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ANFIS – Hybrid Reference Control for Improving Transient Response of Controlled Systems Using PID Controller

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The standard PID controller is known to have performance limitations as it must trade off the transient response performance and the disturbance attenuation level. The paper proposes a hybrid reference control (HRC) with adaptive neuro-fuzzy inference system (ANFIS) to improve transient response performance of PID controller. The ANFIS is used to manipulate the set-point of the PID controller in a specific manner such that the transient response is improved by learning from experimental data. In this structure, the ANFIS-HRC deals with the achieving good transient response performance, whereas the PID controller stabilizes the closed loop system and defines the disturbance attenuation level. As a result, the transient response performances and the disturbance attenuation can be designed independently.

KEY WORDS: *ANFIS; Hybrid reference control; Subtractive clustering; PID controller; transient response*

MATHEMATICS SUBJECT CLASSIFICATION (MSC): *00A72, 68T05, 93C05, 93C42, 93C83, 93D99*
COMPUTING CLASSIFICATION SYSTEM (CCS): *B.1.1 B.4.3, C.5.3, D.1.7, G.1.6, I.2.3*

1. INTRODUCTION

PID (proportional integral derivative) controller is known to have inherent limitations in resulting simultaneously conflicting control design objectives. A PID controller cannot be tuned optimally to satisfy both requirements, i.e. faster transient response to set-point changes and good disturbance rejection. Many methods have been developed to deal with the limitations, such as fuzzy PID self-tuning, fuzzy PID switching, fuzzy precompensator PID, etc. Each method claims improvement over the conventional PID controller and superiority over other methods. Many published papers mainly focused on the selection of the three parameters of the PID controller as the application of fuzzy system in mimicking the knowledge of the operators (Misir and Malki, 2006), (Mohan and Sinha 2008). However, there has been little attention to implement fuzzy logic to perform a similar way to an expert operator who suppresses overshoot by either increasing or decreasing the input of the controlled process. Other successful examples of the application of fuzzy logic in control system design as can be found in (Chiu, 1998), (Devasenapati and Ramachandran, 2011), (Precup et al., 2012), (David et al., 2012).

A combination of PID controller using a fuzzy expert control technique to produce the response stays at a predefined curve with minimal overshoot was considered in (Yasuda et al., 1990). A different method by using fuzzy logic was investigated in (Kim et al., 1994). The method is called as a fuzzy precompensator that compensates the set-point of the conventional closed loop feedback control using PID controller. The method uses the error, the change of error, and a correction term to compensate the set-point by simply taking the sum of the nonlinear mapping of the the error and the change of error with the correction term. The fuzzy logic rule is obtained by trial and error to compensate the overshoots and undershoots present in the output response when the plant has unknown nonlinearities that can yield significant overshoots and undershoots in a conventional PID controller. Further extension of the method was developed in (Pratumsuwan and Thongchaisuratkrul, 2011) that combined the advantages of both fuzzy pre-compensated PID controller (Kim et al., 1994) and fuzzy precompensated fuzzy controller (Pratumsuwan and Thongchai, 2009) to form a pre-compensation of a hybrid fuzzy PID controller. The method was aimed to result in a fast rise time, to produce a small overshoot, and to correct the position with respect to the set point.

Motivated by the method for improving transient response performances called hybrid reference control (HRC) developed in (Joelianto and Williamson, 1997), a fuzzy logic based hybrid reference control (FHRC) to improve transient responses of PID controller was considered in (Joelianto and Tansri, 2007). The main advantage of the HRC method is the capability to yield deadbeat response at any predefined time as the optimal solution. The FHRC method is aimed to control the reference signal (set-point) into a particular temporary reference signal for transient response performances improvement during disturbances or simply the error with respect to the default reference signal is considered very big. In this method, the FHRC manipulates the set-point of the PID controller in a pre-learning manner that will improve the transient response performance when the disturbance rejection properties have been established by PID parameters tuning.

Further extension of a combination of PID controller with fuzzy hybrid reference control (FHRC) was carried out in (Joelianto and Sitanggang, 2009) by adapting substractive clustering in order to determine the number of membership functions and membership functions in a short time. The fuzzy membership functions and the rule base were obtained by using the substractive clustering method (Chiu, 1994), (Chiu, 1997), (Hammouda and Karray, 2000). The combination of PID controller with fuzzy hybrid reference control (FHRC) offers significant improvement as the set-point performance can be independently achieved without affecting the disturbance rejection capabilities. The stability analysis of FHRC was also derived in (Joelianto and Sitanggang, 2009) based on the state space representation of the PID controller, detail description can be found in (Joelianto, 2011) and the hybrid reference control analysis (Joelianto and Williamson, 1997), (Joelianto and Williamson, 2009) with the help of the internal model principle (Francis and Wonham, 1976).

On the other hand, adaptive neuro-fuzzy inference system (ANFIS) has been known to have good features from the fuzzy logic and neural networks. ANFIS as developed by (Jang et al., 1997) is a class of adaptive networks that is functionally equivalent to fuzzy inference systems, where the parameters of fuzzy inference systems are updated by neural networks from a set of training data. ANFIS has the advantages claimed by neural networks (NNs) and the linguistic interpretability of Fuzzy Inference Systems (FIS), wherein both NNs and FIS play active roles in an effort to reach specific goals. ANFIS has been successfully implemented in rainfall-runoff prediction of intermittent river (Keskin et al., 2006), (Aqil et al., 2007), (Jothiprakash et al., 2009), evapotranspiration from weather forecast (Cai and Mu, 2005), stock market and financial decision (Patel and Marwala, 2006), (Cheng et al., 2007), time series prediction of earthquake events (Joelianto et al, 2009), complex large scale systems (Buragohain and Mahanta, 2008), etc.

The adaptive capability of ANFIS makes it almost directly applicable to adaptive control and learning control. The nonlinearity and structural knowledge representation of ANFIS are the primary advantages over classical linear approaches such as in control systems. The paper considers development of ANFIS-HRC to the PID controller in order to improve transient response performances and its application to speed control of AC-motor. The previous version of the paper has appeared in (Joelianto and Anura, 2011). Closed loop stability properties are also briefly discussed.

2. ANFIS – HRC

The structure is referred as ANFIS Hybrid Reference Control abbreviated as ANFIS-HRC.

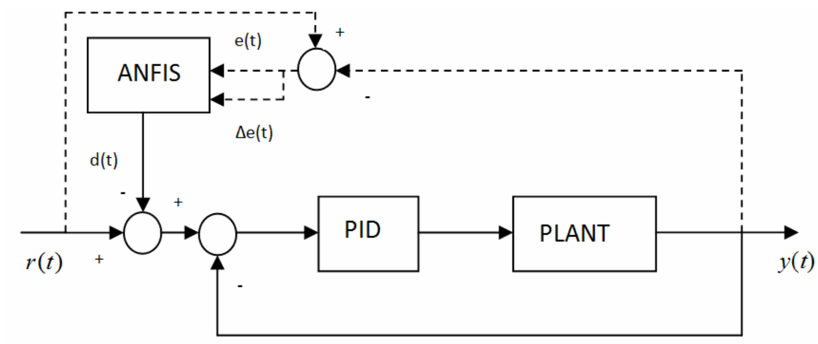


Figure 1. Block Diagram of ANFIS-HRC-PID Controller.

Figure 1 shows the diagram block of ANFIS-HRC-PID controller which has the same structure as FHRC in (Joelianto and Transri, 2007), (Joelianto and Sitanggang, 2009). In Figure 1, the signal $d(t)$ is the output of Fuzzy system that changes temporary the default set-point $r(t)$ during transient response. The action of the Fuzzy system is defined by an enable event t_k is detected by the performance observer embedded in the fuzzy system. This event informs the performance observer that the deviation of the closed loop system output ($y(t)$) to the default reference signal ($r(t)$) is bigger than the prescribed tolerance δ such that

$$|e(t)| = |y(t) - r(t)| \geq \delta \tag{1a}$$

The fuzzy system sends the reference signal ($d(t)$) either continuously or in a predefined time interval (τ) until the performance observer detects another disable event where the error of the closed loop system is now entering the allowable tolerance defined by

$$|e(t)| = |y(t) - r(t)| < \delta \tag{1b}$$

When this event is detected, the fuzzy system then stops sending reference signals ($d(t)$) and return to the default reference signal ($r(t)$) by sending the signal $d(t) = 0$.

The closed loop stability properties of the control system with FHRC have been derived in (Joelianto and Sitanggang, 2009) based on the analytical results on hybrid reference control (HRC) developed in (Joelianto and Williamson, 2009). The stability conditions for ANFIS-HRC follow directly by employing the same arguments as in (Joelianto and Sitanggang, 2009) by replacing fuzzy logic with ANFIS and by considering sampling time as an event. The asymptotic stability of ANFIS-HRC-PID controller is guaranteed if the reference signals generated by the ANFIS are admissible reference signals then the closed loop system is asymptotically stable. The admissible reference signals refers to a condition that the reference signal eventually becomes zero such that the output of the controlled system will track the original reference signal. Hence, the asymtotic stability follows from the asymtotic stability of the closed loop system controlled by the PID controller.

The PID controller in Figure 1 is described by the following equation

$$u(t) = K_c\left(e + \frac{1}{T_i}\int_0^t edt + T_d\frac{de}{dt}\right) \tag{2}$$

where $u(t)$ denotes the manipulated variable of the plant or represents the control signal. The three parameters of the PID controller are denoted by K_c (the controller gain), T_i (the integral time) and T_d (the derivative time). The implementation of the PID algorithm (2) in Labview makes modifications, especially in the integral part by using trapeziodal integration to avoid sharp changes and in the derivative part by taking the derivatif to the process variable to prevent derivative kick (National Instrument, 2001).

2.1. ANFIS

The block diagram of the ANFIS that was first proposed by (Jang et al.,1997) is shown in Figure 2. Each layer consists of several nodes denoted by square and circle. Nodes in the same layer l have the same output function at node i is denoted by O_i^l. In principle, ANFIS is an adaptive network consists of nodes and directional links which form nodes connections. Based on the type of network, all or some of the nodes are adaptive and it is the task of the learning rules to tune the nodes according to an error measure.

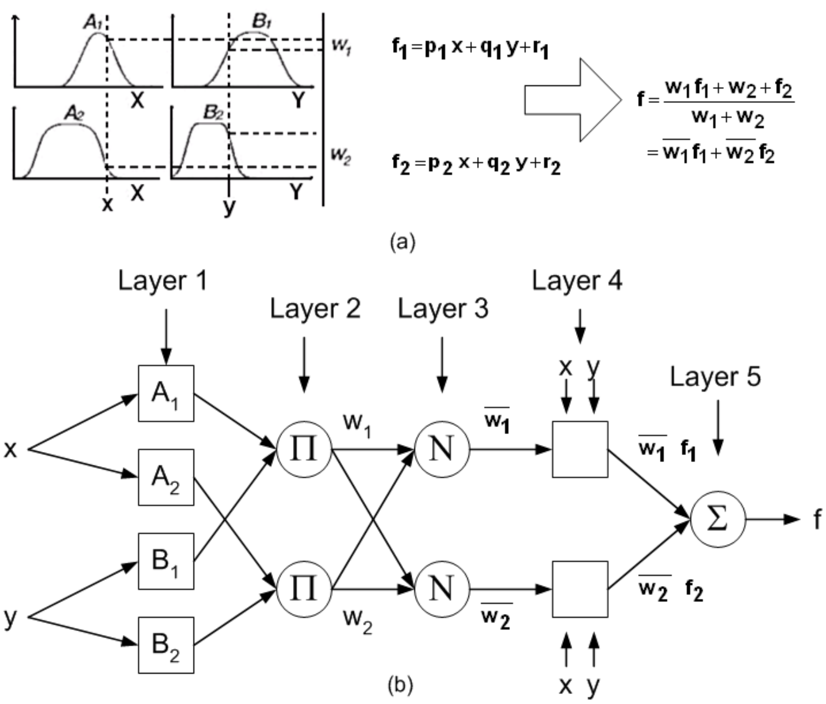


Figure 2. Block Diagram of ANFIS.

For simplicity, it is assumed that the considered fuzzy inference system has two inputs x and y and one output f. A common rule set for a first-order Sugeno fuzzy with two fuzzy if-then rules is given by

Rule 1: If x is A_1 and y is B_1, then

$$f_1 = p_1 x + q_1 y + r_1 \tag{3}$$

Rule 2: If x is A_2 and y is B_2, then

$$f_2 = p_2 x + q_2 y + r_2 . \tag{4}$$

The mechanism in the forward pass can then be explained as follow:

Layer 1

Nodes in this layer are adaptive nodes which represent the membership grade of inputs x and y of fuzzy sets A and B respectively. The output of the node i is denoted by a node function

$$O_i^1 = \begin{matrix} \mu_{Ai}(x), & i = 1,2 \\ \mu_{B(i-2)}(x), & i = 3,4 \end{matrix} \tag{5}$$

The variables A and B are the linguistic labels such as small, medium, large, etc. The membership functions of A and B are Gaussian membership functions defined by

$$\mu_{Gaussian}(x) = \exp\left(-\frac{1}{2}\left(\frac{x-c}{\sigma} \right)^2 \right) \tag{6}$$

The premise parameters $\{c, \sigma\}$ are adaptive and determine the shape of the membership function. They represent the various types of the membership function of fuzzy sets A and B.

Layer 2

Each node in this layer is not an adaptive node which is denoted by Π. The output of the product layer at node i is given by the following equation

$$O_i^2 = w_i = \mu_{Ai}(x) \bullet \mu_{Bi}(y), \qquad i = 1,2 \tag{7}$$

The output of this layer performs as the weight of each fuzzy rule using the t-norm fuzzy operator.

Layer 3

Each node in this layer is a non adaptive node and is denoted by N. Each node normalizes the weight functions (w_i) obtained from the product layer. The normalization is carried out using the following equation

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \qquad i = 1,2 \tag{8}$$

Layer 4

Each node i has defuzzified output which is computed using the following equation

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i), \qquad i = 1,2 \tag{9}$$

where $\overline{w}_i$ denotes normalized activation function from the layer 3. Parameters $\{p_i, q_i, r_i\}$ are consequent parameters in fuzzy rules of the corresponding node i. Nodes in this layer are adaptive in nature.

Layer 5

The layer denoted by Σ is non adaptive and produces output function by adding all inputs from the previous layers. The outputs are calculated using the equation

$$O_i^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, \qquad i = 1,2 \tag{10}$$

Although the Mackey-Glass is often used to develop model (Jang et al., 1997), there are no established rules to build an ANFIS model. Trial error method is the most and popular way in the model development. The objective of an ANFIS is to obtain a relationship of the form:

$$Y_m = f(X_n) \tag{11}$$

where X_n denotes an n-dimensional input vector consisting of variables $\{x_1, x_2, \cdots, x_n\}$ and Y_m is an m-dimensional output vector of interest $\{y_1, y_2, \cdots, y_m\}$.

ANFIS uses hybrid learning algorthm which is a combination of Error Backpropagation (EBP) learning algorithm to update the nonlinear premis parameters and Recursive Least Square Error (RLSE) to update linear consequent parameters. By using hybrid learning algorithm, ANFIS has been known to produce good model closed to the system of interest. Detail hybrid learning process in ANFIS can be found in (Jang et al., 1997).

In the ANFIS-HRC structure, ANFIS represents the relation between the error, the increment of error and the reference signal as a function of the dynamics of the plant and the PID controller. To obtain the dynamics between the error, the delta error and the required set-point compensation, ANFIS uses system identification process by means of numerical learning consists of two stages, i.e. structure identification and parameter identification. Structure of the identification determines an optimal if-then rules of fuzzy inference system, while parameter identification is related to finding the system parameters such as membership functions, linear coefficients, etc.

2.2. Subtractive Clustering

Clustering is a method of grouping data in order to determine their structure where data with same characteristics will be in the same group (Chiu, 1994). Suppose there are n data $\{x_1, x_2, \cdots, x_n\}$ in M dimension that has been normalized. Let x_1^* and P_1^* be the location of the first cluster center and its corresponding potential value respectively. The potential of each data point x_1^* is then revised by using the potential equation

$$P_i \Leftarrow P_i - P_1^* e^{-(\frac{2}{r_b})^2 \|x_i - x_1^*\|^2} \tag{12}$$

where $r_b > 0$ is a constant. Equation (12) shows an amount of potential from each data point as a function of its distance from the first cluster center. The data points near the first cluster center will have greatly reduced potential, and it will not be selected as the next cluster center. The constant r_b denotes the radius defining the neighborhood which will have measurable reductions in potential. To avoid obtaining closely spaced cluster centers, r_b is set to be greater than r_a, a good choice is $r_b = 1.5 r_a$ (Chiu, 1994) or $r_b = 1.25 r_a$ (Chiu, 1997).

Next, the potentials of all data points are revised by using equation (4), the data point with the highest remaining potential is chosen as the second cluster center. The process is then continued until the k^{th}, $i = 1, \cdots, n$ cluster center have been selected, the potential of each data point is revised by the following formula

$$P_i \Leftarrow P_i - P_1^* e^{-(\frac{2}{r_b})^2 \|x_i - x_k^*\|^2} \tag{13}$$

where x_k^* is the location of the k^{th} cluster center and P_k^* is its corresponding potential value. The process of acquiring new cluster center and revising potentials is repeated until the remaining potential of all data points falls below some fraction of the potential of the first cluster center P_1^*.

Although the number of clusters (or rules) is automatically determined by the method, it should be noted that the user specified parameter r_a (the radius of influence of a cluster center) strongly affects the number of clusters that will be generated. A large r_a generally results in fewer clusters with a coarser model, while a small r_a can produce excessive number of clusters and a model that does not generalize well (by over-fitting the training data).

Therefore, the constant r_a acts as a tuning parameter of the desired resolution of the model, which can be chosen based on the resultant complexity and generalization ability of the model. It is clear that choosing r_a very small or very large will result in a poor accuracy because if r_a is chosen very small the density function will ignore the effect of neighboring data points; while if taken very large, the density function will take into account all the data points in the data space. Chiu (1997) suggests that the good value of r_a is between 0.2 and 0.5, while Hammouda and Karray (2000) show that a value of r_a between 0.4 and 0.7 is adequate. In this paper, the substractive clustering approach is used to find the initial membership functions of the ANFIS-HRC system with less number of rules and minimum amount of computational time. The design steps of ANFIS-HRC are shown in the flowchart presented in Figure 3.

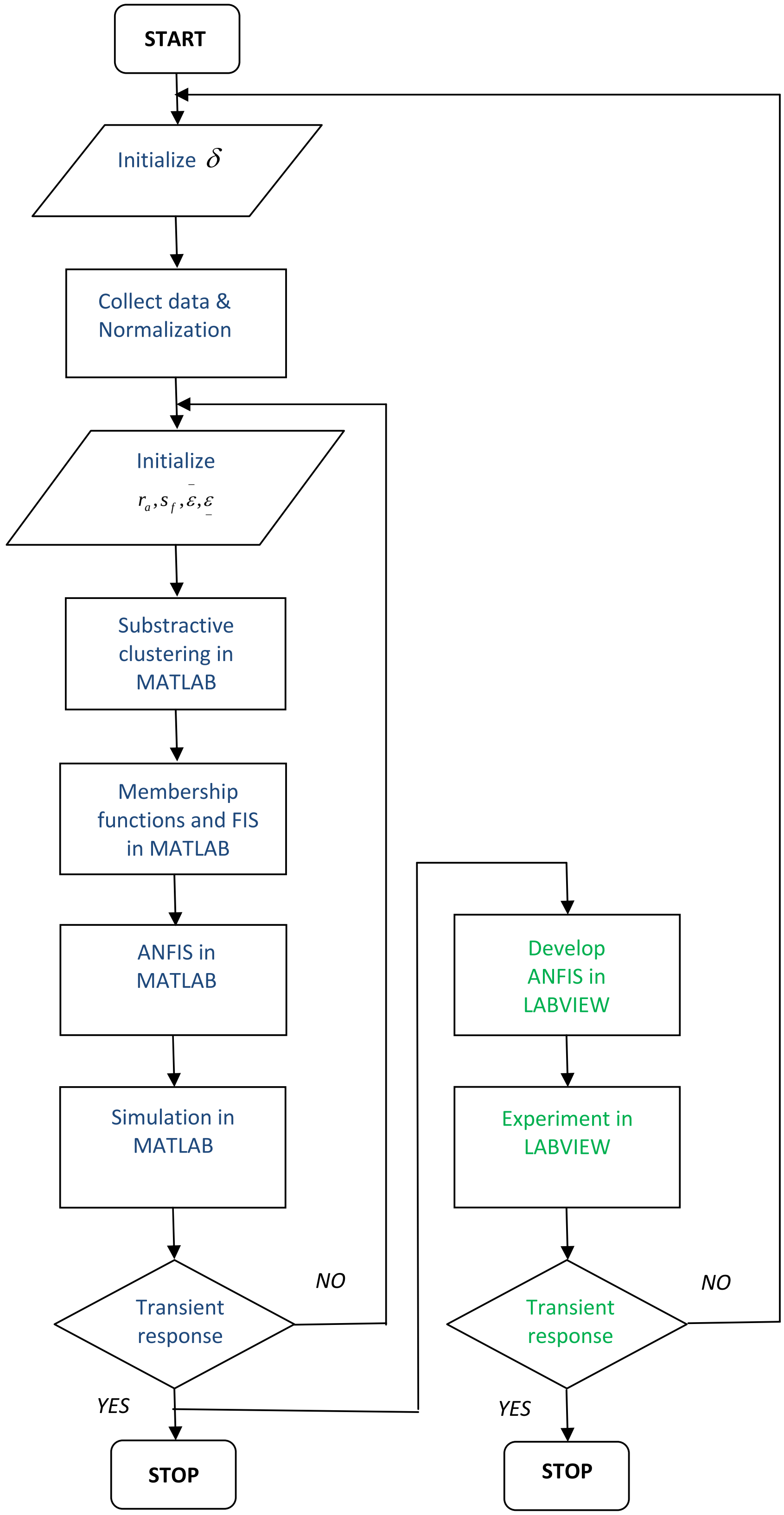


Figure 3. ANFIS-HRC Design Step.

3. ANFIS – HRC DESIGN AND SIMULATION

To develop ANFIS-HRC, the following steps are required:

- Generate data training set consist of error, delta error and increment set-point.
- Apply clustering method.
- Train ANFIS using data training set and the obtained membership function from clustering method.

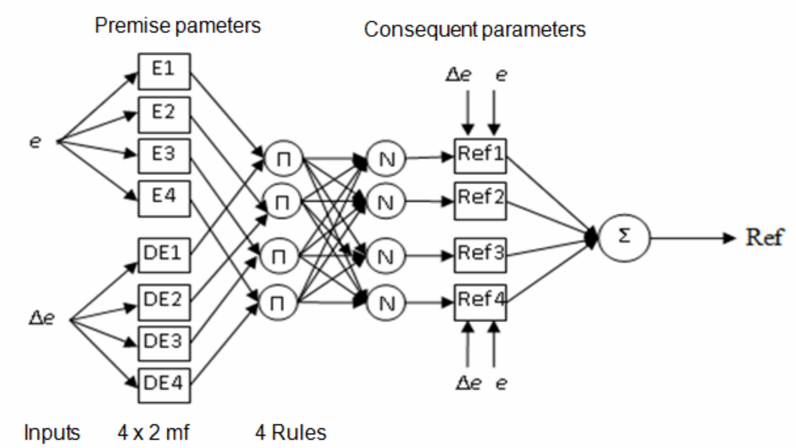


Figure 4. Architecture of ANFIS with 4 membership functions and 4 rules.

For simulation, let consider a seond order system with delay time given by the following transfer function.

$$G(s) = \frac{5e^{-30s}}{s^2 + 9s + 20} \tag{14}$$

The parameters of the PID controller are selected as $K_c = 0.05$, $T_i = 0.6$ seconds, dan $T_d = 15$ seconds and the range of data are as follow: $e(k) \in [-1,1]$, $\Delta e(k) \in [-1,1]$, and $o(k) \in [-3.3]$. First, it is necessary to generate data by simulating the closed loop system controlled by the PID controller with manipulate the set-point. Next, the membership functions and the number of the membership functions are found using the following parameters: $r_a = 0.2$ ($r_{a_e} = r_{a_{\Delta e}} = r_{a_o}$); $s_f = 1.5$ (squash factor); $\bar{\varepsilon} = 0.5$ (accept ratio); $\underline{\varepsilon} = 0.3$ (reject ratio). Figure 5 shows the data used to training ANFIS and the respective cluster centers obtained from substractive clustering. In (Matlab 2012), the squash factor is to specify that the cluster will be far from each other given by the following equation $r_b = s_f \times r_a$.

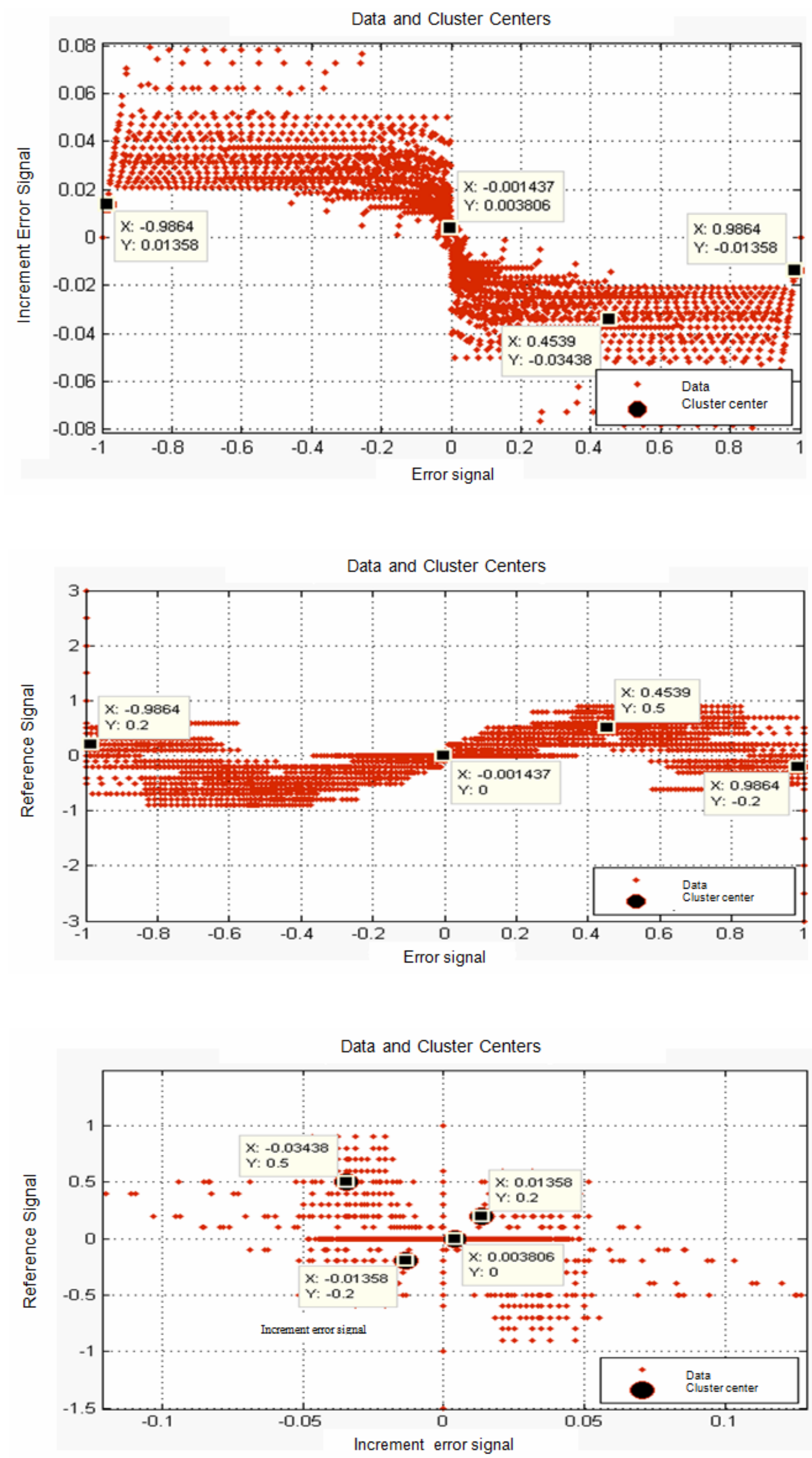


Figure 5. Signal data from error, increment error and set-point.

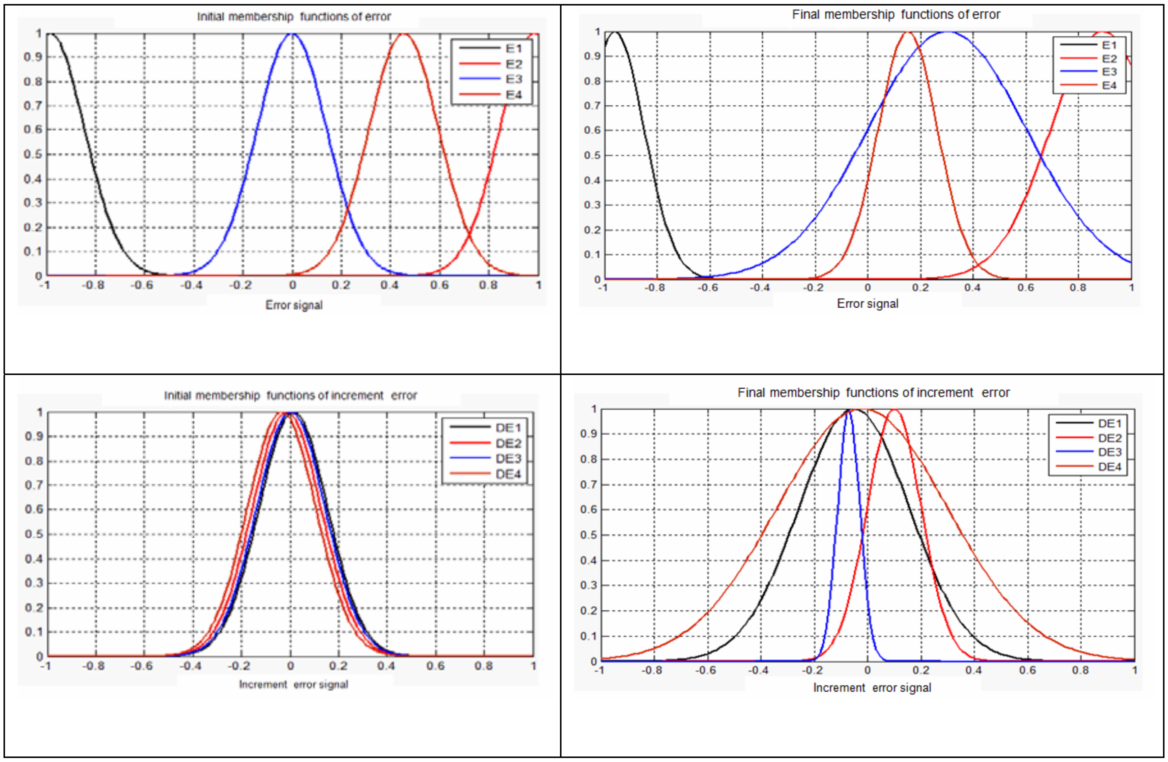


Figure 6. Membership functions error signal and delta error signal.

Initial and final rule base of the fuzzy inference system (FIS) obtained from substractive clustering and from ANFIS error backpropagation (EBP) learning are given in the following.

Initial FIS	**Final FIS**
If error *is* E1 *and* increment error *is* DE1 *then* reference1 *is* -1.648(E1)-0.2724(DE1)-1.359.	*If* error *is* E1 *and* increment error *is* DE1 *then* reference1 *is* -1.521(E1)-0.2815(DE1)-1.236.
If error *is* E2 *and* increment error *is* DE2 *then* reference2 *is* -1.012(E2)-0.2866(DE2)+0.7317.	*If* error *is* E2 *and* increment error *is* DE2 *then* reference2 *is* 1.083(E2)-0.4311(DE2)-1.428.
If error *is* E3 *and* increment error *is* DE3 *then* reference3 *is* 1.054(E3)+1.269(DE3)-0.02124.	*If* error *is* E3 *and* increment error *is* DE3 *then* reference3 *is* 1.428(E3)+2.927(DE3)+0.05941.
If error *is* E4 *and* increment error *is* DE4 *then* reference4 *is* 1.1496(E4)-1.235(DE4)+0.3027.	*If* error *is* E4 *and* increment error *is* DE4 *then* reference4 *is* 0.4221(E4)-0.948(DE4)-0.0228.

Figure 7 depicts the 3D plot of the fuzzy inference system of the ANFIS-HRC after EBP learning.

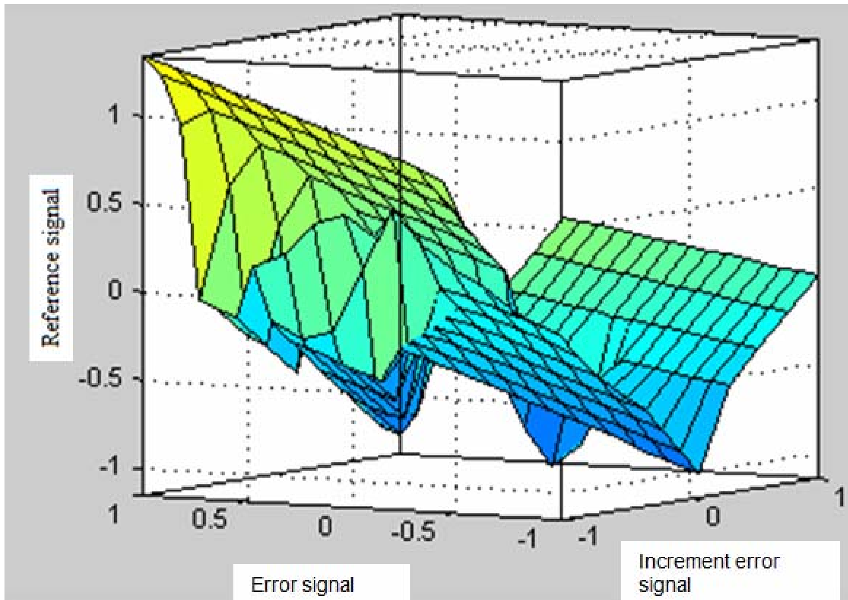
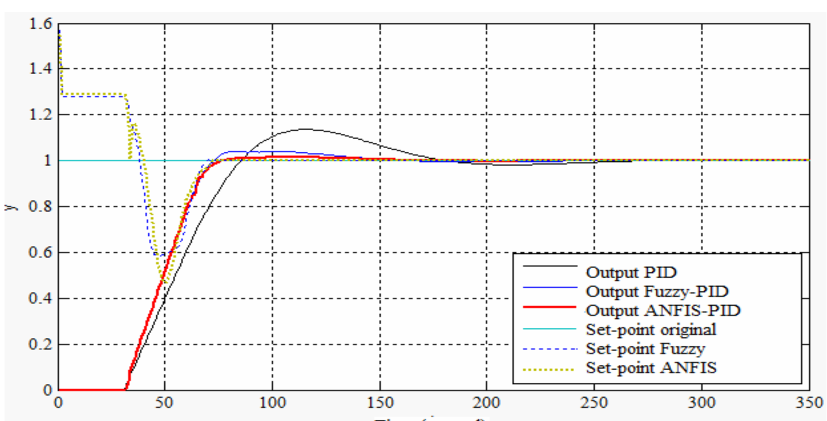


Figure 7. 3-D plot of FIS after EBP learning.

Figure 8 shows the transient response performances of the closed loop system with the PID controller, Fuzzy HRC-PID and the ANFIS-HRC-PID controller. It can be seen that the ANFIS-HRC-PID results in faster transient response with smaller overshoot and control signal magnitude compare with the PID controller. Table 1 shows the value of transient response criteria (rise time T_r , settling time T_s and maximum overshoot $\%M_p$) and integral error criteria (integral squared error (ISE), integral absolute error (IAE)). Either transient response or integral error criteria of the ANFIS-HRC-PID is better than the PID controller. Figure 9 shows the comparison of the response when the original set-point is increased and decreased over a period of time. In this case, the ANFIS-HRC-PID is still outperform the PID controller.



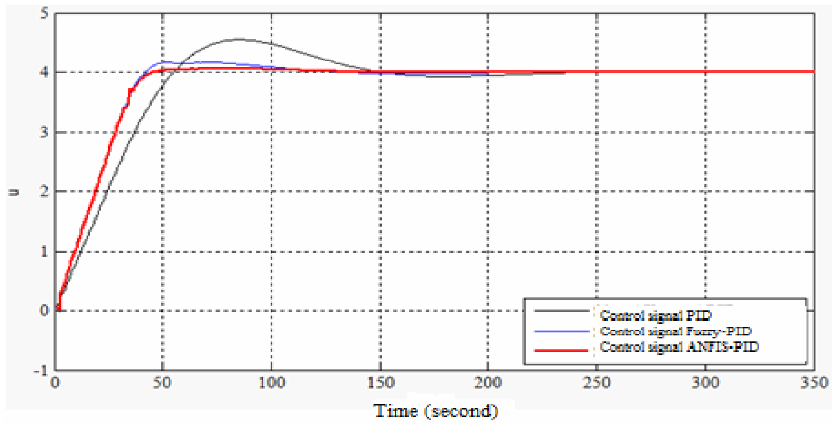
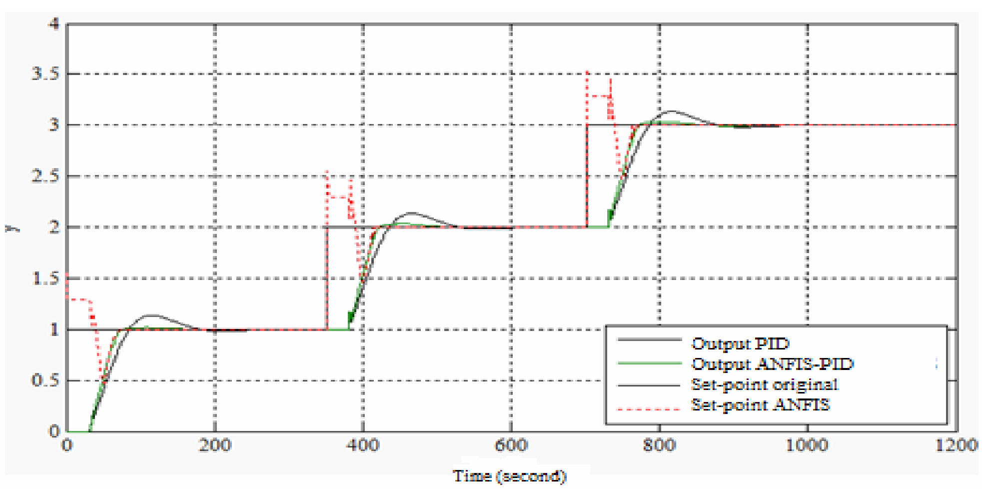


Figure 8. Transient response performance and the control input.

Table 1. Transient Response and Integral Criteria.

	T_r(s)	T_s(s)	$\%M_p$	u_p	$\int u^2 dt$	ISE	IAE
PID	85.42	181.01	13.60	4.54	20.398	0.040	0.067
ANFIS-PID	75.44	171.90	1.60	4.07	19.731	0.038	0.061



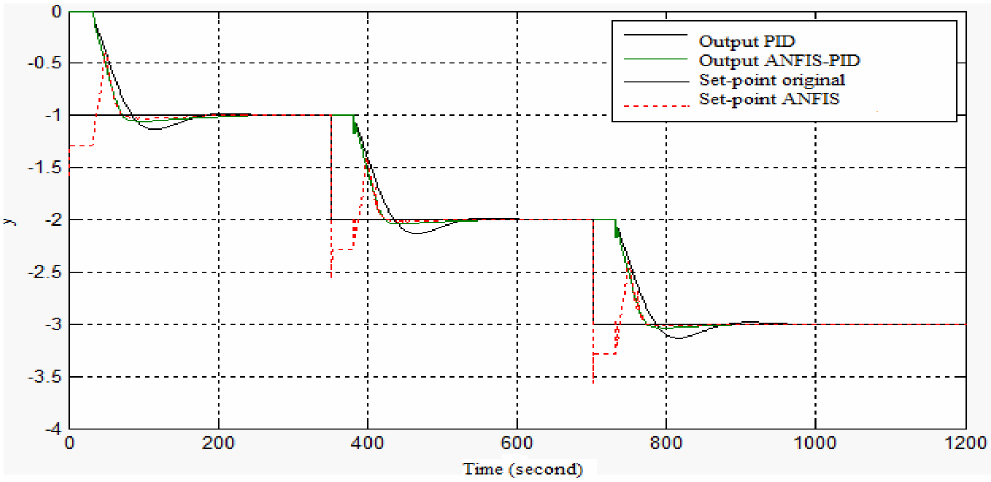


Figure 9. Transient response performance and the control input with changing the original set-point

4. IMPLEMENTATION ON SPEED CONTROL OF AC-MOTOR

This part presents an implementation of ANFIS-hybrid reference control (HRC) for speed control of AC-motor. Figure 10 shows the block diagram of the implementation of ANFIS-HRC to control AC-motor, the analog to digital and digital analog converter and an inverter. The hardware and the wiring are shown in Figure 11. The activation condition δ (in the equation (1a) and the equation (1b)) to initiate the reference signal changes in HRC is set as δ = 2 % of the steady state error.

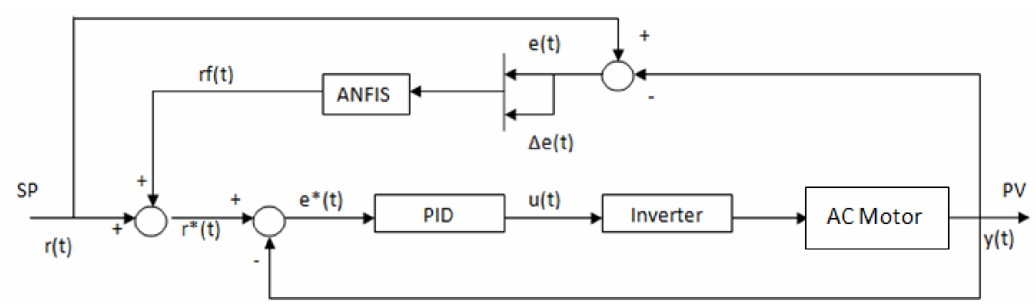


Figure 10. Block Diagram of Blok ANFIS-HRC-PID controller for Speed Control of AC-motor

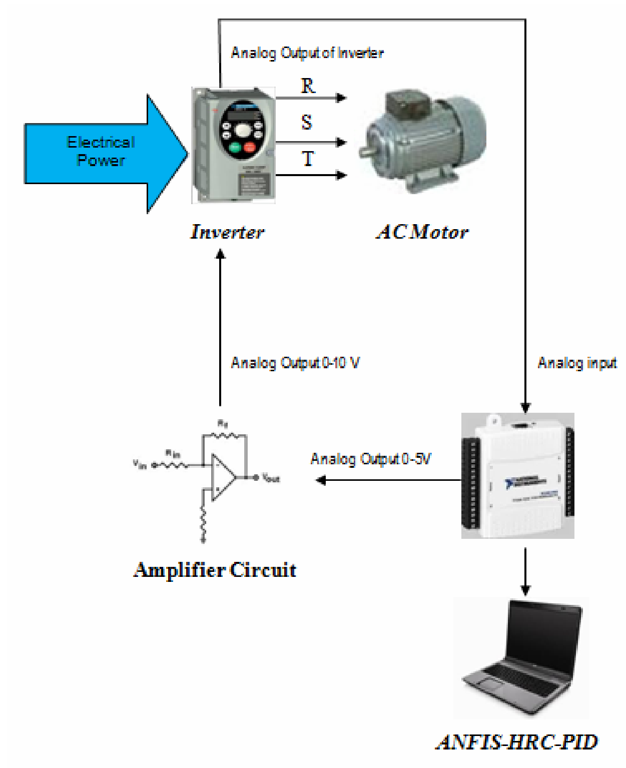


Figure 11. Hardware Configuration of Experimental Setup.

Device specifications in the hardware configuration are as follow:

- AC-motor: 3-phases induction motor, with poles:4, Output : 0.25 HP/0.18 KW, Volt: 220/330 V, AMP: 1.1/0.64, RPM: 1345 rpm
- Inverter: Altivar 31, ATV31HU11M2 type, Input power: 0,5 HP or 0,37 KW
- Analog tp Digital/Digital to Analog: National Instrument (DAQ NI-USB 6008), Input: 0-10 V DC, Output: 0-5 V DC
- LabView Software

Next, the membership functions and the number membership functions are found using the following parameters: $r_a = 0.075$ ($r_{a_e} = r_{a_{\Delta e}} = r_{a_o}$); $s_f = 1.25$ (quash factor); $\bar{\varepsilon} = 0.4$ (accept ratio); $\underline{\varepsilon} = 0.05$ (reject ratio). These parameters imply that a center can be a new cluster center if has density value compared to the highest density value is greater than 0.4. A new candidate of cluster center will be rejected if it has density ratio compared to the highest density is less than 0.05. Figure 12 and Figure 13 show the data used to training in substractive clustering which are obtained by making various paterns of reference signal changes that yield good speed control transient response performances of the AC-motor. This substractive clustering produces 18 cluster points either in the error or in the delta error to initiate the Fuzzy Inference System (FIS). The subtractive clustering method yields RMSE 0.058. It gives Gaussian parameters σ (the variance) and c (the mean) as follow:

- The parameter σ $: L = \begin{bmatrix} 0.0913 & 0.0921 & 0{,}0325 \end{bmatrix}$
- The cluster center matrix (C):

$$C = \begin{bmatrix} -0.0520 & 0 & -0.0186 \\ 0.0890 & 0 & 0.0326 \\ -0.2050 & 0 & -0.0745 \\ 1.5660 & -0.0410 & -0.0745 \\ 0.2330 & -0..0810 & -0.0847 \\ -1.6000 & 0.0510 & -0.6000 \\ 0.6790 & -0.1530 & 0.6000 \\ -0.2370 & 0.0810 & 0.0867 \\ 1.2420 & -0.1220 & 0.6000 \\ -0.7050 & 0.1430 & -0.6000 \\ -1.3170 & 0.1320 & -0.6000 \\ 0.4060 & -0.1120 & 0.1476 \\ 0.9560 & -0.1630 & 0.6000 \\ 1.6490 & 1.6600 & 0.6000 \\ -1.0200 & 0.1530 & -0.6004 \\ -1.6810 & -1.6700 & 0.6004 \\ -0.4100 & 0.1120 & 0.1500 \\ 0.2730 & 0 & 0.0964 \end{bmatrix}$$

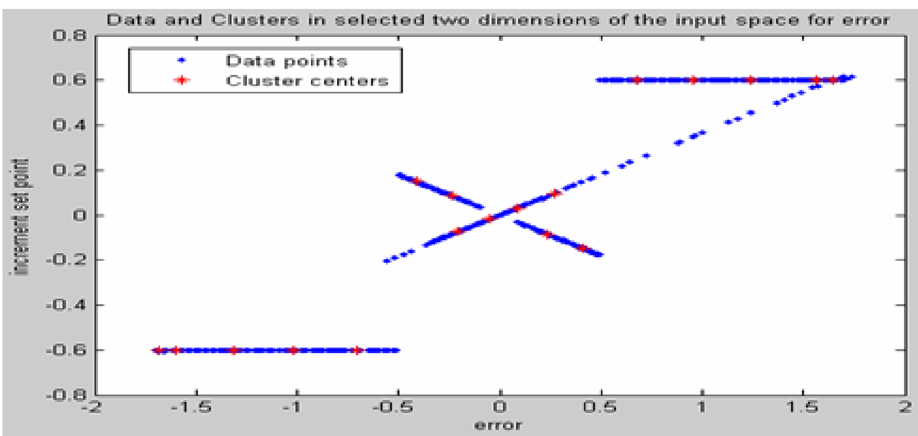


Figure 12. Cluster Centers of Error and Reference Signal Changes

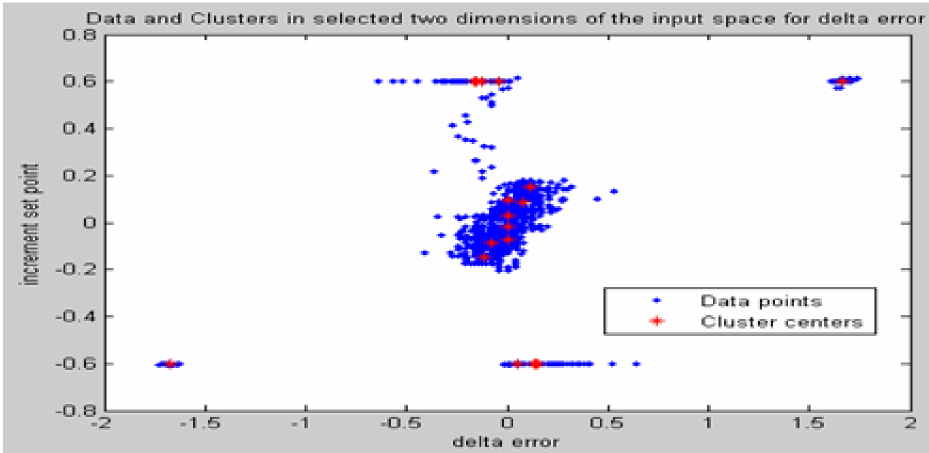


Figure 13. Cluster Centers of Delta Error and Reference Signal Changes.

After working on the substractive clustering to estimate the number of clusters and the cluster centers in a set of data, it is carried out ANFIS learning by using the same data in order to improve the initial FIS formed in the substractive clustering step. The improvement is done by correcting the premise parameters and the consequent parameters. The ANFIS learning uses 3175 input/output pair data, 0.1 learning rate and 100 training epochs. This ANFIS training reduces the RMSE from 0.058 to 0.047.

Both error variables and delta error variables have 18 membership functions. The value range of the error variables and the delta error variables are selected as $[-1.703, 1.739]$ and $[-1.731, 1.741]$ respectively. The FIS obtained from the ANFIS training has 18 rules. The resulted membership functions of the error variables and the delta error variables are shown in Figure 14 and Figure 15 respectively. Table 2 and Table 3 describe the consequent parameters and the rule of ANFIS found after the training process.

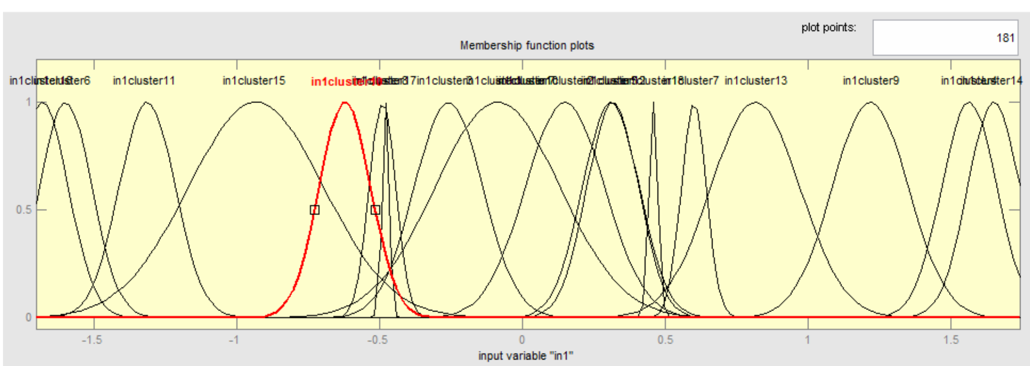


Figure 14. Membership Functions of Error.

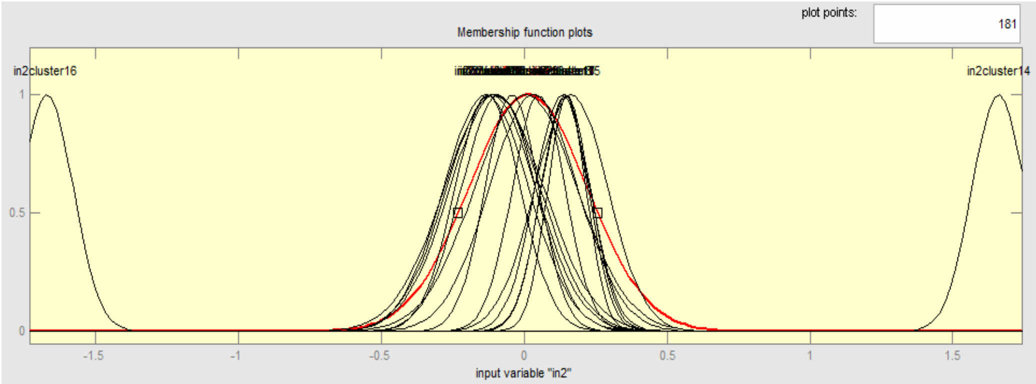


Figure 15. Membership Functions of Delta Error.

Table 2. Consequent Parameters of ANFIS.

	p	q	r
out1cluster1	-0,1279	-0,393	0,151
out1cluster2	3,189	-0,1076	-0,1662
out1cluster3	-0,4487	2,069	-0,3167
out1cluster4	0,04239	-0,0319	0,5301
out1cluster5	15,24	1,587	-4,865
out1cluster6	-0,01251	0,0134	-0,6219
out1cluster7	0	0	0
out1cluster8	10,62	0,1674	4,884
out1cluster9	-0,01052	0,08589	0,6231
out1cluster10	0	0	0
out1cluster11	-0,02461	-0,02843	-0,6342
out1cluster12	-13,2	-1,79	3,543
out1cluster13	-0,02884	-0,07089	0,5969
out1cluster14	0,1294	-0,06217	0,4896
out1cluster15	-0,04987	0,007409	-0,652
out1cluster16	0,01097	-0,0213	-0,619
out1cluster17	-30,35	0,2178	-13,82
out1cluster18	-9,229	2,134	3,972

Table 3. ANFIS Rules.

	Error		Delta Error		Output
If	in1cluster1	And	in2cluster1	then	out1cluster1
	in1cluster2		in2cluster2		out1cluster2
	in1cluster3		in2cluster3		out1cluster3
	in1cluster4		in2cluster4		out1cluster4
	in1cluster5		in2cluster5		out1cluster5
	in1cluster6		in2cluster6		out1cluster6
	in1cluster7		in2cluster7		out1cluster7
	in1cluster8		in2cluster8		out1cluster8
	in1cluster9		in2cluster9		out1cluster9
	in1cluster10		in2cluster10		out1cluster10
	in1cluster11		in2cluster11		out1cluster11
	in1cluster12		in2cluster12		out1cluster12
	in1cluster13		in2cluster13		out1cluster13
	in1cluster14		in2cluster14		out1cluster14
	in1cluster15		in2cluster15		out1cluster15
	in1cluster16		in2cluster16		out1cluster16
	in1cluster17		in2cluster17		out1cluster17
	in1cluster18		in2cluster18		out1cluster18

Next, the identified ANFIS-HRC is then implemented as in Figure 10 by testing on a range value of the reference signal (set-point). The parameters of the PID controller are chosen as $K_c = 0.4$, $T_i = 0.009$ minutes and $T_d = 0.001$ minutes that results in good transient response. Figure 16 shows the transient response of the PID controller and the ANFIS-HRC-PID controller at set-point 1,64 V – 1,70 V or 10 Hz.. It can be seen that the ANFIS-HRC-PID controller is outperform the transient response of the PID controller by producing less overshoot and faster settling time. It is also shown the reference signal produced by means of ANFIS-HRC. At the start, the reference signal leads to large error in order to speed up the response and then it is followed by reducing the error in order to suppress the overshoot.

The control signal is shown in Figure 17. The maximum control signal of the ANFIS-HRC-PID controller is a bit higher compare to the PID controller but the integral squared control signal is smaller than the PID controller. Table 4 shows that the performances of the ANFIS-HRC-PID controller are better than the PID controller except for maximum control signal. Figure 18 shows the transient response performances of the ANFIS-HRC-PID controller for changes set-point in the value range of the set-point used to train the ANFIS-HRC. It can be observed that the performances of th ANFIS-HRC-PID controller are still outperform the PID controller.

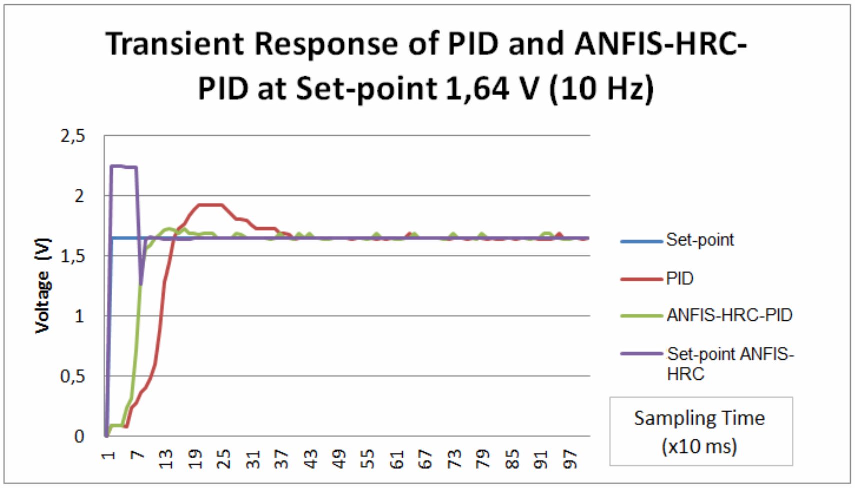


Figure 16. Comparison of Transient Response.

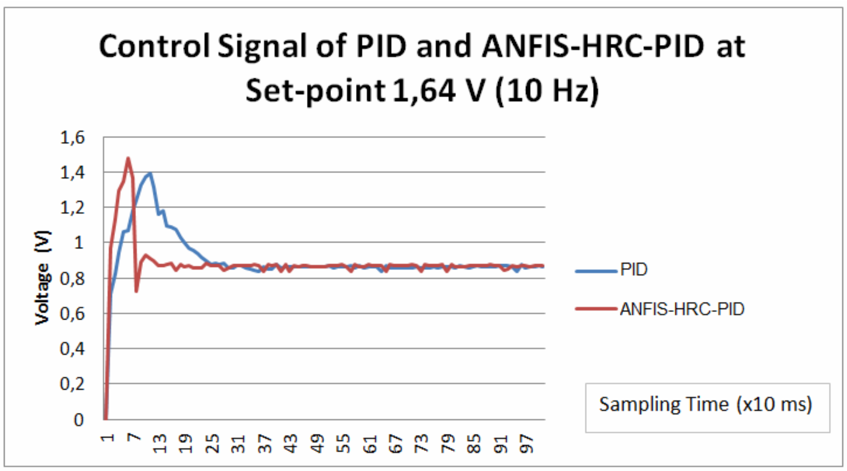


Figure 17. Comparison of Control Signal.

Table 4. Performances.

Controller	$\int u^2\, dt$	Ts	Tr	% Mp	RMSE	IAE	Up (V)
PID	0,8456	390 ms	140 ms	16,83%	0,46	0,1914	1,39
ANFIS-HRC-PID	0,8042	230 ms	100 ms	5,00%	0,35	0,0993	1,47

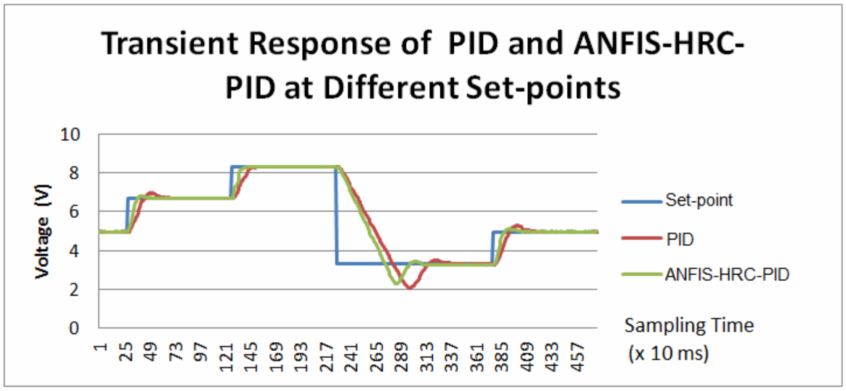


Figure 18. Comparison of Transient Response at Different Set-points.

5. CONCLUSIONS

The paper proposed an ANFIS based hybrid reference control to improve the transient response performance of the closed loop system controlled by PID controller. The design steps consist of generating training data set, obtaining membership functions and number of membership functions using subtractive clustering technique and then training ANFIS. Simulation showed that the proposed method resulted in improved transient response performances and other integral classifications. The proposed ANFIS-HRC was then implemented as a speed controller of AC-motor. The implementation confirmed the transient response performances improvement by means of ANFIS-HRC with the PID controller.

REFERENCES

Buragohain, M., Mahanta, C., 2008, V-fold Technique based ANFIS Model for Complex Large-Scale Systems, *International Journal of Artificial Intelligence (IJAI)* **1** (A08), 34-55.

Cai, J., Mu, J., 2005, Estimation of Daily Reference Evapotranspiration from Weather Forecast Messages, *Proceedings of ICID 21st European Regional Conference*, Frankfurt (Oder) and Slubice, Germany and Poland, 1-7.

Cheng, P., Quek, C., Mah, M.L., 2007, Predicting the Impact of Anticipatory Action on U.S. Stock Market – an Event Study using ANFIS (a Neural Fuzzy Model), *Computational Intelligence* **23**, 117-141.

Chiu, S.L., 1994, Fuzzy Model Identification Based on Cluster Estimation, *Journal of Intelligent and Fuzzy Systems* **2**, 267-278.

Chiu, S.L., 1997, *Extracting Fuzzy Rules from Data for Function Approximation and Pattern Classification*, Fuzzy Information Engineering: A Guided Tour of Applications, Dubois, D., Prade, H., and Yager, R. (Eds.), John Wiley & Sons, Inc., New York, USA, 1-10.

Chiu, S., 1998, Using Fuzzy Logic in Control Applications: Beyond Fuzzy PID Controller, *IEEE Control Systems Magazine* **8** (5), 100-1005.

David, R.C., Dragos C.A., Bulzan, R.G., Precup, R.E., Petriu, E.M., Radac, M.B., 2012*,* An Approach to Fuzzy Modeling of Magnetic Levitation Systems, *International Journal of Artificial Intelligence (IJAI)* **9** (A12), 1-18.

Devasenapati, S.B., Ramachandran, K.I., 2011, Hybrid Fuzzy Model Based Expert System Misfire Detection in Automobile Engines*, International Journal of Artificial Intelligence (IJAI)* **7** (A11), 47-62.

Francis, B.A., Wonham, W.M., 1976, The Internal Model Principle of Control Theory, *Automatica* **12**, 457-465.

Hammouda, K., Karray, F., 2000, *A Comparative Study of Data Clustering Techniques*, SYDE 625: Tools of Intelligent Systems Design, Course project, University of Waterloo, Waterloo, ON, Canada, http://pami.uwaterloo.ca/~hammouda/publications.php (July 18, 2008), 1-21.

Jang, J. –S R., Sun, C-T., Mizutani, E., 1997, *Neuro-Fuzzy and Soft Computing*, Prentice-Hall Inc, Englewood Cliffs, New Jersey.

Joelianto, E., 2011, Robust *H_∞ PID Controller Design Via LMI Solution of Dissipative Integral Backstepping with State Feedback Synthesis*, in Robust Control, Theory and Applications, Andrzej Bartoszewicz (Ed.), InTech, Croatia, 69-88.

Joelianto, E., Anura, D.C., 2011, Transient Response Improvement of PID Controller using ANFIS – Hybrid Reference Control, *Proceedings of 2011 2nd International Conference on Instrumentation, Control and Automation*, Bandung, Indonesia, 292-297.

Joelianto, E., Sitanggang, P.H., 2009, A Substractive Clustering Based Fuzzy Hybrid Reference Control Design for Transient Response Improvement of PID Controller, *ITB Journal of Engineering Science* **41** (2), 167-186.

Joelianto, E., Tansri, O., 2007, Fuzzy Logic Based Hybrid Reference Control for Improving PID Controller Transient Response Performance*, ITB Journal of Science* **39A** (1&2), pp.124-145. (in Indonesian)

Joelianto, E., Widiyantoro, S., Ichsan, M., 2009, Time Series Estimation on Earthquake Events using ANFIS with Mapping Function, *International Journal of Artificial Intelligence (IJAI)* **3** (A09), 37-63.

Joelianto, E., Williamson, D., 1997, Discrete Event Reference Control, *Proceedings of 36th IEEE Conference on Decision Control* **1**, San Diego, CA, USA, 692-697.

Joelianto, E., Williamson, D., 2009, Transient Response Improvement of Feedback Control Systems using Hybrid Reference Control*, International Journal of Control* **82** (10), 1955-1970.

Jothiprakash V., Magar, R.B., Kalkutki, S., 2009, Rainfall-Runoff Models using Adaptive Neuro-Fuzzy Inference System (ANFIS) for an Intermittent River, *International Journal of Artificial Intelligence (IJAI)* **3** (A09), 1-23.

Jovanovic, B.B., Reljin, I.S., Reljin, B.D., 2004, Modified ANFIS Architecture - Improving Efficiency of ANFIS Technique*, Proceedings of 7th Seminar on Neural Network Applications in Electrical Engineering (NEUREL)*, Belgrade, Serbia, 215 – 220.

Keskin, M.E, Taylan, D., Terzi, Ö., 2006, Adaptive Neural-based Fuzzy Inference System (ANFIS) Approach for Modelling Hydrological Time Series*, Hydrological Sciences J.* **51**, 588-598.

Kim, J.H., Kim, K.C., Chong, E.K.P., 1994, Fuzzy Precompensated PID Controllers, *IEEE Transactions on Control Systems Technology* **2** (4), 406-411.

Matlab, 2012, Fuzzy Logic Toolbox: User/s Guide R2012a, The MathWorks, Inc., Natick, MA.

Misir, D., Malki, H.A., 2006, Liapunov Stability for A Fuzzy PID Controlled Flexible-Joint Manipulator, *International Journal of Computer Applications in Technology* **27**, 97-106.

Mohan, B.M., Sinha, A., 2008, Analytical Structure and Stability Analysis of A Fuzzy PID Controller, *Applied Soft Computing Journal* **8**, 749-758.

National Instruments, 2001, *PID Control Toolset User Manual*, National Instruments Corporation, Austin, Texas.

Patel, P., Marwala, T., 2006, *Neural Networks, Fuzzy Inference Systems and Adaptive – Neuro Fuzzy Inference Systems for Financial Decision Making.* in King, I., et al. (Eds.), ICONIP 2006, Part III, LNCS 4234, Springer-Verlag, Berlin, Heidelberg, 430-439.

Pratumsuwan, P., Thongchai, S., 2009, A Two-Layered Fuzzy Logic Controller for Proportional Hydraulic System. *Proceedings of 4th IEEE International Conference on Industrial Electronics and Applications (ICIEA 2009)*, Bangkok, Thailand, 2778-2781.

Pratumsuwan, P., Thongchaisuratkrul, C., 2011, *Pre-compensation for a Hybrid Fuzzy PID Control of a Proportional Hydraulic System*, PID Control, Implementation and Tuning, Tamer Mansour (Ed.), InTech, Croatia, 201-216.

Precup R.E., Tomescu, M.L., Petriu, E.M., Dragomir, L.E., 2011, Stable Fuzzy Logic Control of Generalized van der Pol Oscillator, *International Journal of Artificial Intelligence (IJAI)* **1** (A08), 23-33.

Yasuda, Y., Mano, S.I., Crotty, S., 1990, A PID controller with overshoot suppression algorithm, *Proceedings of Instrument Society of America International Conference (ISA-90)*, New Orleans, LA, USA, 1849-1857.