of load changes. The simulations which are carried out in this work are to test the capability of the network to reject unmeasured disturbances for sever changes in feed flow rates. The chemical process to be controlled is shown in Fig.2 and it is described by the following nonlinear differential equations [10]:

$$\frac{dc_a}{dt} = \frac{q}{V}\left(c_{af}\right) - k_o c_a R$$

$$\frac{dT}{dt} = \frac{q}{V}\left(T_f - T\right) + \frac{\left(-\Delta H\right)k_o c_a}{\rho\ c_p} R$$

$$+ A$$

$$A = \frac{\rho_c c_{\rho c}}{\rho\ c_p V} q_c \left[1 - \exp\left(-\frac{hA}{q_c \rho_c c_{pc}}\right)\right]$$

$$\times \left(T_{cf} - T\right)$$

$$R = \ \exp\left(-\frac{E}{RT}\right)$$

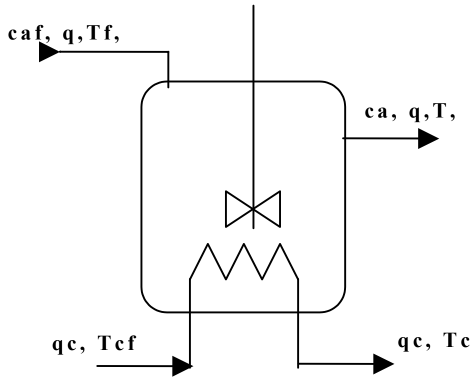

Fig. 2 The chemical plant

The nominal operating conditions of the chemical plant are given in Table1

5.1 Simulation Results:

Figures (3-6) show the capability of the designed network to reject +(-) 30%unmeasured disturbances in the feed flow rates. The disturbances are occurred at time t=8 min. After one min, the self-learning fuzzy neural network returns the controlled variable (ca) to its original value 0.084 mol/l.

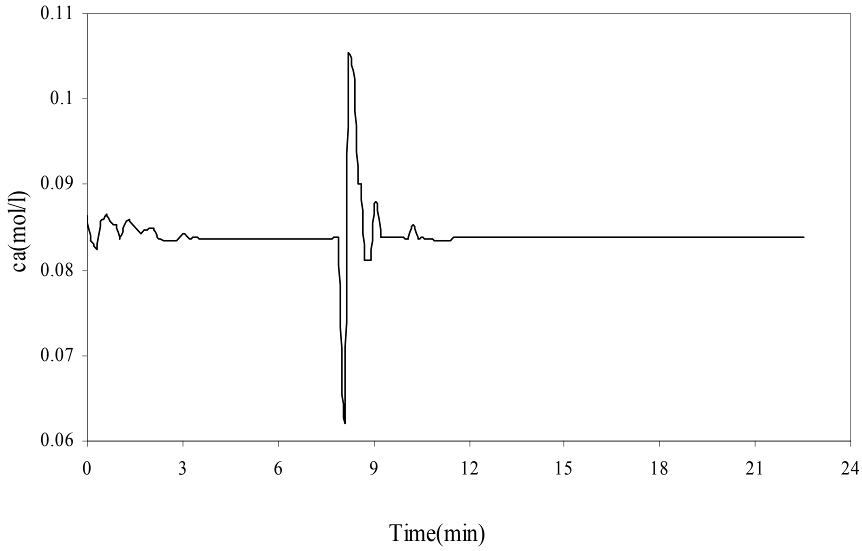

Fig.3 Disturbance rejection performance for -30% unmeasured disturbance in the feed flow rate

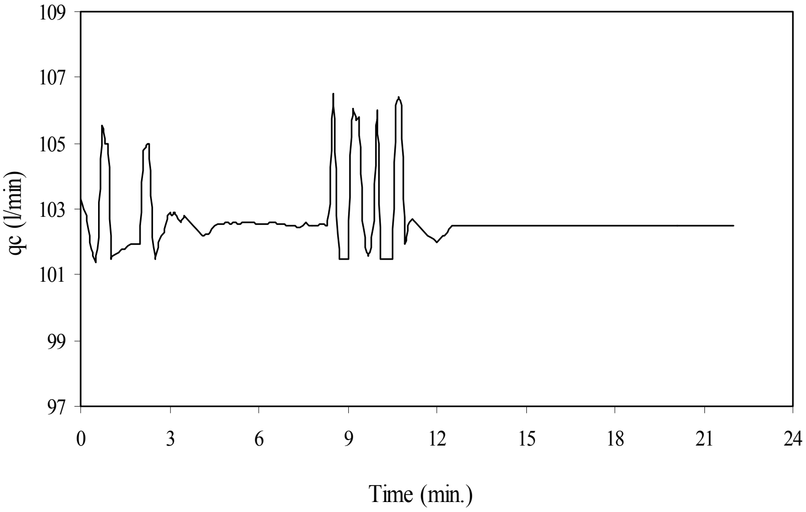

Fig.4 The coolant flow rate

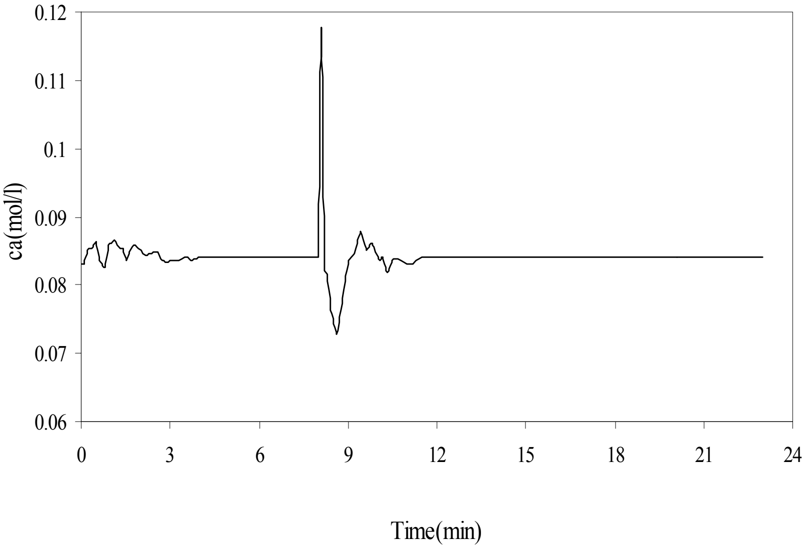

Fig. 5 Disturbance rejection performance for +30% unmeasured disturbance in the feed flow rate

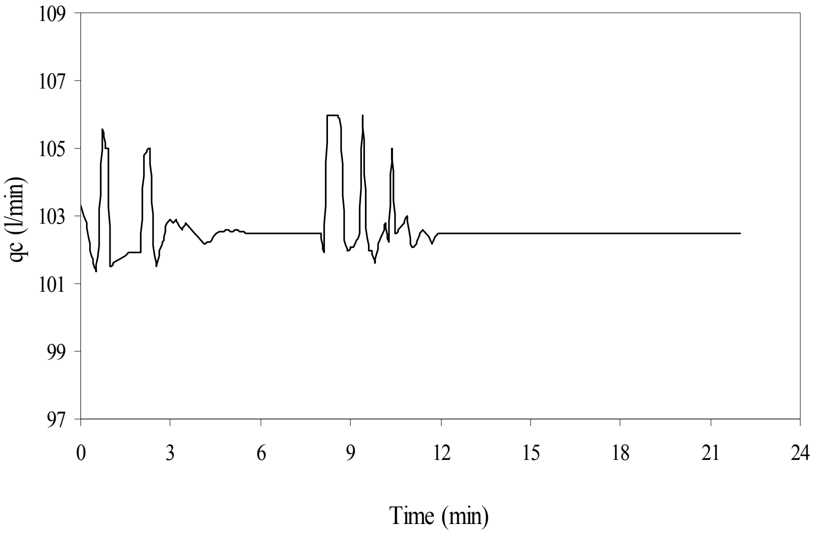

Fig. 6 The coolant flow rate

6 Conclusion:

The proposed self-learning fuzzy neural network based on structured fuzzy logic processors has the ability of fast learning the sign of the process after the first leaning epoch. Also, the network determines automatically the equality index .The simulation results prove that the designed network is capable of determining the actual relative cardinality .It proves good performances and the ability to reject unmeasured disturbances and keep tracking the set-points even with sever change in feed flow rates.

Nomenclature:

ca is the effluent concentration of the component a,
T is the process temperature,
q is the feed flow rate,
qc is the coolant flow rate,
E is activation energy,
cp. is heat capacity,
h is heat transfer coefficient,
ko is pre-exponential factor,
V is tank volume,
A is the area,
ΔH is the of the reaction.
ρ is density of reactor contents.

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