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Design and Stability Discussion of a Hybrid Intelligent Controller

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Abstract: In this paper, the pitch angle control of a laboratory model helicopter is discussed. The control has some specific features. As a main feature, it is observed that the steady state control command is completely dependent on the setpoint, so error-based controller design is not applicable to this case. Moreover, the system has a highly oscillating dynamics. In order to solve this control problem, two controllers are designed, an artificial neural network, whose input is the setpoint, is used to provide the steady state control command, and a fuzzy inference system ,whose input is the error of the system, is used to provide the transient control command. The total control command is the sum of the aforementioned two control commands. It is proved that both ANN and FIS are bounded-input bounded-output (BIBO) systems.

1. INTRODUCTION

Both artificial neural networks and fuzzy controllers have been extensively investigated in the control of helicopters since 1990's (Philips et al, 1996, Sabbato and Zheng, 1997). In the field of neural networks, Enns and Si used the technique of approximate dynamic programming to control a model helicopter (Enns and Si, 2003). A few researches also have performed control of YAMAHA model helicopter using double ANN controllers and a combination of ANN with nonlinear controllers (Hashimoto et al, 2002, Nakanishi and Inoue, 2002). ANN has also been employed as a part of a robust nonlinear feedback control of a model helicopter by researchers of Georgia Institute of Technology (Kutay et al, 2005, Rysdik and Calise, 2005). Neural networks have been applied in the combination with linear controllers for helicopter control purposes, as well (Wu at al, 2006). As the bridge of fuzzy logic and neural networks, neuron-fuzzy networks have been involved in helicopter control (Amaral et al, 2002a, Amaral et al, 2002b, Amaral and Crisostomo, 2001a). Among two main types of fuzzy inference systems, Mamdani type ones have attracted more attention for helicopter control purposes (Sanchez et al,2007,Kadmiry and Driankov,2004, Chen and Li,2001, Tanaka et al,2004,Mohammadzaheri et al,2006) and Sugeno models have been rarely used (Hou et al,2006). In many cases, fuzzy controllers have been applied in the presence of some other types of controllers such as PID, LQR and sliding mode controllers or in the presence of other artificial intelligence components such as neural networks and genetic algorithm (Philips et al, 1996, Sabbato and Zheng, 1997, Sanchez et al, 2007, Chen and Li, 2001, Tanaka et al, 2004). Although model or real helicopters usually are of 2 to 6 degrees of freedom, the researches are usually concerned with constrained situations to reduce the variables and degrees of freedom and let complicated theories be tested (Sanchez et al,2007, Tanaka et al, 2004, Mohammadzaheri et al, 2006,Lower et al,2006, Amaral and Crisostomo,2001b), yet complicated MIMO models of helicopter have also been controlled by fuzzy and ANN controllers (Enns and Si,2003, Kadmiry and Driankov,2004, Chen and Li,2001, Tanaka et al,2004, Amaral and Crisostomo,2001b).

2. BACKGROUND THEORY

This section includes the brief introduction and main features of utilized artificial neural network and fuzzy inference system.

2.1 Main features of Utilized Artificial Neural Network

In this research, a fully connected perceptron with three layers of neurons and two layers of connections is used. The neurons of input and output layers have linear activation functions with slope of 1, and hyperbolic tangent function is employed as the activation function of hidden layer neurons. Mean of squared errors is used as the performance function and Nguyen-Widrow method is utilized to designate initial values of connection weights. The training algorithm is Levenberg-Marquardt batch error back propagation.

2.2 Main features of Utilized Fuzzy Inference System

In this research, a non-weighted zero-order Sugeno type fuzzy inference system with AND connectors, are used as fuzzy controller. A scheme of such a system is shown in Fig.1. In Sugeno-type FIS, Antecedents are linguistic (fuzzy) values with membership functions. All the generated membership grades using this functions (in the range of 0 and 1) pass through a function namely T-norm. The output of the T-norm is the weight of the rule.

$$weight\ of\ rule(w_i) = \text{Tnorm}(all\ \ membership\ grades), \quad (1)$$

In this research, T-norm function is "minimum". For instance, if the membership grade of j th membership function of i th rule (having M membership functions) of FIS is shown as μ_j^i, the weight of i th rule is:

$$w_i = \operatorname*{Min}_{j=1}^{M} \mu_j^i. \tag{2}$$

A weight associated with each rule (w_i) emerged form this step. In a zero-order Sugeno-type FIS, the consequents of rules are constant numbers (r_i), independent from current conditions or antecedents.

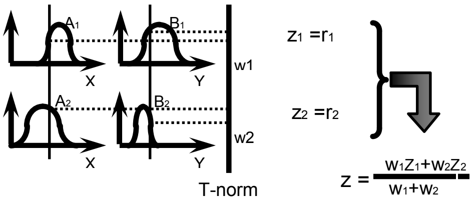

Fig.1: A scheme of a Sugeno-type FIS

The total output of FIS, having N rules, is calculated using following equation:

$$output\ of\ FIS = \frac{\sum_{i=1}^{N} r_i w_i}{\sum_{i=1}^{N} w_i}. \tag{3}$$

3. MECHANICAL MODELLING

The model helicopter used in this research is a two input-two output system. The model helicopter is of two degrees of freedom, the first possible motion is the rotation of the helicopter body around the horizontal axis (change in pitch angle) and the second is rotation around the vertical axis (change in yaw angle). The helicopter is produced to rotate from -170° to 170° in yaw and from -60° to 60° in pitch. System inputs are voltages of main and rear rotors, and yaw and pitch angles are considered as the outputs.

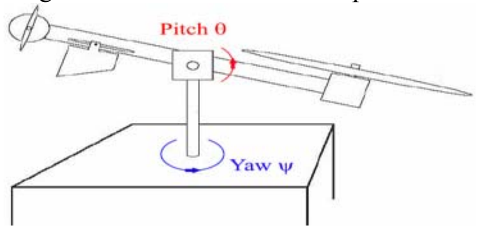

Fig.2: A scheme of model helicopter

A mechanical modelling is done using Newton and Euler laws, and following differential equations are setup for the system (Mohammadzaheri et al,2006):

$$\frac{d\omega_R}{dt} = \frac{1}{I_R}(T_{Main\,Rotor\,/\,Electrical} - T_{Main\,Rotor's\,Air\,Friction} - T_{Main\,Rotor's\,Mechanical\,Friction}), \tag{4}$$

$$\frac{d\omega_S}{dt} = \frac{1}{I_S}(T_{Rear\,Rotor/\,Electrical} - T_{Rear\,Rotor's\,Air\,Friction} - T_{Rear\,Rotor's\,Mechanical Friction}), \tag{5}$$

$$\frac{d\theta}{dt} = \omega_\theta, \tag{6}$$

$$\frac{d\omega_\theta}{dt} = \frac{1}{I_H}(T_{Main\,Rotor,R} - T_{Rear\,Rotor,R} - T_{friction,R} - T_{weight,R} + T_{Change in\,Rotational\,Plane,R}), \tag{7}$$

$$\frac{d\psi}{dt} = \omega_\psi, \tag{8}$$

$$\frac{d\omega_\psi}{dt} = \frac{1}{I_V}(T_{Rear Rotor,S} - T_{Main\,Rotor,S} - T_{friction,S} + T_{Change in\,Rotational\,Plane,S}). \tag{9}$$

where, ω_R : Main rotor angular velocity,

ω_S : rear rotor angular velocity

θ : pitch angle

ψ : yaw angle

I_R : main rotor moment of inertia

I_S : rear rotor moment of inertia

I_H : body moment of inertia around horizontal axis

I_V : body moment of inertia around vertical axis

In this research, a special situation is studied. In this situation, the input voltage of rear rotor (U_S) is set to "zero", so rear rotor angular velocity (ω_S) equals zero, as well. As a result, the only input of the system is the input voltage of main rotor (U_R). Moreover, the pitch angle is considered as the unique output. Inasmuch as the effect of rear rotor on pitch angle is practically negligible, the studied situation can be useful for pitch angle control of MIMO system. In the studied situation rear rotor does not generate any torque and consequently, in case of change in the rotational plane, the pitch angle is not influenced by rear rotor. Therefore, (7) is simplified as (10). This equation with (4) and (6) can represent the system behaviour:

$$\frac{d\omega_\theta}{dt} = \frac{1}{I_H}(T_{Main\,Rotor,R} - T_{friction,R} - T_{weight,R}), \tag{10}$$

$$\frac{d\theta}{dt} = \omega_\theta, \tag{6}$$

$$\frac{d\omega_R}{dt} = \frac{1}{I_R}(T_{Main\,Rotor\,/\,Electrical} - T_{Main\,Rotor's\,Air\,Friction} - T_{Main\,Rotor's\,Mechanical\,Friction}), \tag{4}$$

In these equations, the torques can be defined as a function of system's parameters, and the pitch angle can be available after integration.

4. PROBLEM STATEMENT

As it is previously stated, the controlled system is a highly nonlinear model helicopter whose input is the voltage of main rotor and the pitch angle is also considered as the output. The aim is the control of pitch angle so that the pitch angle approaches the desired value, quickly enough. The desired pitch is in the range of [-50° 35°]. This system's dynamic is of two main unordinary features which cause this problem to be considered as an unusual and difficult control problem.

1) In this system (open loop), it usually takes very long for the system to obtain the steady state situation (even for zero input). The steady state situation is obtained only after

tens of severe fluctuations (Fig.3). If a quick convergence is aimed, this problem should be overcome.

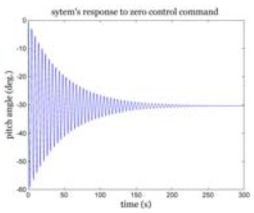

Fig.3: open loop response to zero input and initial condition

2) Controllers that compute the control command based on the "error" are called error-based controllers which are widely used for control purposes. In error-based controllers, the control algorithm is not practically sensitive to the setpoint. For example in state space control:

$$control\ input = u = F_c(e, \frac{de}{dt}, \ldots, \frac{d^r e}{dt^r}), \quad \text{or}$$

$$u = F_c(e(k), \ldots, e(k-r)). \tag{11}$$

where; e: error, r: system's order, and if the "steady state control command" (u_{ss}) is considered as the control command in the equilibrium point, where error and its derivatives are zero:

$$u_{ss} = F_c(0,0,\ldots,0). \tag{12}$$

PID controllers have integrator terms, but, considering the influence of initial conditions on error, error integral can not be good presenter of setpoint, especially in the discrete domain or in the presence of disturbances. In total, in error-based controllers, the setpoint doesn't affect the control command directly, and the error plays the main role. But, in the discussed model helicopter, in order to obtain a specific pitch angle (setpoint), a particular steady state control command is needed. For instance, after reaching to the setpoints of -30° and 30°, entirely different control commands are needed so that the error remains around zero. These steady state control commands are independent from initial conditions. In order to challenge this control problem, the setpoint should directly be considered in control algorithm.

5. CONTROL LAW

In order to control the unusual pitch dynamic of model helicopter, the control command is defined as the sum of two different commands, namely "steady state" (u_{ss}) and "transient" (u_{tr}) control commands:

$$u = u_{ss} + u_{tr}. \tag{13}$$

A hybrid intelligent control is designed, including an artificial neural network and a fuzzy inference system. ANN is responsible for generating steady state control command and transient control command is created by FIS. ANN is a non-error-based controller and influenced only by setpoint whereas FIS is an error-based controller.

5.1 Design of Utilized Artificial Neural Network

Through tests, it is known that, in the laboratory conditions, any tested input voltage, in the range of [-0.55v +0.99v] leads a specific steady state pitch angle in the permitted range of [-60° 60°], independent from initial conditions. In the aforementioned range of input voltages, all voltages with the interval of 0.01v are exerted on the system in the simulation environment, and their relevant steady state pitch angle is recorded (Fig.4). As a result, a series of data is obtained. 90% of these data (9 in each 10) is selected as training data.

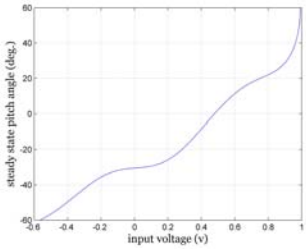

Fig.4: input voltage versus steady state pitch angle

This data are trained to an ANN inversely, that is, the steady state pitch angle is considered as the inputs and input voltage is assumed as the output. A single input single output perceptron with a 10-neuron hidden layer having hyperbolic tangent activation functions is used to be trained; in this research, training is finished after 300 epochs. After training, it is expected that, the ANN receives the desired pitch angle (θ_d) and returns the voltage approaching the system to that angle in long term (10~15 minutes). The achieved ANN is checked by the data not used in the training. The average checking error is 0.1134×10^{-3} v. This error is about 10 times less than minimum interval between voltages of training data. This checking accuracy is completely acceptable and unlikely to be beaten by other methods. For instance, adaptive neuron-fuzzy inference system (ANFIS) is also been tried, the obtained checking error by ANFIS is higher than utilized ANN by 500%. This ANN is used to calculate steady state control command (u_{ss}). Equation (14), shows the relation of u_{ss} and θ_d:

$$u_{ss} = \sum_{i=1}^{10} [T_i \tanh(W_i \theta_d + {}_1b_i)] + {}_2b \tag{14}$$

where; W_i: the weight of ith connection between input and hidden layers

T_i: the weight of ith connection between hidden and output layers

${}_1b_i$: the weight of connection between bias of input layer and ith neuron of hidden layer

${}_2b$: the weight of connection between bias of hidden layer and output neuron

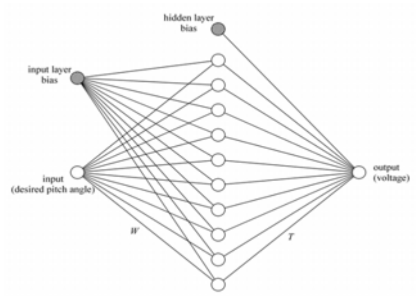

Fig.5: ANN controller

5.2 Design of Fuzzy Inference System

As it is previously stated, fuzzy controller is error-based. Control error "*e*" and its differential "*de*" are input signals of fuzzy controller which "*de*" is the difference between current and previous error:

$$de(k) = e(k) - e(k-1), \tag{15}$$

where; $e(k) = setpoint - \theta(k),$ (16)

and the output signal is transient control command (u_{tr}).

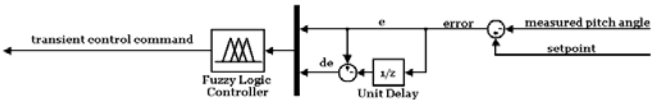

Fig.6: Fuzzy controller inputs signals

"e" has two membership functions namely, "negative" and "positive", and three membership functions are associated with "*de*" namely "negative" , "positive" and "good".

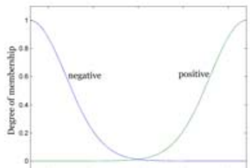

Fig.7: Membership functions of "*e*"

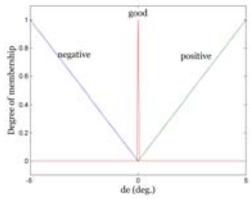

Fig.8: Membership functions of "*de*"

The membership functions of *"de"* are triangular, but the membership functions of *"e"* are Gaussian. Each Gaussian membership function is of two variables (c and σ) . Equation (17), shows a typical Gaussian membership function:

$$\mu_A^x = \exp[-\frac{1}{2}(\frac{x-c}{\sigma})^2] \tag{17}$$

For positive membership function of "*e*", c =120 and σ =30 and for negative membership function; c =-120 and σ =-30.

An approximate relation (shown in Table.1) can be distinguished by field experiment which may be helpful in the design of fuzzy controllers.

Table.1: Relation between input voltage and pitch angle

Input voltage (U_R or u)	Impact on pitch angle (θ)
positive	increasing (counter clock wise rotation)
negative	decreasing(clock wise rotation)

The fuzzy logic controller involves three main general design ideas; these general ideas are derived from experiments and the observation of the system's behaviour:

1) <u>"When the error absolute value is high and getting higher, force the system to rotate in the direction of error to vanish it"</u> (see (23) and Table.1). For instance, if setpoint is 20° and current pitch angle is 30°, the error is -10°. In this case, providing that *de* is negative (absolute value of error is increasing), according to the first general idea, a negative voltage is exerted on the system to rotate it in negative (clock wise) direction. This idea leads two following fuzzy rules:

R1: If *e* is *negative* and *de* is *negative* then u'_{tr} *=-0.1(volt)*

R2: If *e* is *positive* and *de* is *positive* then u'_{tr} *=0.1 (volt)*

2) "When the error differential is very small, set the transient input equal to zero". This general idea of fuzzy control design, is regarding the steady state situation. After approaching the setpoint, because of fluctuating nature of model helicopter, a trivial error may be appeared at any time. This error causes some control input, and chattering appears. The rule generated based on second general idea avoid chattering effectively.

R3: If *e* is *good* then u'_{tr} *=0*

3) "When the error absolute value is high and getting lower, force the system to rotate in the direction opposite to error direction, strongly". This apparently weird design idea is the key point of successful control of the system. This idea, practically commands the system not to get close the setpoint, when the system is approaching it. In this unusual system, quicker convergence to the setpoint is not the main matter. In reality, the biggest problem is that the system easily passes the setpoint after reaching it. In this system, severe and repeating overshoots are observed which should be overcome for the control of system. Steady state control command (u_{ss}) is enough for the system to reach the setpoint quickly, and halting the overshoot is the role of transient control command (u_{tr}). If u_{tr} accelerate the system towards setpoint, the overshoot is magnified. The alternative is that u_{tr} decelerate the system when approaching the setpoint to avoid the overshoot. This idea leads to the 4th and 5th rules of fuzzy controller.

R4: If *e* is *negative* and *de* is *positive* then u_{tr} *=0.3 (volt)*

R5: If *e* is *positive* and *de* is *negative* then u_{tr} *=-0.3(volt)*

According to (2) and (3) in background theory section, the transient command control, will be calculated as below:

$$u_{tr} = \frac{\sum_{i=1}^{4} u'_{tr)_i} \times \operatorname*{Min}_{j=1}^{2} \mu_j^i}{\sum_{i=1}^{4} \operatorname*{Min}_{j=1}^{2} \mu_j^i + \mu_{good}(de)}. \tag{18}$$

Fig. 9, shows the total control system.

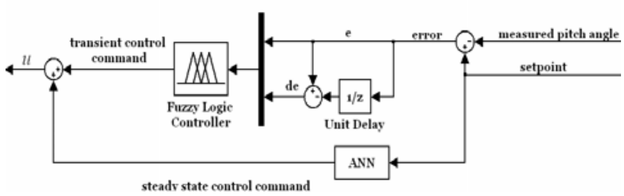

Fig.9 : total control system

6. STABILITY DISCUSSION

The stability is studied based on these three assumptions, the first two ones are experimental assumptions as the result of numerous experiments and the last one is mathematically proved:

A. It is assumed that the contents of Table.1 are correct, for $u \in [-1.5, 1.5]$ as in all experiments has been observed.

B. It is assumed that, if control command is in the range of [–0.50, 0.95] pitch angle remains in the range of [-50°, 35°]. This is observed through the experiments.

C. if $-50^\circ \le \theta_d \le 35^\circ$ then: $\begin{cases} -0.5 \le u_{ss} \le 0.95 \\ -0.3 \le u_{tr} \le 0.3 \end{cases}$

The control system is supposed to be designed to approach the model helicopter's pitch angle to the setpoints in the range of [-50°, 35°]. As a result, for pitch angles higher than 35°, the error is always negative (see (16)) and for pitch angles lower than -50°, the error is always positive:

$\theta < -50^\circ \Rightarrow e > 0$

(19)

$\theta > 35^\circ \Rightarrow e < 0$

(20)

In case of instability, the absolute value of error increases; that is, *de* and *e* have same sign. Moreover, while the system becomes unstable, the system passes out the range of [-50°, 35°]. In order to stability check, the system is studied in such critical situations (pitch angle out of [-50°, 35°] and *e.de*≥0).

$$critical\,situation: \begin{cases} \theta \notin [-50^\circ, 35^\circ] \\ e.de \ge 0 \end{cases} \quad (21)$$

From assumption C, it is concluded that:

$$\text{for} -50^\circ \le \theta_d \le 35^\circ : -0.80 < u < 1.25 \quad (22)$$

Now, considering (22) and above assumptions, the stability is checked. Based on the control command value (see (22)), three situations is considered for the system;

I. $-0.5 < u < 0.95$

II. $u \ge 0.95$

III. $u \le -0.5$

Situation I: According to assumption B, system in the situation I is stable.

Situation II: if $u \ge 0.95$ and *e*>0, considering Table.1, the error will decrease and in this situation instability is unlikely to happen. But, if $u \ge 0.95$ and *e*<0 the system's error (the pitch angle, see (19)) increases and system becomes unstable (having unbounded output with bounded setpoint). This specific situation is named as the first critical situation:

The first critical situation:

$$\begin{cases} u \ge 0.95 \\ e < 0 \end{cases} \quad (23)$$

Situation III: if $u \le -0.5$ and *e*<0, considering Table.1, the error decreases and the pitch angle, which is currently low, increases. In this situation system is not subject to unbounded output and instability. On the opposite, when $u \le -0.5$ and *e*>0, the currently low pitch angle starts and continues to decrease to an unbounded value. This is the second critical situation:

$$\text{The second critical situation: } \begin{cases} u \le 0.5 \\ e > 0 \end{cases} \quad (24)$$

The aforementioned critical situations can lead the system to an unstable situation. Now, it is proved that, these situations are impossible to happen.

Proof:

The first critical situation: if *e*<0, according to (23), *de*<0. As a result, only 1st and 5th rules of fuzzy controller may be active in this situation whose outputs are -0.1 and 0. According to (3); for the first critical situation: $-0.1 \le u_{tr} \le 0$. Considering assumption C, $-0.5 < u_{ss} < 0.95$. Therefore: $-0.6 \le u < 0.95$, and the first critical situation is impossible to happen.

The second critical situation: similar to the first critical situation, if *e*>0 then $de > 0$ (21). This situation may activate 2nd and 5th rules of fuzzy controller. Considering, (3): $0 \le u_{tr} \le -0.1$, therefore (considering assumption C): $-0.5 < u \le 1.05$. Consequently, the second critical situation is also impossible.

In total it can be concluded that, the system doesn't approach to an unstable situation.

It should be noted, the basis of this proof is existence of mathematically proved BIBO controllers (assumption C) and assumptions A and B, which are not mathematically proved. In reality, since the mathematical model of system has not been involved in the stability discussion (despite model-based control), a whole mathematical stability proof seems to be impossible. Instead of model, two experimental assumptions are involved. This point of view can be helpful, in stability study of intelligent controllers as non-model based controllers.

7. SIMULATION RESULTS

Figure 10, shows the controlled system response, with initial value of zero, for setpoints of -50°, 35° (maximum and minimum setpoints),10° and -10°, both for ANN and hybrid controllers.

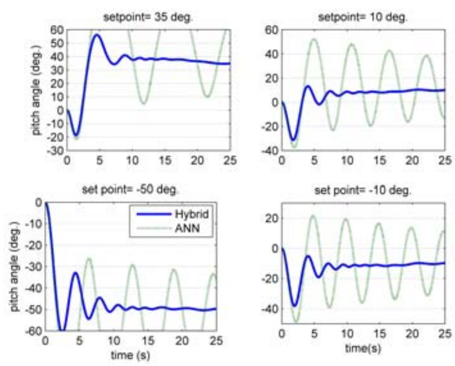

Fig.10 : closed loop response with ANN and hybrid controller

Adding the FIS, not only improves the performance incredibly, but also, causes the consumed energy to decline and leads lower maximum overshoot. In order to represent energy consumption, an Energy Consumption Criterion is defined as: $ECC = \int_0^T |u(t)|\,dt$. (25)

Table.2 shows *ECC* and settling time for ANN and hybrid controllers, for the setpoints shown in Fig.10. Settling time is considered as the time needed for the controller to reduce the absolute value of error to lower than 5° so that the error does not exceed 5° anymore (unless the exertion of a disturbance or a change in system's parameters or setpoint).

Table.2: Settling time and ECC for Fig.10

Set point	**Controller Type**	***ECC* (V.s)**	**Settling time (s)**
-50°	ANN	10.12	82.62
	Hybrid	9.49	8.18
-10°	ANN	9.63	91.52
	Hybrid	9.40	6.29
10°	ANN	14.85	99.52
	Hybrid	14.07	6.68
35°	ANN	23.56	96.39
	Hybrid	23.55	9.33

Inasmuch as error-based controllers are unlikely to be able to control the pitch angle of this model helicopter as stated in problem statement section (unless controllers which are designed only for one setpoint not a wide range of setpoints), it is impossible to compare newly designed hybrid intelligent control with more prevalent ones as a part of simulation results. However, considering highly oscillating nature of system, the achieved results seem acceptable.

8. CONCLUSION

In this research, a hybrid intelligent control system is designed for pitch angle control of a laboratory model helicopter. It is observed that the steady state control command (regarding error =zero) is completely dependent on the setpoint. Therefore, an artificial neural network is designed and trained so as to provide the steady state control command using setpoint. Moreover, a fuzzy controller is designed to output transient control command to be added with steady state control command. The sum of two control commands (the outputs of ANN and FIS) causes the system to approach its desirable pitch angle quickly and efficiently.

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