Comparative Analysis of Tuning a PID Controller using Intelligent Methods

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Abstract: A proportional integral derivative (PID) controller is the most commonly used controller in controlling industrial loops due to its simple structure, robust nature and easy implementation. Tuning a PID controller is an important task. The conventional methods for tuning a PID controller have certain limitations. These limitations can be taken care by tuning the PID controller using intelligent techniques. This paper presents the intelligent methods based on fuzzy logic, artificial neural network (ANN), adaptive neuro fuzzy inference system (ANFIS) and genetic algorithms (GA) for tuning a PID controller. The controller tuned by the given methods has been used for concentration control of a continuous stirred tank reactor (CSTR). Simulation results reveals that intelligent methods provide better performance than the conventional Zeigler Nichols (ZN) method in terms of various performance specifications.

Keywords: PID controller; Fuzzy logic controller (FLC); ANN; ANFIS; GA; CSTR

1 Introduction

PID controllers are the most commonly used controllers in process industries. About 90% of industrial loops use PID controllers. This is because of its simple structure, easy implementation, robust nature and less number of tuning parameters [1]. The control signal provided by PID controller is dependent upon three terms and is given by [2]:

$$u(t) = K_P e(t) + K_i \int_0^t e(t)dt + K_d \frac{de(t)}{dt} \tag{1}$$

$u(t)$ is the control signal, $e(t)$ the error signal which is the difference between the reference signal $r(t)$ and the system output $y(t)$. K_p, K_i and K_d are the proportional gain, the integral gain and the derivative gain respectively. These are the parameters to be tuned. There are various conventional methods for PID controller tuning. One of them is the Ziegler–Nichols (ZN) method [3]. In this method the parameters of the PID controller are determined by finding out the proportional gain at which the output becomes oscillatory corresponding to a step input. This gain is called as the critical gain and the frequency of oscillation as critical frequency. The downside of the ZN method is that it results in high value of maximum overshoot. In processes such as plastic glove manufacturing it is undesirable to have high overshoot. Therefore, the ZN method cannot be used for such systems. The other tuning method that appears in the literature is the Cohen–Coon technique [4], where the main design criterion is related to disturbance rejection but it can only be used for first order models including large process delays. The relay auto-tuning method [5] eliminates the possibility of driving the plant close to the stability limit. But the method is difficult to apply in case of processes with large time delays [6]. Morari [7] proposed the internal model control (IMC) based method for tuning a PID controller but it is hard to implement for systems with first order plus dead time. Tunings methods based on optimization has been discussed by Astrom [3]. In these methods the design criterion is based on minimization of certain performance criterion such as integral of square error (ISE) or integral of time multiplied by absolute error (ITAE). Another method for tuning a PID controller is the pole placement method [3] in which the tuning is based on keeping the closed loop poles at desired locations. However the method is not suitable for higher order systems.

In this paper the intelligent methods based on fuzzy logic, ANN, ANFIS and GA for tuning a PID controller have been compared. The controller tuned by the various methods has been used for concentration control of a CSTR. The intelligent methods provide better performance in terms of various performance specifications than the conventional Zeigler Nichols method while the steady state error remains same at zero.

This paper is organized in 4 sections. Section 1 gives the general introduction of the paper. Section 2 represents the problem formulation. In Section 3 the tuning of PID controller using various intelligent methods such as fuzzy logic, ANN, ANFIS and GA has been discussed. The results, comparison and discussion are given in Section 4. At the end conclusion and brief list of references is given.

2 Problem Formulation

The aim of this paper is to tune a PID controller using various intelligent methods for concentration control of a continuous stirred tank reactor. The input output transfer function of the reactor is given by [4]:

$$G(s) = \frac{-1.1170s + 3.1472}{s^2 + 4.6429s + 5.3821} \tag{2}$$

The reactor transfer function is a second order system with right half plane (RHP) zero. The control objective is to keep the various performance specifications such as rise time t_r, settling time t_s, maximum overshoot M_p, maximum undershoot M_u and steady state error e_{ss} within desirable limits.

3 Intelligent Methods for Tuning a PID Controller

3.1 Fuzzy Logic

Conventional PID controller does not give acceptable performance for systems with uncertain dynamics, time delays and non-linearity [8]. Hence it is necessary to automatically tune the PID parameters for obtaining satisfactory response. The automatic tuning of PID controller has been done using fuzzy logic. Based on expert knowledge a fuzzy logic system transforms a linguistic control strategy into an automatic control strategy [9]. Figure 1 shows the block diagram of a fuzzy PID controller. The fuzzy PID controller has been implemented using fuzzy logic toolbox in MATLAB [11].

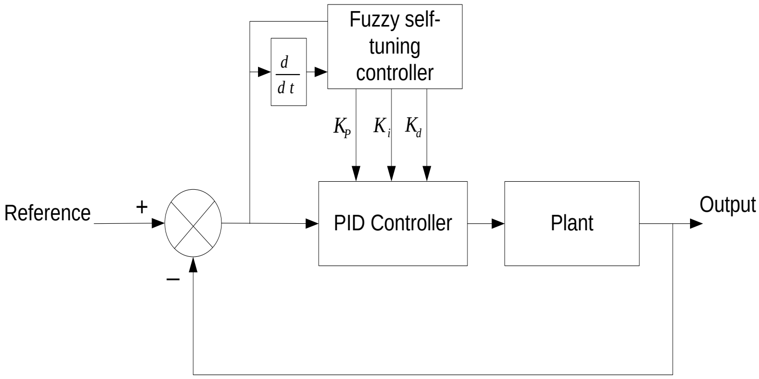


Figure 1
Block diagram of a fuzzy-PID controller [10]

The inputs to the controller are the error (e) and the rate of change of error (Δe) while the outputs are controller gain K_P, K_i & K_d . The structure of fuzzy-PID controller is a two input-three output structure as shown in Figure 2. For finding the range or the universe of discourse of the input and output membership functions the PID controller has been tuned using the conventional Zeigler Nichols method. From there the range of the input as well as output membership functions have been found. The membership functions of these inputs fuzzy sets are shown in Figure 3. The linguistic variable levels are assigned as: negative big (NB), negative small (NS), zero (Z), positive small (PS) and positive big (PB). Similarly, the fuzzy set for error change (Δe) is presented as NB, NS, Z, PS, PB. The ranges of these inputs are from -1.44 to 1.56 and -15.7 to 4.3 respectively.

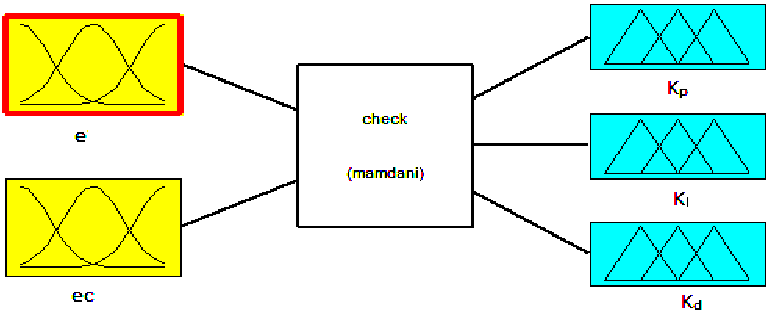
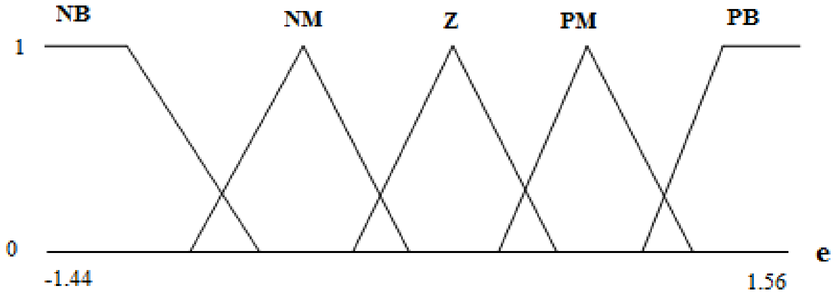
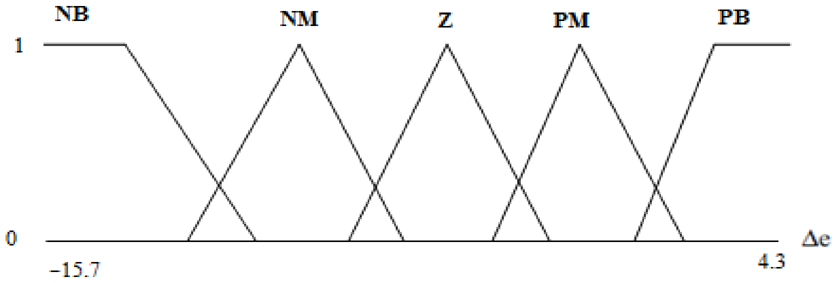


Figure 2
Two input three output FLC structure



(a)



(b)

Figure 3

Input fuzzy sets (a) error (e) (b) Change of error (Δe)

The output membership functions are shown in Figure 4. For the output fuzzy sets the scaling of range has been done corresponding to the formulas given below [10-12]:

$$K_P^{'} = \frac{K_P - K_{P\min}}{K_{P\max} - K_{P\min}}$$

$$K_I^{'} = \frac{K_i - K_{i\min}}{K_{i\max} - K_{i\min}}$$

$$K_d^{'} = \frac{K_d - K_{d\min}}{K_{d\max} - K_{d\min}} \tag{3}$$

The minimum and the maximum values of various gains have been obtained by analyzing the step response of the given process using Zeigler Nichols method.

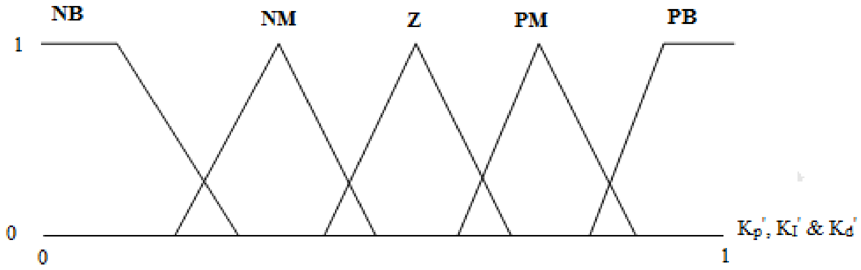


Figure 4

Output fuzzy sets $K_P^{'}, K_i^{'} \,\&\, K_d^{'}$

The rule base for the fuzzy-PID controller is shown in Table1 [12] which can be implemented for tuning the PID controller.

Table1

Rule base for fuzzy-PID controller

e Δe	NB	NM	Z	PM	PB
NB	NB	NB	NM	NM	Z
NM	NB	NM	NS	Z	PM
Z	NM	NM	Z	PM	PM
PM	NM	Z	PM	PM	PB
PB	Z	PM	PM	PB	PB

The simulink blockset for fuzzy PID controller implemented for concentration control of a CSTR is shown in Figure 5.

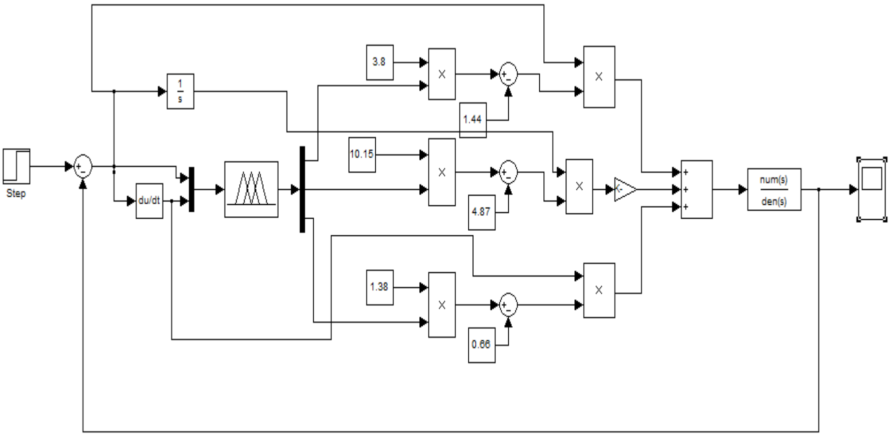


Figure 5

Fuzzy-PID controller implementation in MATLAB Simulink

3.2 Artificial Neural Networks

An ANN is a computational model comprising of artificial neurons operating as a unit for processing information from input to output. [13]. Figure 6 shows the block diagram of PID controller tuning using neural network. The ANN structure used is a single neuron structure [14].

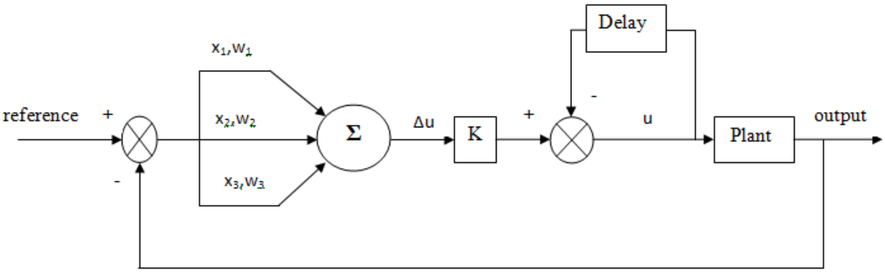


Figure 6
Closed loop control system with single neuron ANN structure [14]

The neuron weights w_1, w_2 & w_3 will act as the gains of the PID controller. With the help of some learning algorithm the weights of the neural network are modified to attain the desired goal. The proportional error $x_1(k)$, the integral error $x_2(k)$ and the derivative error $x_3(k)$ are given by:

$$x_1(k) = e(k) - e(k-1)$$

$$x_2(k) = e(k)$$

$$x_3(k) = e(k) - 2e(k-1) - e(k-2) \tag{4}$$

These error signals are multiplied with their corresponding weights and act as the input to the single neuron.

The neuron output is given by [14]:

$$u(k) = u(k-1) + K\sum_{i=1}^{3} w_i(k)x_i(k) \tag{5}$$

K is a constant for speeding up or slowing down the closed loop response,

The various steps in tuning a PID controller using ANN are as follows:

Step 1: Choose random values for the weights.

Step 2: Calculate the error which is the difference between the reference input and the output.

Step3: The gains of PID controller are decided by supervised delta learning method, using the error signal.

Step 4: The output of the single neuron i.e. Δu is multiplied with a gain K to obtain a better closed loop response.

Step 5: The updated weights will act as the proportional gain, the integral gain and the derivative gain respectively.

Supervised delta learning algorithm for updating the weights has been given by [14]:

$$w_1(k) = w_1(k-1) + \eta_P e(k-1)u(k-1)$$

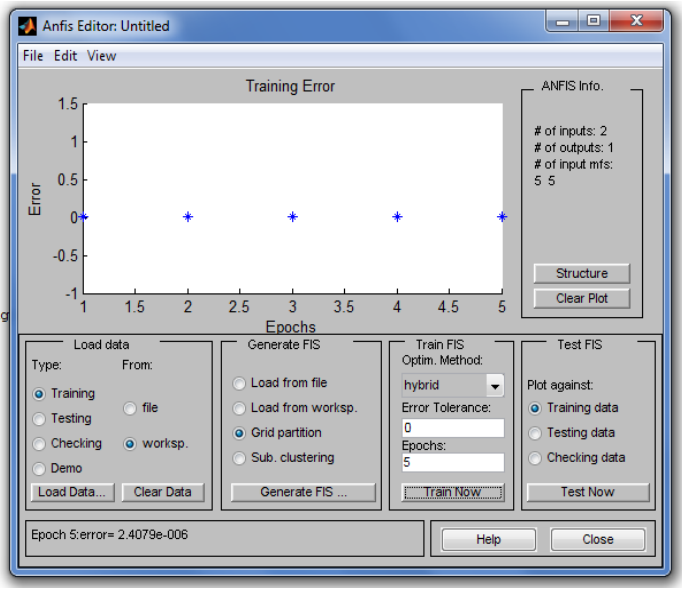
$$w_2(k) = w_2(k-1) + \eta_I e(k-1)u(k-1)$$

$$w_3(k) = w_3(k-1) + \eta_D e(k-1)u(k-1) \tag{6}$$

η_P, η_I and η_D are the proportional, integral and the derivative learning speeds. Based upon the above steps ANN with single neuron has been implemented on CSTR for tuning of PID controller.

3.3 Adaptive Neuro Fuzzy Inference System (ANFIS)

ANFIS is a special type of neural network which combines the features of both neural networks and fuzzy logic. ANFIS develops a Takagi Sugeno fuzzy inference system (FIS) with the help of an input output data set [15-16]. By using error back propagation algorithm the membership functions of the ANFIS are developed. The inputs to the proposed adaptive neuro fuzzy controller are the error (e) and the rate of change of error (de/dt) while the outputs are the proportional gain K_P, the integral gain K_i and the derivative gain K_d. The input output data set has been taken from a PID controller tuned using conventional method. The proposed approach has been implemented using ANFIS editor in MATLAB as shown in Figure 7. The ANFIS model structure is a two input single output feed-forward structure having three hidden layers as shown in Figure 8 [17]. The simulink implementation of the given method is shown in Figure 9.



# of inputs: 2
# of outputs: 1
# of input mfs:
5 5

Type: ● Training

From: ● worksp.

● Grid partition

Optim. Method: hybrid

Error Tolerance: 0

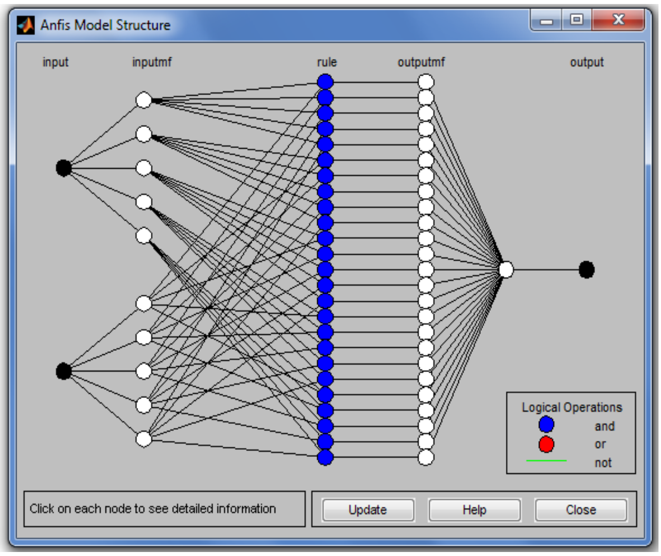
Epochs: 5

Plot against: ● Training data

Epoch 5:error= 2.4079e-006

Figure 7

ANFIS Editor



Click on each node to see detailed information

Figure 8

ANFIS structure

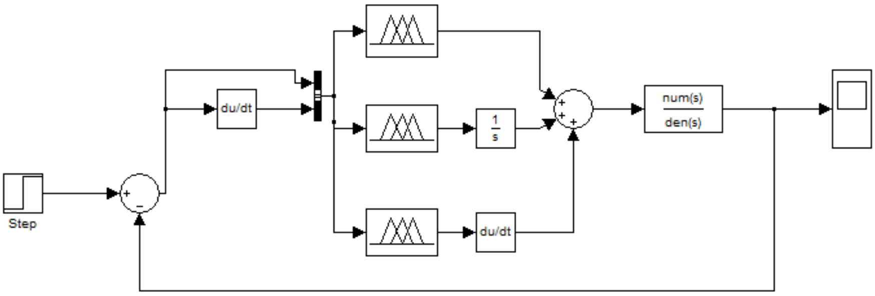


Figure 9
Adaptive neuro fuzzy controller implementation using MATLAB simulink

3.4 Genetic Algorithms

GA is a derivative free random optimization technique based on the ideas of natural selection and evolutionary processes. The fundamental components of GA are encoding, reproduction, crossover and mutation [13]. GA encodes a number into a binary string called chromosomes. Depending upon the value of evaluation function also called the fitness function the parents are selected from a group of binary strings to perform the operations of crossover and mutation. Figure 10 shows the block diagram for tuning of PID parameters using GA [18-19].

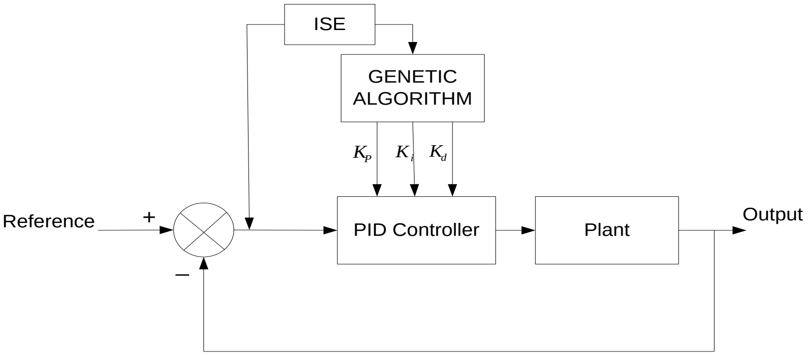


Figure 10
Block diagram of PID controller tuning using GA [17]

Auto-tuning of the PID controller has been done using GA by minimizing the integral of square error (ISE). The ISE criterion is defined as $ISE = \int (r(t) - y(t))^2 \, dt$. The various steps in finding the parameters of a PID controller are:

Step 1: Define the Plant transfer function.

Step 2: Initialize $K_P, K_i \; \& \; K_d$ and calculate ISE.

Step 3: Obtain pbest and gbest values.

Step 4: Calculate new population using mutation.

Step 5: Obtain pbest1 and gbest1.

Step 6: Compare pbest and pbest1.

Step 7: Compare gbest and gbest1.

Step 8: Obtain the new values of $K_P, K_i \; \& \; K_d$ and find out the step response for the closed loop system.

4 Results, Comparison and Discussions

The closed loop response of the reactor transfer function subjected to a step input with the different methods has been shown in Figure 11 to Figure 14 using different tuning methods.

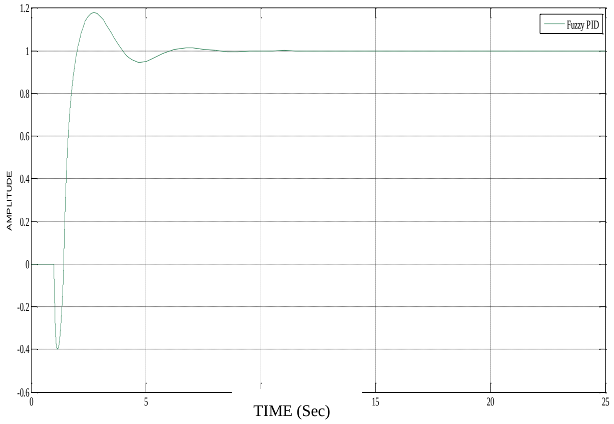


Figure 11
Step response using Fuzzy based PID controller

Due to RHP zero the system shows inverse response behavior.

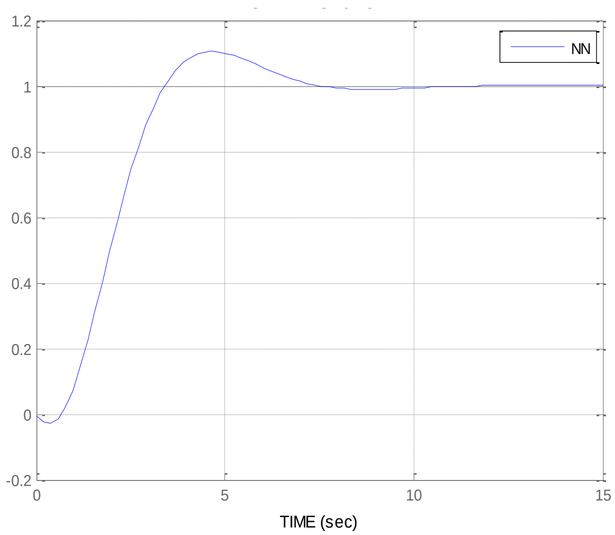


Figure 12
Step response using ANN based PID controller

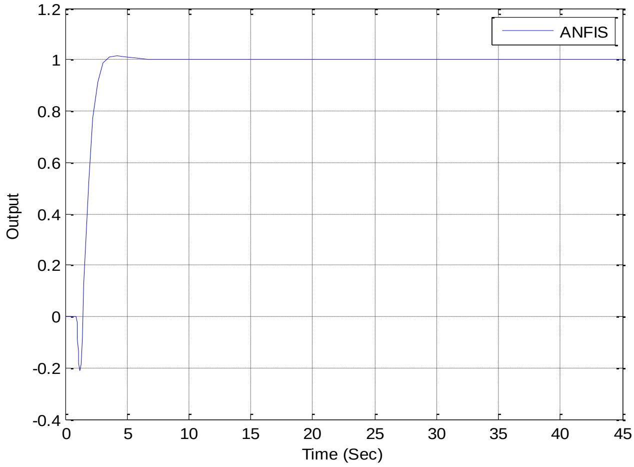


Figure 13
Step response using ANFIS based PID controller

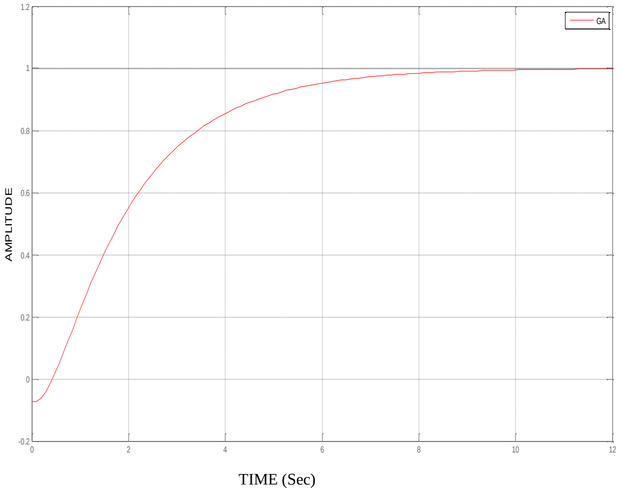


Figure 14
Step response using GA based PID controller

The comparison among different tuning methods in terms of various performance specifications such as rise time, settling time, overshoot, undershoot and steady state error using the intelligent and conventional tuning methods has been shown in Table 2.

Table 2
Comparison among different methods for tuning a PID controller

Parameters	**Tuning Methods**				
	ZN	Fuzzy	ANN	ANFIS	GA
Rise time t_r (sec)	1.789	1.865	2.98	2.578	4.84
Settling time t_s (sec)	3.745	5.624	6.85	3.425	7.12
Overshoot M_P (%)	20.05	17.95	10.47	1.0149	0
Undershoot M_u (%)	44.46	39.98	2.948	21.2	7.2923
Steady state error e_{ss}	0	0	0	0	0

From Table 2 it can be concluded that:

- The various performance specifications have been improved greatly using the intelligent methods except the rise time which is less in case of ZN method.
- The best performance in terms of settling time and overshoot has been given by ANFIS. Moreover undershoot in case of ANFIS method is less than the ZN and fuzzy PID methods. This is due to the fact that ANFIS

uses the combined features of neural networks and fuzzy logic in a single structure.

- The performance of ANN based PID controller is better than the ZN, fuzzy and GA based PID controller in terms of overshoot and undershoot. The maximum undershoot in case of ANN is even less than ANFIS based method.
- The steady state error remains zero in all the tuning methods.

Conclusion

In this paper the intelligent methods for tuning a PID controller have been compared. The different methods include fuzzy logic, artificial neural network, adaptive neuro fuzzy inference system and genetic algorithm. The controller tuned by the different methods has been used for concentration control of a continuous stirred tank reactor (CSTR) which is a second order system with right half plane zero. Simulation results show that the best performance has been achieved by ANFIS in terms of settling time and overshoot while the moderate performance has been given by ANN tuned PID controller as it reduces the overshoot and undershoot to a great amount in comparison to the Zeigler Nichols method.

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