Intelligent Controller Design for a Chemical Process

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Abstract

Chemical process control is a challenging problem due to the strong on-line non-linearity and extreme sensitivity to disturbances of the process. Ziegler – Nichols tuned PI and PID controllers are found to provide poor performances for higher-order and non–linear systems. This paper presents an application of one-step-ahead fuzzy as well as ANFIS (adaptive-network-based fuzzy inference system) tuning scheme for an Continuous Stirred Tank Reactor CSTR process. The controller is designed based on a Mamdani type and Sugeno type fuzzy system constructed to model the dynamics of the process. The fuzzy system model can take advantage of both a priori linguistic human knowledge through parameter initialization, and process measurements through on- line parameter adjustment. The ANFIS, which is a fuzzy inference system, is implemented in the framework of adaptive networks. The proposed ANFIS can construct an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs. In this method, a novel approach based on tuning of fuzzy logic control as well as ANFIS for a CSTR process, capable of providing an optimal performance over the entire operating range of process are given. Here Fuzzy logic control as well as ANFIS for obtaining the optimal design of the CSTR process is explained. In this approach, the development of rule based and the formation of the membership function are evolved simultaneously. The performance of the algorithm in obtaining the optimal tuning values has been analyzed in CSTR process through computer simulation.

Keywords*:* Ziegler – Nichols tuning, Fuzzy Logic, ANFIS, CSTR Process.

1. INTRODUCTION

System Modeling based on conventional mathematical tools (e.g., differential equations) is not well suited for dealing with ill-defined and uncertain systems. In contrast, a fuzzy inference system employing fuzzy if-then rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analysis. Some basic aspects of this approach are discussed below.

1) No standard methods exist for transforming human knowledge or experience into the rule base and database of a fuzzy inference system.
2) There is a need for effective method for tuning the membership functions (MF's) so as to minimize the output error measure or maximize performance index.

The regulation and control of CSTR process is a typical problem found in a variety of industries including pharmaceuticals, biotechnology and chemical processing. Normally in process control laboratories, the processes are subjected to load disturbances. ANFIS as well as Fuzzy provide a good regulation against sudden changes and restore the desired process state within a shortest possible time. There are many methods for tuning PID controllers. Some of them are Ziegler-Nichols (ZN), Cohen and Coon (CC), Internal Model Control (IMC) and Performance criteria optimization (PCO). Ziegler-Nichols tuning [1] is one of the most widely used method to tune the PID controllers. Tuning the controller by Ziegler-Nichols method does not provide optimum system response since they are dependent on the exact mathematical model of a process. Cohen and Coon method [2] requires limited process knowledge but it offers low damping and high sensitivity to the system. Internal model control [3] is easy to shape sensitivity function but for unstable plants it cannot be applied. The adaptive learning algorithm of Universal Learning Network (ULN) represents the modeling and control of nonlinear black box systems with large time delay [4]. The main difficulty in control is due to the disturbances and parameter uncertainties. The fuzzy modeling or fuzzy identification, first explored systematically by Takagi and Sugeno [5], has found numerous practical applications in control, prediction and inference [6], [7]. Rest of the paper is organized as follows.

System description is given in Section 2. Section 3 introduces the basics of fuzzy inference system. Section 4 describes the structures and learning rules of adaptive networks. Simulation is given in Section 5. Simulation Results are shown in Section 6.Section 7 concludes this paper with some extensions of this work.

2. SYSTEM DESCRIPTION

A chemical system common to many chemical processing plants, known as a continuous stirred tank reactor (CSTR), was utilised as a suitable test for, TSK Fuzzy control, ANFIS control and PID control. It suffices to know that within the CSTR two chemicals are mixed, and react to produce a product compound with concentration Ca(t). The temperature of the mixture is $\vartheta(t)$ .A schematic representation of the system is shown in Fig. 1.The reaction is exothermic, producing heat which acts to slow the reaction down. By introducing a coolant flow rate qc(t), the temperature can be varied and hence the product concentration controlled. This system can be described by the following nonlinear simultaneous differential equations1 which effectively combine the laws of chemical reaction and thermodynamics:

$$\dot{C}a(t) = Q(Ca0 - Ca(t))/V - k0Ca(t)e{-}E/R\vartheta(t) \quad \ldots\ldots(1)$$

$$\dot{\vartheta}(t) = Q(\vartheta 0 - \vartheta(t))/V + k1Ca(t)e{-}E/R\vartheta(t) + k2qc(t)\,(1 - e{-}k3/qc\,(t))\,(\vartheta c0 - \vartheta(t)) \ldots\ldots (2)$$

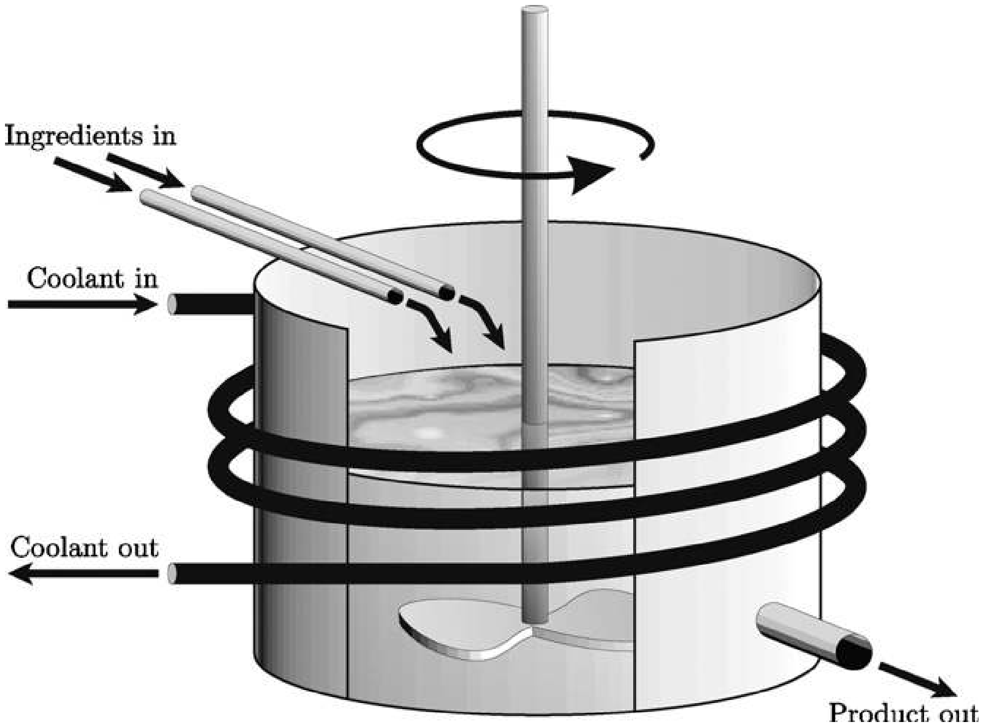

FIGURE 1: CSTR process

Parameter	Description	Nominal value
Q	Process flow rate	100 l/min
V	Reactor volume	100 l
k0	Reaction rate constant	7.2 × 1010 1/min
E/R	Activation energy	1 × 104 K
ϑ0	Feed temperature	350K
ϑC0	Inlet coolant temperature	350K
ΔH	Heat of reaction	−2 × 105 cal/mol
Cp, Cpc	Specific heats	1 cal/gK
ρ,ρc	Liquid densities	1 × 103 g/l
Ca0	Inlet feed concentration	1mol/l
ha	Heat transfer coefficient	7 × 105 cal

TABLE 1: The CSTR parameters

Consider the flow rate qc(t) as the input and product concentration Ca(t) as the output of the system. As seen from Fig. 2, the gain and damping of the system vary widely over the whole operating region, from 0.08 mol/l to 0.13 mol/l.

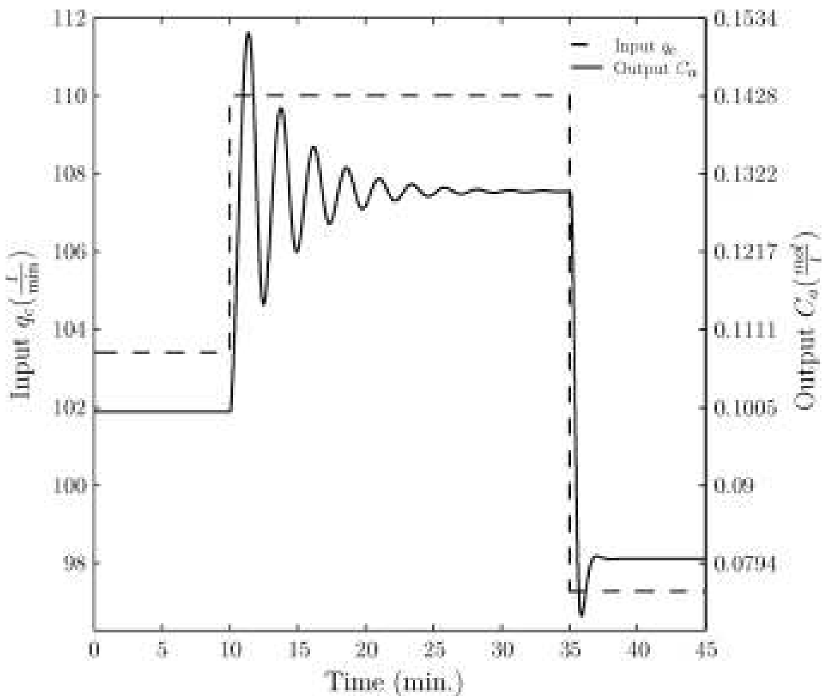

FIGURE 2: Open-loop step response of the CSTR

3. FUZZY INFERENCE SYSTEM

Fuzzy inference systems are also known as fuzzy-rule-based systems, fuzzy models, fuzzy associative memories (FAM).It is also known as fuzzy controllers when used as controllers. Basically a fuzzy inference system is composed of five functional blocks.

- a rule base containing a number of fuzzy if-then rules.
- a database which defines the membership functions of the fuzzy sets used in fuzzy rules.
- a decision-making unit which performs the inference operation of the rules.
- a fuzzification interface which transforms the crisp inputs into degrees of match of the linguistic variables.
- a defuzzification interface which transforms the fuzzy results of the interface into crisp output. Usually, the rule base and the database are jointly referred to as the knowledge base.

The overall output is the weighted average of each rule's crisp output induced by the rule's firing strength (the product or minimum of the degrees of match with the premise part) and output membership functions. The output membership functions used in this scheme must be monotonic functions [8]. The overall fuzzy output is derived by applying "max" operation to the qualified fuzzy outputs (each of which is equal to the minimum of firing strength and the output membership function of each rule). Various schemes have been proposed to choose the final crisp output based on the overall fuzzy output; some of them are centroid of area, bisector of area, mean of maxima, maximum criterion, etc [9],[10].

4. ADAPTIVE NETWORKS: ARCHITECTURES AND LEARNING ALGORITHM

This section introduces the architecture and learning procedure of the adaptive network which is in fact a superset of all kinds of feed forward neural networks with supervised learning capability. The basic learning rule of adaptive networks is based on the gradient descent and the chain rule, which was proposed by Werbos [11] in the 1970's. However, due to the state of artificial neural network research at that time, Werbos' early work failed to receive it's desired attention .

4.1 Architecture and Basic Learning Rule

An adaptive network is a multilayer feed forward network in which each node performs a particular function (node function) on incoming signals as well as a set of parameters pertaining to this node. The formulas for the node functions may vary from node to node, and the choice of each node function depends on the overall input-output function which the adaptive network is required to carry out. Note that the links in an adaptive network only indicate the flow direction of signals between nodes; no weights are associated with the links.

4.2 ANFIS: Adaptive-Network-based Fuzzy Inference System.

Functionally, there are almost no constraints on the node functions of an adaptive network except piecewise differentiability. Structurally, the only limitation of network configuration is that it should be of feed forward type. Due to these minimal restrictions, the adaptive network's applications are immediate and immense in various areas. We propose a class of adaptive networks which are functionally equivalent to fuzzy inference systems.

4.2.1. ANFIS Architecture

For simplicity, we assume the fuzzy inference system under consideration has two inputs x and y and one output z.

Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugeno's type [8].
Rule 1: If x is A_1 and y is B_1, then $f1 = p_l x + q_1 y + r_1$ (3)
Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$ (4)

Then the fuzzy reasoning is illustrated in Fig. 3 and the corresponding equivalent ANFIS architecture is shown in Fig. 4

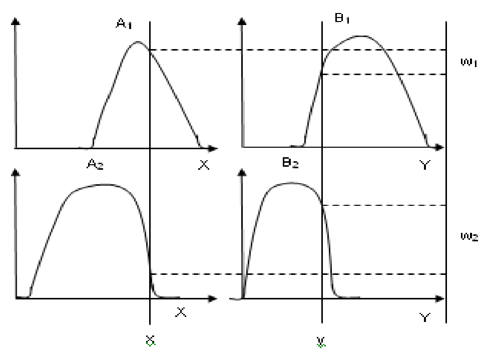

FIGURE 3: Fuzzy Reasoning

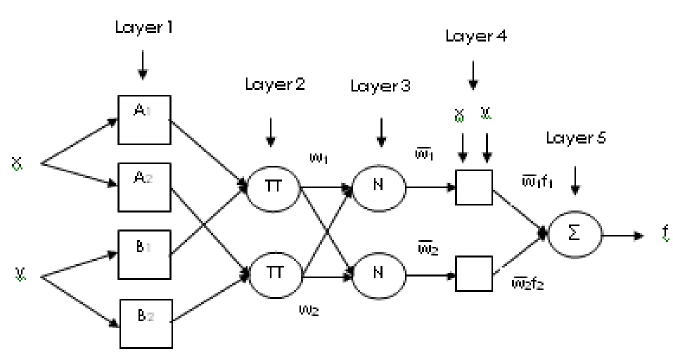

FIGURE4. Equivalent ANFIS

The node functions in the same layer are of the same function family as described in [12], [13].

Layer 1: Every node i in this layer is a square node with a node function:

$O_{1,i} = \mu A_i(x)$ for i = 1,2 or (5)
$O_{1,i} = \mu B_{i-2}(y)$ for i = 3,4 (6)

Where x (or y) is the input to node i, and A_i(or B_{i-2}) is the linguistic label (small , large, etc.) associated with this node function. In other words, $O_{1,i}$ is the membership grade of a fuzzy set A(= A_1,A_2,B_1 or B_2), and it specifies the degree to which the given input x (or y) satisfies the quantifier A. Usually we choose (x) to be bell-shaped function as :

$$\mu A_i(X) = \frac{1}{1+\left[\left(\frac{X-c_i}{a_i}\right)^2\right]b_i} \quad (7)$$

Where {a_i, b_i, c_i} is the parameter set. As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership functions for a fuzzy set. Parameters in this layer are referred to as premise parameters.

Layer 2: Every node in this layer is a circle node labeled TT, whose output is the product of all the incoming signals:

$O_{2,i} = w_i = \mu A_i(x)\ \mu B_i(y)$ i = 1,2 (8)

Each node output represents the firing strength of a rule. (In fact, other T-norm operators that performs generalized AND can be used as the node function in this layer.)

Layer 3: Every node in this layer is a circle node labeled N. The ith node calculates the ratio of the ith rule's firing strength to the sum of all rules firing strengths:

$$O_{3,i} = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \quad (9)$$

For convenience, outputs of this layer will be called normalized firing strengths.

Layer 4: Every node i in this layer is a square node with a node function:

$O_{4,i} = \overline{w_i}\, f_i = \overline{w_i}\,(p_i x + q_i y + r_i)$ (10)

Layer 5: The single node in this layer is a fixed node labeled Σ that computes the overall output as the summation of all incoming signals
Overall Output is given by:

$$O_{5,i} = \frac{\sum w_i f_i}{\sum w_i} \quad (11)$$

5. SIMULATION

5.1. Fuzzy logic control simulation

In this paper, we have presented a Fuzzy logic control for obtaining the optimal design of the CSTR process. In this approach, the development of rule base and the formation of the Gaussian membership function are evolved simultaneously. The fuzzy rules we have used in this work is shown in Fig 5. In order to extract the best crisp value for defuzzification, mean of maximum method is used. The performance of the algorithm in obtaining the optimal values of Fuzzy controller parameters has been analyzed in CSTR process through computer simulation.

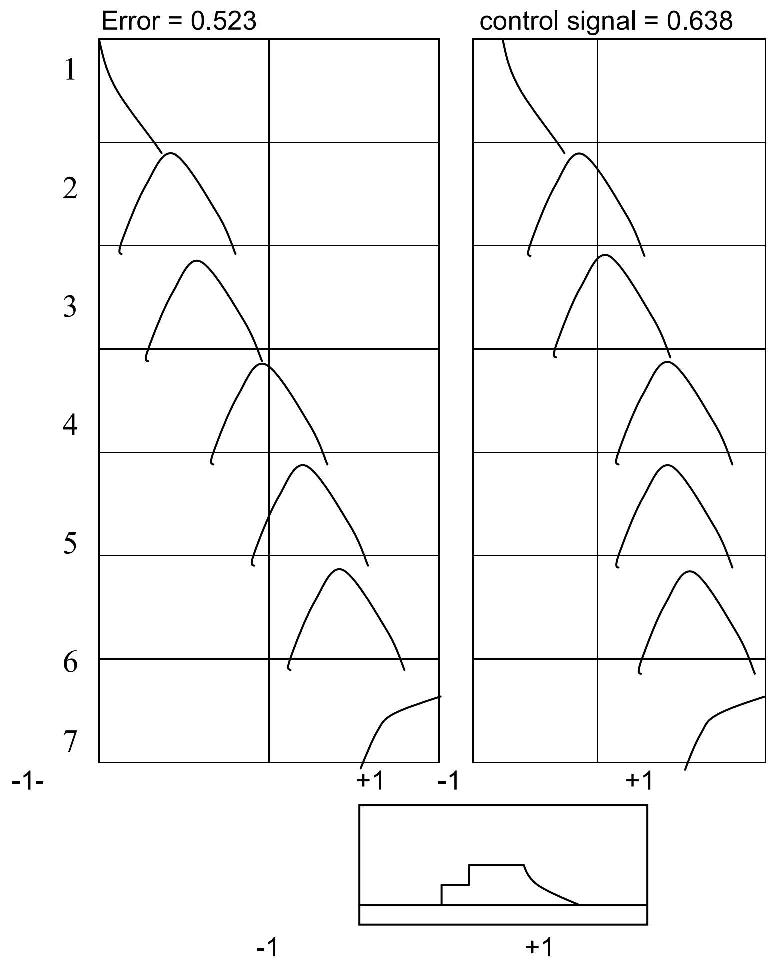

FIGURE 5: Fuzzy Rules

In this approach, the development of rule base and the formation of the membership function are evolved simultaneously. The input and output membership functions chosen for tuning are shown in Fig 6(a) and Fig 6(b) respectively.

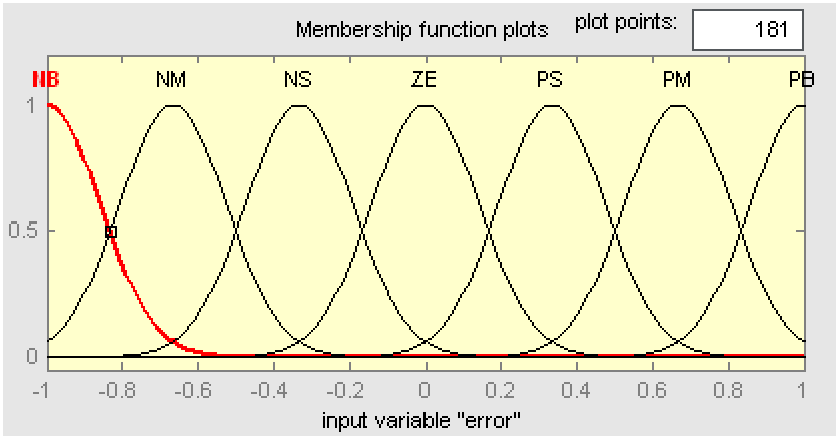

FIGURE 6 :(a). Input membership function plot

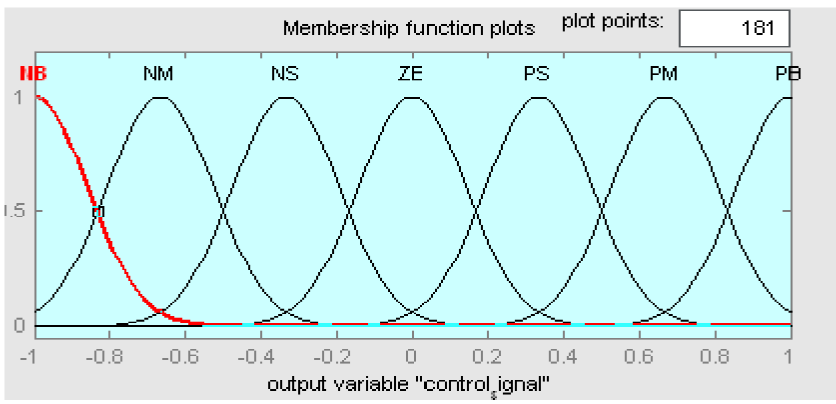

FIGURE 6(b). Output membership function plot

5.2. ANFIS simulation

Here an ANFIS tuning for obtaining the optimal design of the CSTR process is simulated. The ANFIS rules and model structure we have chosen in our work are shown in Fig 7 and Fig 8. It is found that the development of ANFIS makes the CSTR process more efficient. The configuration of ANFIS can be reduced and is smaller than Mamdani fuzzy system. The ANFIS model structure chosen has five layers. The performance of the algorithm has been analyzed in CSTR process through computer simulation.

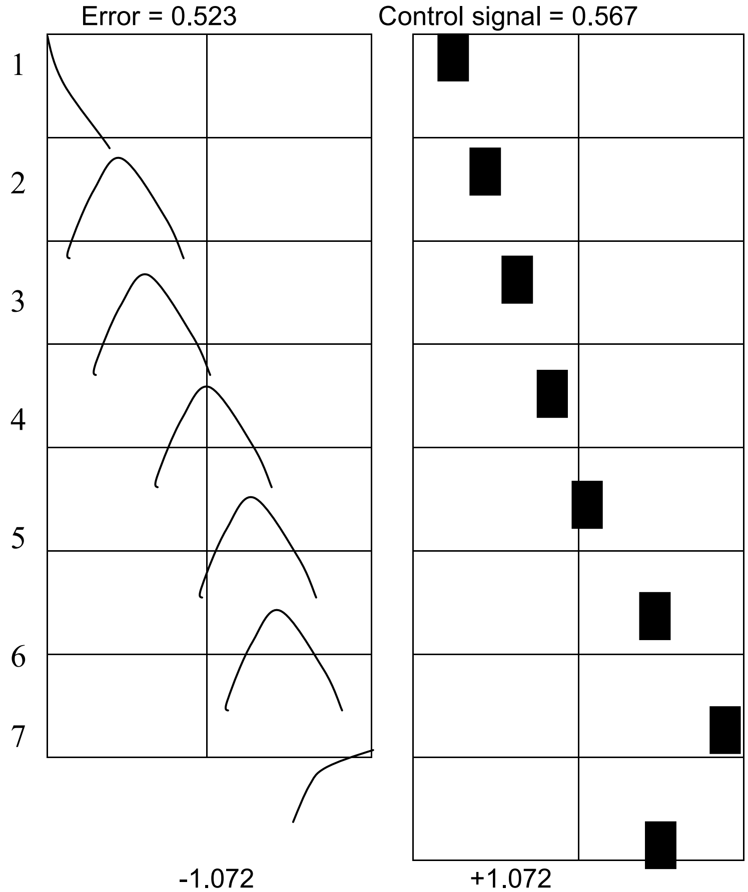

FIGURE 7: ANFIS Rules

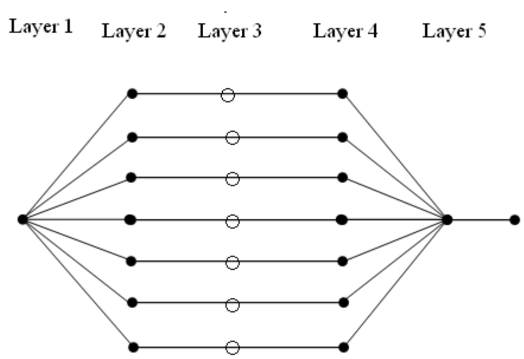

FIGURE 8: ANFIS Model Structure

6. SIMULATION RESULTS

The tuning of a CSTR process is carried out by both Fuzzy Logic as well as ANFIS. The development of ANFIS makes the CSTR process more efficient than that of using a fuzzy. The configuration of ANFIS can be reduced and made smaller than Mamdani fuzzy system. The responses of CSTR for temperature change which is the main disturbance using Z.N,fuzzy logic and ANFIS are shown in Fig 9. The response of CSTR for change in setpoint using Z-N,Fuzzy andANFIS are shown in Fig 10 and The simulation results are given in Table 2.It is seen from the table that that ANFIS tuned CSTR process

Gives the better performance in all aspects(Delay Time, Rise Time, Peak Time, Settling Time and Peak Overshoot).The fuzzy logic tuned CSTR process is better than Ziegler – Nichols tuned CSTR process.

Tuning Methods	Delay Time(Secs)	Rise Time (Secs)	Peak Time (Secs)	Settling Time (Secs)	Peak Overshoot(%)
Ziegler - Nichols	2	1	9.5	50	18
FuzzyLogic	1.2	0.8	7.5	32	14
ANFIS	0.8	0.6	6.0	20	8

TABLE 2 Comparison of various Tuning Methods

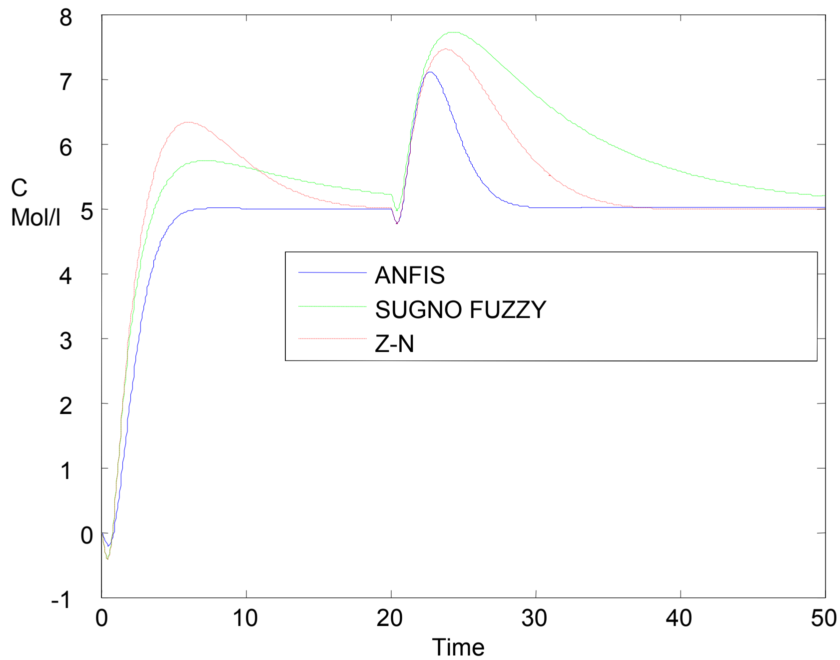

FIGURE 9: Response of CSTR process for Temperature change

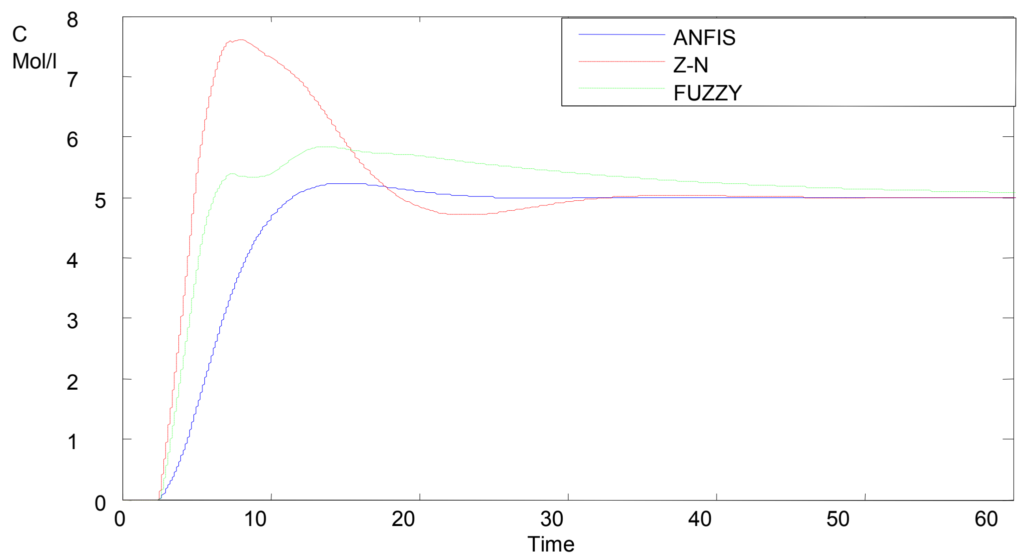

FIGURE10. Response of a CSTR Process for set point variations

7. CONCLUSION

We have described the tuning of an industrial CSTR process using Fuzzy – Logic control as well as ANFIS. This paper describes an intelligent method to tune the controller for a CSTR process. It also discuss the temperature variation and variation in concentration both are in interacting in nature are dealt with this intelligent method .

The controller developed here clearly give the solution of the MIMO process where both concentration and temperature are controlled simultaneously .

The tuning of the controller for CSTR process using Z-N, Fuzzy, and ANFIS for variations in concentration and temperature. Results show that the performance obtained by ANFIS method is better than Z-N and Fuzzy tuning methods. The ANFIS configuration is reduced and smaller than Fuzzy system. Simulation of response of CSTR for change in set point and temperature(disturbance) configuration are shown in Fig 10and Fig9..The performance are compared and tabulated in Table 2.

The ANFIS controller designed here gives better response than other methods [12],[14] &[17] in the simulation mode. This method incorporates the knowledge base system which makes it more intelligence.

Thus in this paper, the parameter notification is solved through the learning rule. By employing a proper learning procedure, the proposed process can refine the ANFIS model to obtain the tuning of the CSTR process.

8. REFERENCES

1. K.J. Astrom, & T. Hagglund, "*The future of PID control Control Engineering Practice",* pp.1163 -1175. 2001.

2. F. G. Shinskey, *"process control system: application, design and tuning"* (McGraw-Hill, 4th Ed., 1996).

3. K. Yamada, & K. Watanabe, "*A State Space Design Method of Stable filtered Inverse Systems and Its Application to H2 Suboptimal Internal Model Contro"l*, Proc. IFAC96,1996, pp.379-382.

4. A.P. Loh, K.O. Looi, & K.F. Fong, "*Neural network modeling and control strategies for a CSTR neutralization process",* Journal of Proc. Control, 6: 355-362.1995.

5. T. Takagi, & M. Sugeno, Fuzzy identification of systems and its applications to modeling and control,*IEEE Trans. Syst., Man, Cybern.,vol. 15*, pp. 116-132, 1985.

6. S. J. Qin, & G. Borders, *"A multiregion fuzzy logic controller for nonlinear process control",* IEEE Transactions on Fuzzy Systems, 2:74–81.1994,

7. Rajani K. Mudi, Chanchal Dey, & Tsu – Tian Lee, *"An improved auto – tuning scheme for PI controllers*", Journal of science Direct ISA Transactions ,47 : 45 – 52,2008.

8. T. Takagi, & M. Sugeno, "*Derivation of fuzzy control rules from human operator's control actions"*, Proc. IFAC Symp. Fuzzy Inform. Knowledge Representation and Decision Analysis, pp. 55-60. July 1983,

9. C.-C. Lee, "*Fuzzy logic in control systems: Fuzzy logic controller-Part I*." IEEE Trans. Syst., Man, Cybern., 20: 404 -418, 1990.

10. *"Fuzzy logic in control systems: Fuzzy logic controller-Part II".* IEEE Trans. Syst., Man, Cybern., 20: 419-435, 1990

11. P. Werbos, beyond regression: "*New tools for prediction and analysis in the behavioral sciences"*. Doctoral diss. Harvard Univ., Cambridge, MA, 1974.

12. Luis E. Zarate, Peterson Resende, & M. Benjamin*," A Fuzzy Logic and Variable Structure Base Controller for CSTR Control*". Annual conference of IEEE, 2001.

13. "*Rule extraction using generalized neural networks*," Proc. 4th IFSA World Congress, July 1991.

14. Tipsuwanporn.V, S.Intajag, K.Witheephanich, N.Koetsam-ang and S.Samiamag, *"Neuro-Fuzzy Controller Design for Industrial Process Contro*l"s, PP :1656-1661, SICE 2004.

15. Toru Yamamoto and Sirish L. Shah, "*Design of a Performance-Adaptive PID controller",*.International conference on Networking,Sensing and Control IEEE 2007 pp547-552.2007.

16. Xiao-Feng Li, Jian Sun, Hui-Yan Wu, Wei-Dong Zong, *"Application of the fuzzy PID to the Power Plant*", IEEE 2007

17. Yun Li,Kiam Heong Ang and Gregory C.Y.Chong, "*PID Control System Analysis and Design – Problems, Remedies, and Future Directions*". IEEE control system magazine, February 2006 pp. 32-41,2006

18. Yamada.K, & K. Watanabe, "*A State Space Design Method of Stable filtered Inverse Systems and Its Application to H2 Suboptimal Internal Model Control"*, Proc. IFAC96, 1996, pp.379-382.1996