Design of MRAFC for CSTR Process

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ABSTRACT
In this work, non-linear control of CSTR for reversible reaction is carried out using Fuzzy Logic as design tool. The Model Reference Adaptive Control approach in used to design Fuzzy controller. The idea is to have a control system that will be able to achieve improvement in the level of conversion and to be able to track set point change and reject load disturbance. We use PID control scheme as benchmark to study the performance of the controller. The comparison shows that Model Reference Adaptive Fuzzy Controller performs better than PID controller in the extreme range of non-linearity.

This paper represents a preliminary effort to design a simplified Model Reference Adaptive Fuzzy Control scheme for a class of non-linear process. Future works will involve further investigation of the effectiveness of thin approach for the real industrial chemical process.

Categories and Subject Descriptors
I.2.1 [Applications and Expert Systems]: *Industrial automation.*

General Terms
Design, Experimentation.

Keywords
Fuzzy Logic, Adaptive Control, Reference Model, PID Controller.

1 INTRODUCTION
While non-adaptive fuzzy control1 has proven its value in some applications, it is sometimes difficult to specify the rule base for some plants, or the need could arise to tune the rule-base parameters if the plant changes. This provides the motivation for adaptive fuzzy control, where the focus is on the automatic on-line synthesis and tuning of fuzzy controller parameters (i.e., the use of on-line data to continually "learn" the fuzzy controller, which will ensure that the performance objectives are met). The first adaptive fuzzy controller called the linguistic self-organizing controller (SOC) was introduced in [1]; several applications of this method have been studied (see the references in [2]). More recently, the "fuzzy model reference-learning controller" (FMRLC) was introduced in [2]–[4], its extensions in [5], and both simulation and implementation studies [4]–[8] have shown this method to be quite successful. Many other adaptive fuzzy control techniques exist and the reader is referred to [9] - [11] for a more complete overview.

The problem with the SOC and FMRLC is that while they appear to be practical heuristic approaches to adaptive fuzzy control there is no proof that these methods will result in a stable closed-loop system (verification of stability is important, especially for safety-critical systems). Recently, however, several researchers have explored ideas from conventional adaptive and neural control to establish stability conditions for a variety of adaptive fuzzy control techniques [1]–[4] and neural control methods [3]. Generally, these techniques can be split into two categories: direct and indirect adaptive fuzzy control. In indirect adaptive fuzzy control, there is an identifier mechanism that produces a model of the plant, which is then used to specify the controller (i.e., we update the controller parameters indirectly by first estimating the model parameters). In direct adaptive control, a model of the plant is not estimated; instead, we directly tune the controller parameters using plant data. Regardless of the method chosen or whose approach one takes, the practical value of these adaptive controllers is questionable since

1) There have been very few comparative analyses with conventional adaptive or non-adaptive nonlinear control methods;

2) There seem to be no experimental studies to determine how well these techniques perform in implementation, especially relative to conventional adaptive or non-adaptive nonlinear control techniques.

A complete assessment that would clarify how the above adaptive controllers would perform relative to all conventional methods and a wide variety of experimental settings is clearly beyond the scope of this or any single paper. Here, we use three case studies to compare the adaptive fuzzy controllers (both direct and indirect) in [1]–[3], to some of the more popular conventional linear and nonlinear methods. A case study we focus on is a CSTR process. We develop conventional PID and adaptive fuzzy controllers, and provide simulation results.

2 NON-LINEAR CSTR PROCESS
A CSTR (Continuous Stirred Tank Reactor) is a highly non-linear process. A schematic of the CSTR system is shown in Figure 1. A single irreversible, exothermic reaction is assumed to occur in the reactor.

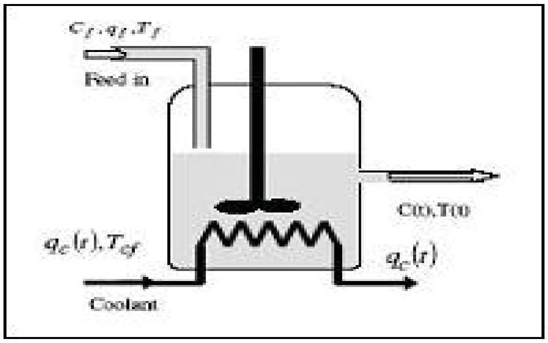

Figure 1 CSTR Plant Model

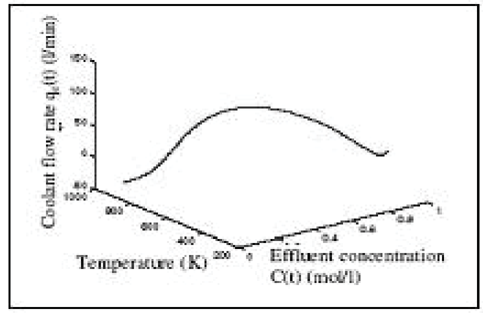

Figure 2 Non-linearity of CSTR

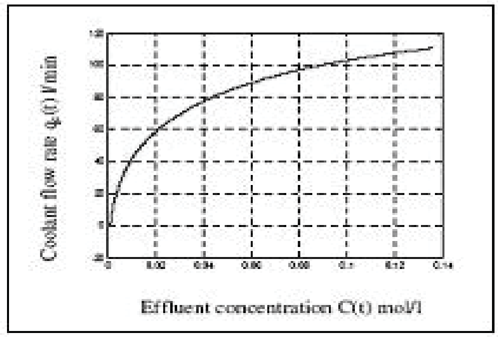

Figure 3 Stable Equilibrium Area

Table 1. Nominal CSTR Operating Conditions

q = 100 l/min, product flow rate	C =1 mol/l, input concentration
T =350 K, input temperature	T =350 K, temperature of coolant
K1=1.44*10^{13} Kl/min/mol,	V =100 l , container volume
E / R =104 K, activation energy	K_2= *0.01* / l , constant
K3=700 l/min, constant	*K= 7.2 * 10^{10}* min-1 , constant

The process model consists of two non-linear ordinary differential equations [15] as follows.

$$\dot{T}(t)=\frac{q_f}{V}\left(T_f-T(t)\right)+K_1C(t)\exp\left(-\frac{E}{RT(t)}\right)$$
$$+\;K_2q_c(t)\left[1-\exp\left(-\frac{K_3}{q_c(t)}\right)\right]\left(T_{cf}-T(t)\right) \tag{1}$$

$$\dot{C}(t)=\frac{q_f}{V}\left(C_f-C(t)\right)-K_0\,C(t)\exp\left(-\frac{E}{RT(t)}\right) \tag{2}$$

where $q_c(t)$ is the coolant flow rate, T(t) is the temperature of solution and C(t) is the effluent concentration. The model parameters defined, and the nominal operating conditions are shown in table 1. The objective is to control C(t) by manipulating

$q_c(t)$. Figure 2 is the locus of equilibrium distribution of input *c q* (t) versus output C(t) and T(t); the CSTR exhibits highly non-linear dynamical behavior. Eigen value analysis shows that the stable equilibrium regime of the CSTR lies in

C(t) $\in$ (0, 0.13566) & $q_c(t) \in$ (0, 110.8),
which is shown in figure 3.

3 PID AND FUZZY LOGIC CONTROLLER

3.1 PID Controller

The three term proportional integral and derivative PID controller account for more than 95% of installed automatic feedback controller. PID controller gave optimal control for 1st order system without and delays. There are three classes of PID in this work; the class chosen has the generic form:

$$U(t)=K_p e(t)+K_I\int e(t)\,dt+K_D\frac{d}{dt}e(t) \tag{3}$$

The variable *e(t)* represents the tracking error, the difference between the desired value (*r*) and the actual output (*y*). PID controller will use this error signal. PID will take appropriate action according to the law and pass the signal (*u*) to the plant to adjust the appropriate manipulated variable.

3.2 Fuzzy Logic Controller

Fig. 1 shows a block diagram of a CSTR Process using a FLC. The FLC has two inputs speed error *e(k)* and change in speed error d*e(k)* and one output $C_{ref}(k)$.

$$\begin{aligned} e(k+1)&=y_{sp}-y_p(k+1)\\ de(k+1)&=e(k+1)-e(k) \end{aligned} \tag{4}$$

To obtain normalized inputs and output for fuzzy logic controller, the constant gain blocks are used as scaling factors α, β,γ as shown in Fig. 4.

$$E(k+1) = \alpha\, e(k+1)$$
$$dE(k+1) = \beta de(k+1) \quad (5)$$

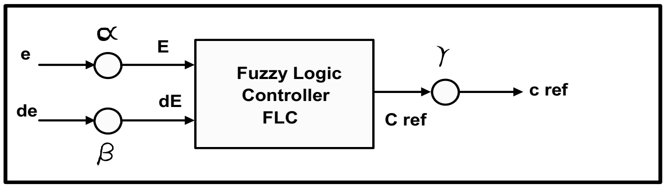

Figure 4 Scaling Factors

The FLC consists of three stages: the fuzzification, rule execution, and defuzzification shown in figure 5. In the first stage, the crisp variables *e(k)* and d*e(k)* are converted into fuzzy variables *E(k)* and d*E(k)* using the triangular membership functions shown in Fig. 6.

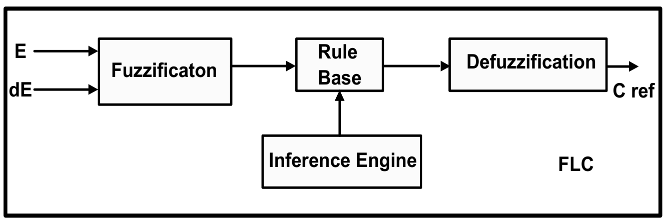

Figure 5 Fuzzy Logic Controller Structure

Each universe of discourse is divided into five fuzzy sets: NL (negative large), NS (negative small), ZE (zero), PS (positive small) and PL (positive large). Each fuzzy variable is a member of the subsets with a degree of membership varying between 0 (non-member) and 1 (full-member).

In the second stage of the FLC, the fuzzy variables *E* and d*E* are processed by an inference engine that executes a set of control rules contained in (5 × 5) rule bases. The control rules are formulated using the knowledge of the CSTR Behavior. Each rule is expressed in the form

$$Rule1: IF\ x\ is\ A\ AND\ Y\ is\ B\ THEN\ Z\ is\ C$$

Different inference algorithms can be used to produce the fuzzy set values for the output fuzzy variable C_{ref}. In this paper, the max-min inference algorithm is used, in which the membership degree is equal to the maximum of the product of *E* and d*E* membership degree.

The inference engine output variable is converted into a crisp value c_{ref} in the defuzzification stage. Various defuzzification algorithms have been proposed in the literature. In this paper, the centroid defuzzification algorithm is used, in which the crisp value is calculated as the centre of gravity of the membership function.

The definition of the spread of each partition, or conversely the width and symmetry of the membership functions, is generally a compromise between dynamic and steady state accuracy. Equally spaced partitions and consequently symmetrical triangles are a very reasonable choice. The universe of discourse is normalized over the interval [-1,1]. So, we need to multiply the controller input and output variables by adjusting gains in order to accommodate these variables into the normalized intervals [3,4].

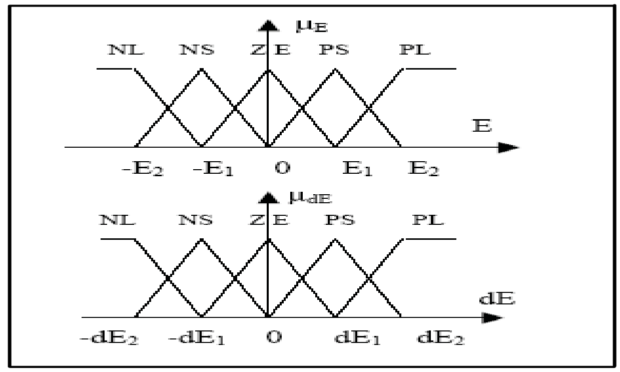

Figure 6 Membership Function of the Controller

4 MODEL REFERENCE ADAPTIVE FUZZY CONTROLLER

Fuzzy control systems based on model reference adaptive control have been reported by a number of researchers. The principal components of this system are the reference model, a primary or direct fuzzy logic controller (FLC), and an adaptation mechanism. The reference model embodies the desired performance characteristics of the overall system.

Typically, this is a first order or well-damped second order linear system although it could alternatively be nonlinear [4].

The direct fuzzy logic controller is implemented using a simple adaptive control based on the gradient algorithm method. The role of the adaptation mechanism is to adjust the characteristic of the FLC in response to the error $e_m(t)$ between the outputs of reference model and plant, in order to minimize that error in some sense. The adaptation mechanism may be subdivided into an inverse plant model designed to give an indication of the required correction, ΔU(t) , to the output signal *U*(t) and an updating algorithm in order to affect that correction via the direct FLC [5,6].

The updating algorithm modifies the FLC characteristic such that its output *U*(t) is altered by the correction value ΔU(t) . The MRAFC is depicted in Fig. 7. It is presented as learning a more global control function with faster convergence. The adaptation is affected by adjusting the centre values of the output fuzzy sets [4,5,7].

In the proposed scheme, the error and change of error measured between the motor speed and the output of a reference model are applied to a fuzzy logic adaptation mechanism. The latter will force the system to behave like the model by modifying the knowledge base of the fuzzy controller or by adding an adaptation signal to the fuzzy controller output.

$$e_m(k+1) = y_m(k+1) - y_p(k+1)$$
$$de_m(k+1) = e_m(k+1) - e_m(k) \quad (6)$$

The internal structure of the MRAFC is identical to that of the direct FLC: the fuzzification, rule execution, and defuzzification.

As in the case of FLC, FMRAC rules are formulated based on the knowledge of the drive behavior and common sense.

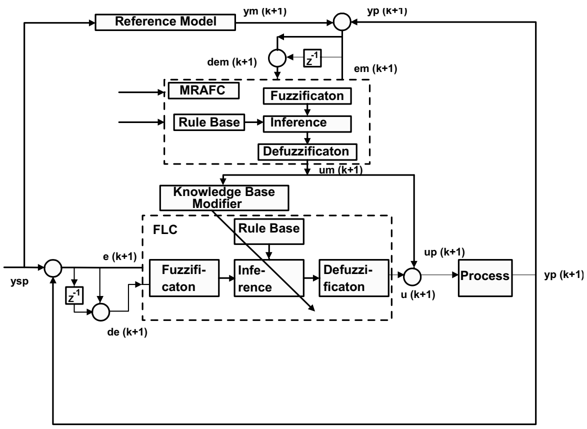

Figure 7 Model Reference Adaptive Fuzzy Controller

5 SIMULATION RESULTS AND CONCLUSIONS

Figure 8 shows response for both MRAFC and PID controller. For PID controller, the controller setting that gave the best performance was found to be Kc = 3.15, Ki = 0.4 and Kd = 8. The response is not without of overshooting, which is very high and small inverse response. For the case of MRAFC the overshoot is very small but in both cases, they brought the reaction almost into complete conversion.

The next performance test involved a set point tracking problem the set point was allowed to change in random fashion. Figure 9 shows the result obtained using the model reference model adaptive fuzzy control strategy. The system behavior shows perfect tracking with no overshoot although the system is somehow sluggish which may be accommodated for the system under consideration. The dotted line in fig 9 shows the performance of a PID controller. Overshoot is observed and settling time for the first set point is quite long. But for the subsequent set points PID response looks similar to MRAFC with small over shoot. The plots also show an unsymmetrical response of PID control for different set points, implying that the system behave nonlinearly for PID control.

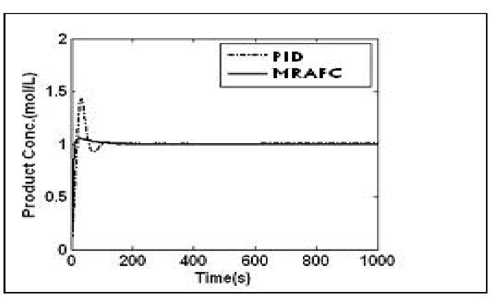

Figure 8 Response for CSTR using PID and MRAFC for given set point

From the results obtained in our simulation we can see that the MRAFC was able to track set point change and reject the uncertainties resulting from external disturbances and plant model mismatches. The responses were somehow sluggish in the faces of external disturbances but give no oscillatory behaviors. For PID controller, the performance deteriorated for set point changes and under the influence of external disturbances. This reason for poor performance can be adduced because of high non-linearity of the CSTR.

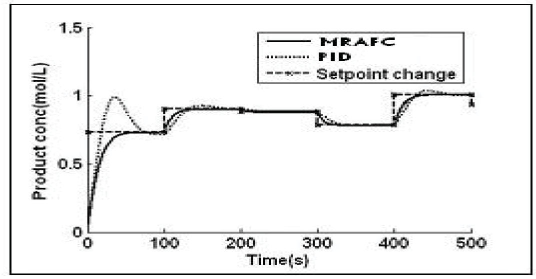

Figure 9 Response of PID and MRAFC for set point change

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