Back to Session Subjects

RECONFIGURABLE NEURAL CONTROLLER FOR HELICOPTER

M. Vijaya Kumar[1], S. Suresh[2], S. N. Omkar[2], R. Ganguli[2] and Prasad Sampath[1]

[1] Rotary Wing Research and Design Centre
Hindustan Aeronautics Limited, INDIA
e-mail: afcs.rwrdc@hal-india.com

[2] Aerospace Engineering Department
Indian Institute of Science, INDIA
e-mail: omkar@aero.iisc.ernet.in

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Abstract: The purpose of this paper is to design a reconfigurable neural flight control system to improve its stability, manoeuvrability and agility of helicopter. The reconfigurable neural flight control system uses feedback error learning control (FENC) methodology to achieve the desired flying quality requirements. FENC methodology uses neural controller in the outer loop to enhance the performance of the inner conventional controller. Firstly, the linear mathematical model is derived from the non-linear six degree-of-freedom dynamic equations. Then, linear quadratic regulator theory is applied to the linearized model to design a control system which satisfies the Aeronautical Design Standard (ADS-33) specifications. The outer neural controller parameters are adapted to compensate for the intrinsic nonlinearities of the helicopter and the parameter uncertainty in the model development. The neural controller is reconfigured on-line to provide necessary performance under centre-of-gravity variations. The robustness of the proposed control scheme is evaluated using flying quality attitude quickness criterion for different forward speed conditions. The attitude quickness parameters for pitch, roll and yaw responses for the flight conditions hover, 100 Kmph, 200 Kmph and 290 Kmph are studied and are shown to meet the Level 1 requirement of ADS-33 for all these conditions. The paper also presents an obstacle clearance maneuver to illustrate the effectiveness of the proposed control scheme.

Nomenclature

$\boldsymbol{A}$	system matrix
ACAH	attitude command and attitude hold
ADS-33	aeronautical design standards
$\boldsymbol{B}$	control matrix
HQR	handling quality requirement
$\boldsymbol{L}, \boldsymbol{M}, \boldsymbol{N}$	moment components at C.G
RCAH	rate command and attitude hold
X, Y, Z	total forces acting at C.G
u, v, w	vehicle velocities,
$\mathbf{x}$	state vector $\mathbf{x} = [u, v, w, p, q, r, \phi, \theta, \psi]$
β_{1s}, β_{1c}	longitudinal and lateral cyclic inputs, *rad*
β_0, β_{0t}	main and tail rotors collective inputs, *rad*
ϕ, θ, ψ	Euler angles (roll, pitch and yaw), *rad*

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1. INTRODUCTION

Control laws and design methods for flight control systems have evolved over the past few decades. Early control systems used very simple fixed form feedback structures with gains being first tuned by the control engineers in flight and then a subsequent scheduling of the gains with respect to a critical aircraft parameter. More recently, complex multivariable feedback laws have been designed using modern multivariable tools that optimally trade off among command responses, disturbance responses and robustness characteristics of the final closed-loop combination**.** Typically, helicopter control requires flight control schemes which explicitly account for the intrinsic nonlinearities of the system. In addition, tactical military flight requirements for agile helicopters and stringent day-visual civil flight regulations demand more accurate track control through out the flight envelope [1-4]. The complex gain scheduling, which requires time-consuming flight tests and stringent requirements, can be circumvented using nonlinear adaptive control system design.

Because of their powerful ability to approximate linear or nonlinear functions, neural network aided controllers are able to adapt to changes in system dynamics quickly and still provide good performance. This has generated a great deal of interest in using neural network models for identification and control of dynamical systems with unknown nonlinearities. Considerable effort has gone into the mathematical investigation of neural network based adaptive techniques for controlling highly uncertain, nonlinear and complex systems [5]. The model reference adaptive control, dynamic inversion, feedback linearization, adaptive critic and feedback error learning neural control scheme are the various neural network techniques widely used in the literature [6]–[12].

In this paper, we explore the use of feedback error learning control (FENC) methodology [13] to develop a reconfigurable controller for helicopters performing nonlinear maneuvers. The FENC scheme uses a conventional controller in the inner loop to stabilize the system dynamics, and the neuro-controller enhances the performance of the inner controller through on-line learning. In the early formulation [12], PID controller was used as the inner loop controller and in this study an LQR controller is used. The error for updating the neural network is based on the conventional controller's output signals as it truly reflects the error between the commands and actual outputs. The neural controller is trained to minimize the deviation between the reference signal (pilot command signal) and actual output of the helicopter. The necessary bounded signal requirement for neural network learning is satisfied using the inner conventional controller. Assuming that the inner conventional controller provides necessary bounded signals in fault and non-nominal conditions, the neural network is further adapted to provide the required tracking performance. In this paper, full state feedback is used to develop the baseline controller to satisfy the ADS-33 requirements under nominal flight conditions.

For our simulation study, we consider a typical four-bladed helicopter similar to BO105. The linear model is derived at the nominal flight condition (IAS = 290 KMPH) and a baseline LQR controller is designed to provide the necessary stability requirements. The commonly used attitude command attitude hold (ACAH) system is considered for pitch axis and the rate command attitude hold (RCAH) system is considered for the roll and yaw axes. In case of the pitch axis, the outer neural controller is designed to track the pitch attitude command, whereas in roll and yaw axes, the neural controllers are trained to follow the roll/yaw rate command. The performances of the controllers are evaluated at different flight conditions and also under aerodynamic parameter uncertainties. An attitude quickness parameter is used to evaluate the controller performance. The online learning ability is demonstrated using the parameter uncertainty. Finally, we also present an obstacle clearance maneuver case as an example to illustrate the efficacy of the designed controller.

2. HELICOPTER MODEL

The helicopter considered in this study has four bladed main and tail rotors with twin engine model. The mathematical model used in this paper is derived from a simplified generic non-linear helicopter model [14]. A center-spring approximation is used to model the main rotor and a coning disk model is used for tail rotor. Combination of look-up tables and polynomial functions of incidence and sideslip angles (approximation of wind tunnel data) are used to calculate the forces and moment components contributed by the fuselage subsystem. A two-dimensional flow is assumed to represent the airfoils using a constant aero-dynamic lift coefficient. The main and tail rotor airfoils have a simple drag model comprising zero-lift and lift dependent coefficients. The detailed assumptions and simplifications in force and moment calculations are discussed in [14]. The three main and a tail rotor actuators are modeled as a simple first order system. The actuators drive the input signals to the control surfaces. In general, the helicopter flight mechanic model can be described using the six degree-of-freedom (6-DOF) model as

$$
\begin{aligned}
\dot{u} &= -(wq - vr) + \frac{X}{M_a} - g\sin\theta \\
\dot{v} &= -(ur - wp) + \frac{Y}{M_a} - g\cos\theta\sin\phi \\
\dot{w} &= -(vp - uq) + \frac{Z}{M_a} - g\cos\theta\cos\phi \\
I_{xx}\,\dot{p} &= (I_{yy} - I_{zz})\,qr + I_{xz}(\dot{r} + pq) + L \\
I_{yy}\,\dot{q} &= (I_{zz} - I_{xx})\,rp + I_{xz}(r^2 - p^2) + M \\
I_{zz}\,\dot{r} &= (I_{xx} - I_{yy})\,pq + I_{xz}(\dot{p} - qr) + N \\
\dot{\phi} &= p + q\sin\phi\tan\theta + r\cos\phi\tan\theta \\
\dot{\theta} &= q\cos\phi - r\sin\phi \\
\dot{\psi} &= q\sin\phi\sec\theta + r\cos\phi\sec\theta
\end{aligned} \tag{1}
$$

where u,v and w are the translational velocities in three orthogonal directions of the fuselage fixed axis system, p, q and r are the angular velocities and ϕ, θ *and* ψ are the Euler angles defining the orientation of the body axes relative to the earth. The force and moment components contributed by each subsystem of the helicopter are calculated and transformed to helicopter center of gravity reference system. The non-linear 6-DOF helicopter model is trimmed, and the linearized mathematical model is derived at the nominal flight condition (at 290 Kmph for example) using the analytical methods given in Ref. [14]. The helicopter response can be expressed in terms of linear equations as

$$
\begin{aligned}
\dot{\boldsymbol{x}} &= \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{u} \\
\boldsymbol{y_p} &= \boldsymbol{C}\boldsymbol{x}
\end{aligned} \tag{2}
$$

where the state vector $\boldsymbol{x}$ comprise of $\boldsymbol{x} = [u, v, w, p, q, r, \phi, \theta, \psi]^T$ and control inputs $\boldsymbol{u}$ comprise of $[\beta_{0,}\, \beta_{1s}, \beta_{1c}, \beta_{0T}]^T$ *and* $\boldsymbol{y_p}$ is the output vector. The linear system is augmented with the actuator dynamics. In general, the pitch, roll and yaw axes are controlled and the collective channel is left open. This is partly due to the safety reasons and also the channel is stable [14]. The controlled outputs are q, θ and ϕ and the measured outputs are *p, q, r,* φ and θ. The open loop unstable poles at different flight conditions are given in Table. 1. From the table, we can see that the open-loop helicopter model have some undesirable characteristics. The presence of unstable poles and zeros clearly indicate the need to design a controller to stabilize the helicopter model. Also, the presence of parameter uncertainty and inherent nonlinearity, leads to the requirement of adaptive controller design. In this paper, we present a neural adaptive controller to stabilize the helicopter model and follow the command accurately. For this purpose, we consider ACAH system for pitch and RCAH system for the roll and yaw axes. In the following section, we present the details of reference model generation.

Table 1. Longitudinal and lateral modes.

Flight Condition	Phugoid	Pitch subsidence	Heave subsidence	Dutch-roll	Roll subsidence
Hover	0.0635 ± j0.544	-2.4	-0.419	0.0000738 ± j0.544	-8.0
100 Kmph	0.0347 ± j0.344	-2.66	-0.868	0.594 ± j1.74	-7.58
200 Kmph	0.362 ± j0.256	-4.24	-0.302	0.784 ± j2.34	-7.37
290 Kmph	1.50 & 0.146	-5.82	-0.213	1.01 ± j3.23	-7.04

2.1. Reference Model

For helicopter control, the most commonly used command control systems are rate command attitude hold (RCAH) and attitude command attitude hold (ACAH). In this paper, we design ACAH in pitch axis and RCAH in roll axis. Also, we design the command filter for RCAH and ACAH such that the command filter response satisfies the ADS-33 handling quality specifications. The command filter serves as a model for desired response when helicopter is subjected to the pilot input signal.

Attitude Command and Attitude Hold System: For ACAH system in the longitudinal axis, the ADS-33 handling quality specifications require the following characteristics for the helicopter.

- Pitch attitude shall return to within 10% of peak or one degree, whichever is greater, following a pulse input, in less than 10sec [1].
- A step input to longitudinal cyclic (δ_{1s}) shall produce a proportional pitch attitude change within 6 sec.
- The pitch attitude shall remain constant between 6 and 12 seconds following the pilot input

The command filter is designed such that it satisfies the attitude quickness criterion (ratio of peak pitch rate to change in pitch attitude $q_{pk} \;/\Delta\theta_{pk}$ for Level 1 flying quality requirement). The damping ratio (τ) of the filter is between 0.6 and 0.8 and the natural frequency is 5 radian/sec. The neural controller is designed to track the response of the filter accurately based on

$$TF = \frac{7.5}{s^2 + 7s + 25} \quad (3)$$

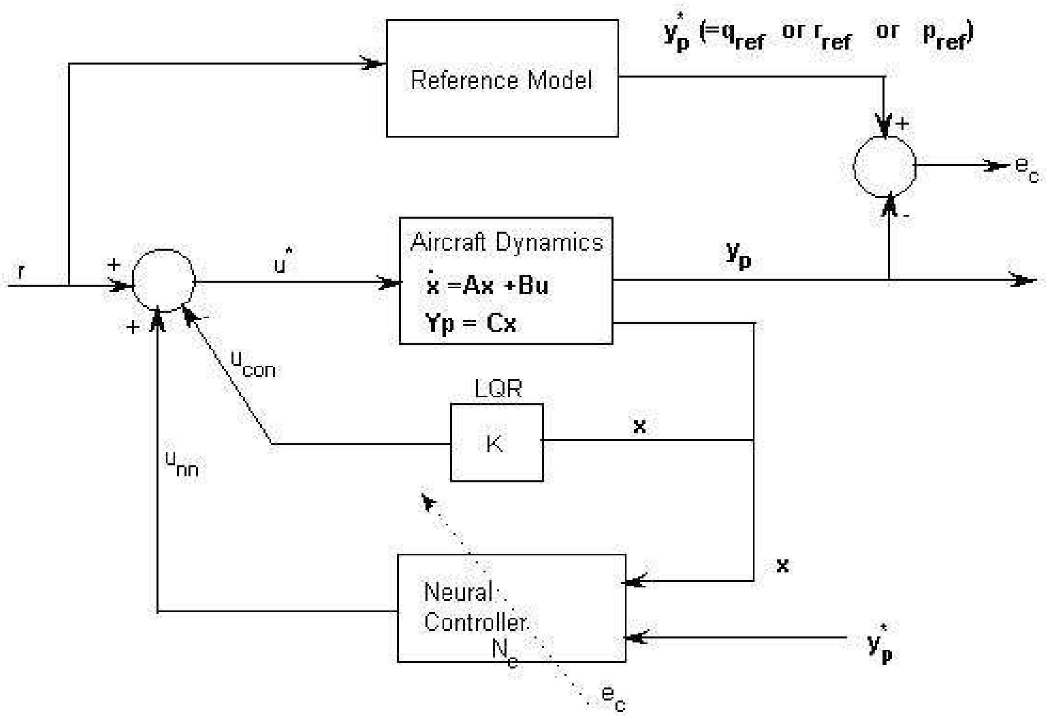

Fig. 1. Block diagram of feedback error learning neural control (FENC) Scheme

Rate Command and Attitude Hold System: For RCAH response system in roll and yaw axes, the ADS-33 handling quality requires:

- Rate response to step input should have first order response characteristic.
- The rise time should be less than 2.5s.

The reference command input (*r*) is passed through a washout filter to smoothen the transition response. The rate response filter is designed to satisfy the above requirements.

$$TF = \frac{2.5s}{s^2 + 7s + 25} \quad (4)$$

The command filters are designed to provide Level 1 handling qualities and the neural controllers are designed such that it follows the reference command signal accurately.

3. RECONFIGURABLE ADAPTIVE NEURAL FLIGHT CONTROLLER DESIGN

The configurable neural flight controller design uses the most widely used feedback error learning control scheme. The block diagram of FENC scheme is shown in Fig. 1. The reference model used is explained in the previous section. The linear quadratic regulator (LQR) block provides the conventional full state feed back controller and N_c is the neural controller. In FENC scheme, the conventional full state feedback controller in the inner loop is used to stabilize the helicopter and the neural controller in the outer loop approximates the unknown nonlinearity and provides the necessary tracking performance. The neural controller is trained to minimize the deviation between the reference signal (pilot command signal) and the actual output of the helicopter. The control effort applied to the helicopter is the sum of the conventional and neural controller signals,

$$u(k) = u_{nn}(k) + u_{con}(k) + r(k) \tag{5}$$

where $\boldsymbol{u_{nn}}$ is neural network output and $\boldsymbol{u_{con}}$ is the conventional control input from the linear quadratic regulator. The output of the reference model $\boldsymbol{y_p}^*$ (q_{ref} in case of pitch axis) is to be compared with the state output $\boldsymbol{y_p}$ (q in case of pitch axis) and the error e_c is used for the control.

The conventional LQR is designed based on the linearized model at the nominal flight condition. The LQR controller is able to stabilize the helicopter at various level flight conditions. In this study, Non-linear Auto Regressive eXogenous input (NARX) Model neural network is used to approximate the unknown nonlinearity. The stability and convergence of above the approach is discussed in Ref. [13].

In this section, the Non-linear Auto Regressive eXogenous input (NARX) Model network models with corresponding learning algorithms chosen are briefly discussed. Figure 2 shows this network, which is similar to that of the model proposed in [15]. The structure is that of a feed forward Artificial Neural Network (ANN) with linear filters. In this case the output of the plant can be described by,

$$y(t+1) = f\left(u(t), u(t-1), \ldots u(t-n+1), y(t), y(t-1), \ldots y(t-n+1)\right) \tag{6}$$

A series parellel model is used and the network output is then given by

$$\hat{y}(t+1) = N\left(u(t), u(t-1) \ldots, u(t-n+1), y(t), y(t-1), \ldots y(t-n+1)\right) \tag{7}$$

where, *N(.)* is the network approximation function. Bipolar sigmoidal function is used as the squashing function at hidden as well as output layer. The network model is trained using Back Propagation Through Time (BPTT) algorithm as described in [15]. For details of the NARX network model and learning algorithm, one can refer to [15,16].

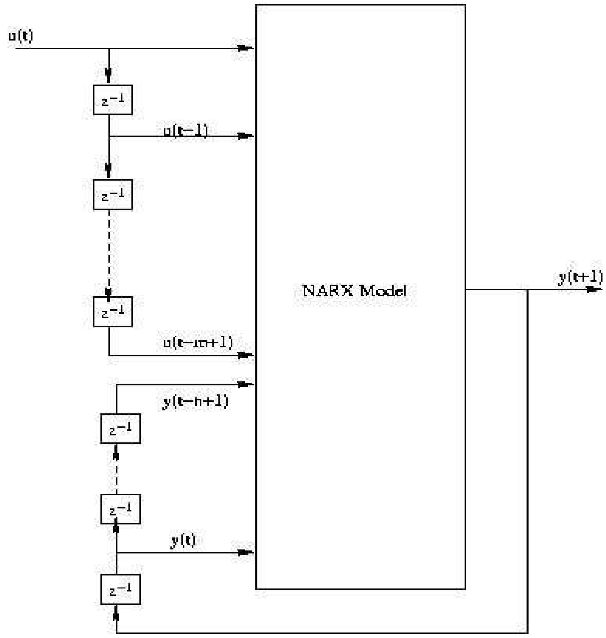

Fig.2 Nonlinear Auto Regressive eXogeneous Input Network Architecture.

4. SIMULATION STUDIES AND RESULTS

In our simulation studies, the helicopter model is trimmed at different flight conditions. A helicopter having a soft in plane four-bladed hingeless main rotor and a four bladed tail rotor with conventional mechanical controls is used for the simulation studies. Using the analytical methods presented in Ref. [14], the linear system is derived at different flight conditions. Based on the linear model, we derive the neural flight controllers using an adaptive control scheme to follow the pilot command signals. First, we present the simulation results for the FENC scheme under the nominal flight condition. Finally, we also present the simulation results for an obstacle avoidance maneuver.

4.1. Baseline Neural Controllers

The proposed adaptive neural control scheme is applied to a helicopter model. Simulation studies are carried-out using a linear model trimmed at different level flight conditions. Based on the linear model, we derive the feedback gains using LQR approach. The baseline controller is designed to decouple the modes of the helicopter. Three different neural controllers NN_{lat}, NN_{lon} and NN_{dir} in roll, pitch and yaw axes respectively are designed based on the multilayer perceptron network with a linear filter. The ACAH and RCAH system are developed at the nominal flight condition. The designed controllers are tested at other flight conditions. Now, we first present the simulation results for ACAH system in pitch axis.

Pitch Attitude Neural Controller: The inputs to the neural controller are the u, w, q and θ responses and output of the controller (N_{lon}) is the longitudinal cyclic input (β_{1s}). The performance capabilities of the neural controller are tested with a reference pulse input of 0.05 radian. The response of the helicopter and the reference input and outputs are shown in Fig. 3. From Fig. 3, it can be seen that the pitch attitude of helicopter exactly follows the reference command signal. Also, the control effort required to follow the command signal is less than the maximum limit. From the figure, we can say that the FENC controller stabilizes the helicopter and also provides necessary tracking performance. The controller is also tested with the same command signal at other flight conditions. The controller is adapted on-line to compensate for the variation in plant dynamics. The results show that the controller is able to stabilize and track the command accurately.

Roll Rate Neural Controller: The inputs to the neural controller are the p, r, ϕ and ψ responses and output of the controller (N_{lat}) is the lateral cyclic input (β_{1c}). The performance of the neural controller is tested with a reference pulse input of 0.05 radian. The response of the helicopter and the reference input and outputs are shown in Fig. 4. From Fig. 4, it can be seen that the roll rate of helicopter exactly follows the reference command signal. Also, the control effort required to follow the command signal is less than the maximum limit. From the figure, we can say that the FENC controller is able to stabilize the helicopter and also provides necessary tracking performance.

Yaw Rate Neural Controller: The inputs to the neural controller are the p, r, ϕ and ψ responses and output of the controller (N_{dir}) is the tail rotor collective input (β_{0T}) to the helicopter model. The performance capabilities of the neural controller are tested with a reference pulse input of 0.05 radian. The response of the helicopter and the reference input and outputs are shown in Fig. 5.

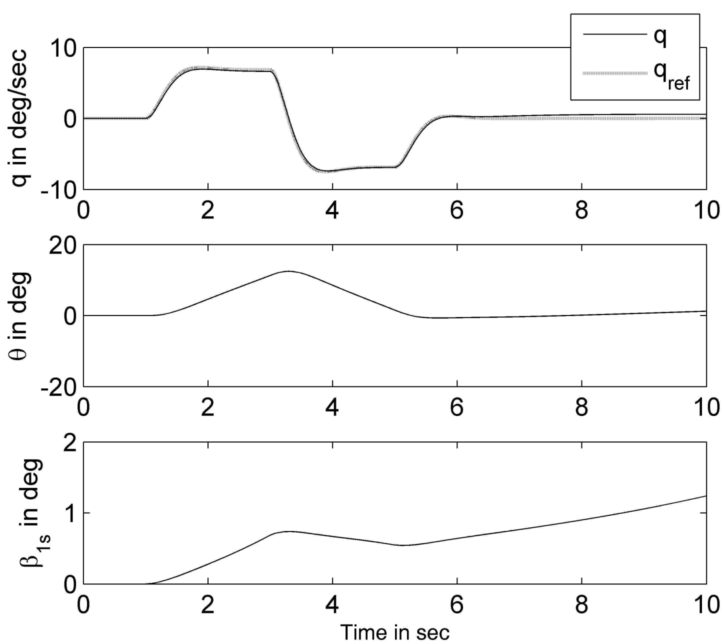

Fig. 3. Helicopter response and control surface deflection for pitch attitude command signal.

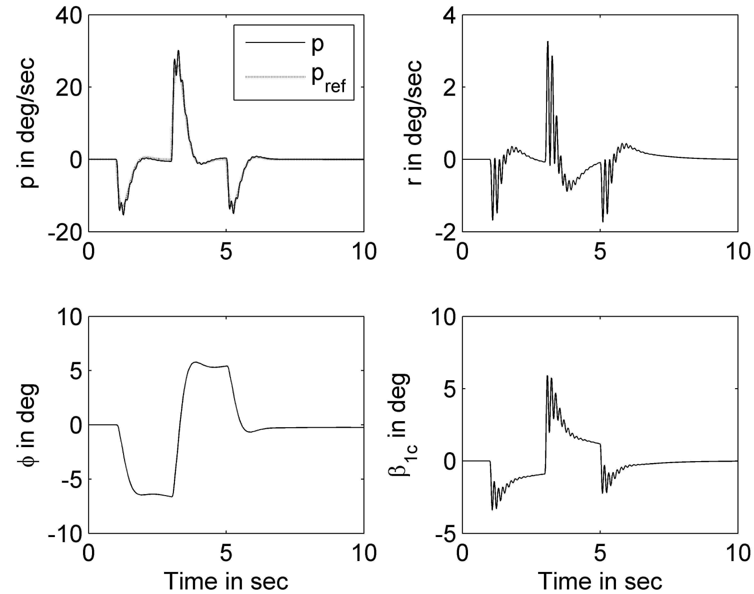

Fig. 4. Helicopter response and control surface deflection for roll rate command signal.

From Fig. 5, it can be seen that the yaw rate of helicopter exactly follows the reference command signal. Also, the control effort required to follow the command signal is less than the maximum limit. From the figure, we can say that the controller is able to stabilize the helicopter and also provides necessary tracking performance.

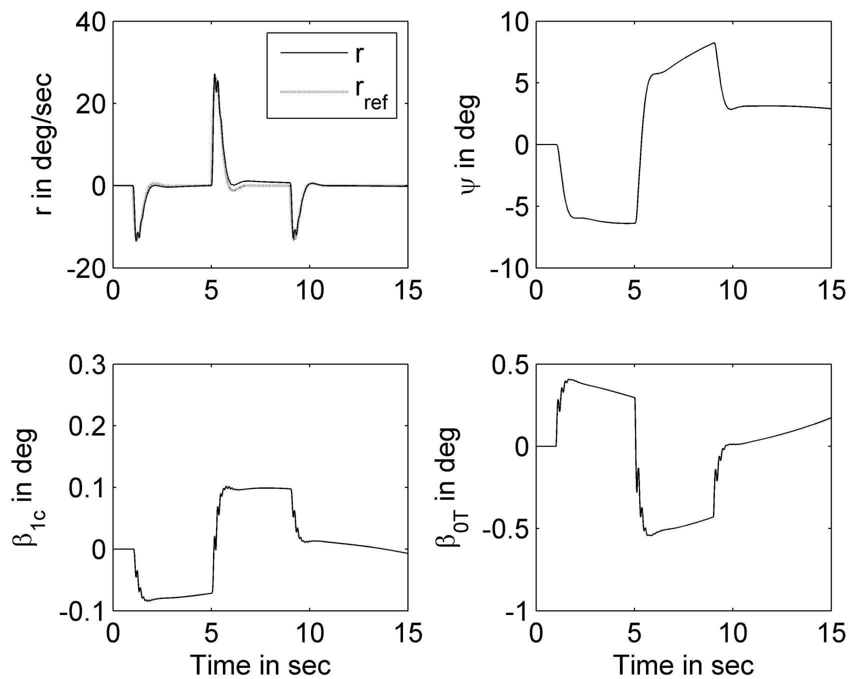

Fig.5. Helicopter response and control surface deflection for yaw rate command signal

The qualitative performance of the FENC controller is studied at different flight conditions such as hover, 100 Kmph, 200 Kmph and 290 Kmph and is found to be satisfactory. It is observed that the FENC controller stabilizes and track the command accurately under normal flight conditions.

4.2 Performance under Parameter Uncertainty Condition

Now, we study the robustness of the controllers by testing the performance of the controller in a flight condition with variation in centre of gravity (C.G). Using the analytical methods presented in Ref. [14], the linear system is derived at a forward speed of 290 Kmph in aft C.G., and forward C.G. The stability characteristics of the longitudinal dynamics vary with variations in the longitudinal C.G.. The helicopter is unstable at aft C.G compared to the forward C.G conditions. The performance of the pitch controller is evaluated with respect to variation of the C.G. at 290 Kmph aft and forward C.G. Fig. 6 gives the response of the helicopter to a longitudinal cyclic input. The controller was trained at a trim condition of 290 Kmph with a forward C.G. and tested with 290 Kmph with an aft C.G. without on-line training and with on-line training. From the figure, we can see that the on-line training improves the performance of the controller and that the controller is capable of reconfiguring during on-line training. From the above results, we can clearly see that the controller adapts for parameter uncertainty and nonlinearity and reduces the tracking error of the baseline controller.

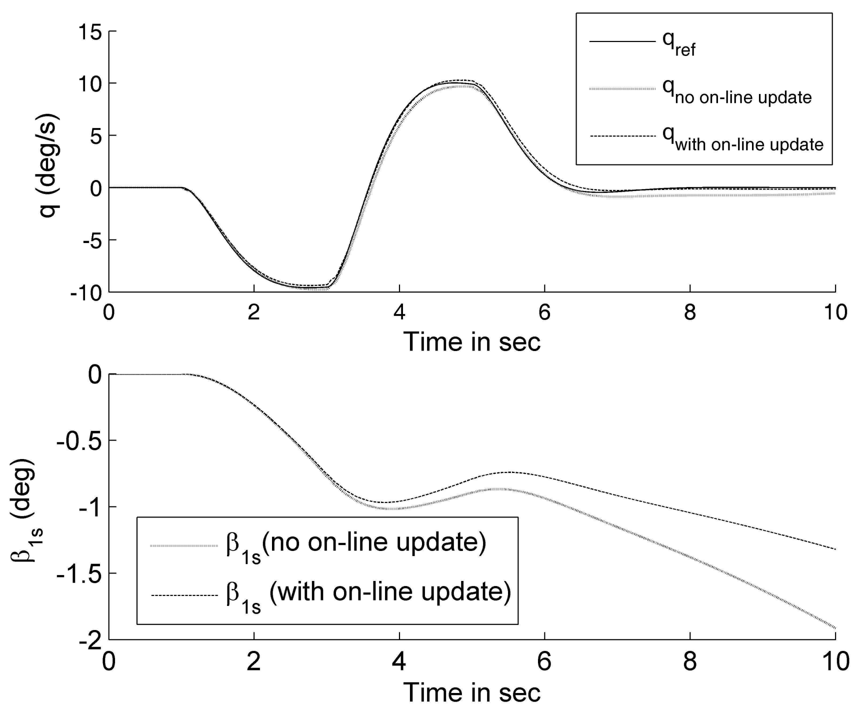

Fig.6 Pitch response under C.G. variation.

4.3 Performance Under Obstacle Clearance Maneuver

In this section, the performance of the neural controller developed in the previous section is tested for executing an obstacle clearance maneuver. The importance of designing an adaptive nonlinear controller to control the above maneuver lies in the fact that this maneuver range in a short time and it brings out all the nonlinearities of the helicopter.

The obstacle clearance maneuver starts with steady straight and level flight at nominal flight condition (forward speed of 290 Kmph). A pitch-up command to the helicopter is applied to increase the pitch attitude (θ) from its trim value to 10 deg in a duration of 3 seconds. The pitch attitude is kept constant for 5 seconds duration and it is decreased to the initial trim value at 8 seconds. Now, the helicopter maintains straight and level flight condition at nominal flight condition. The performance capabilities of the designed controller for executing the obstacle clearance maneuver is presented based on the results from this simulation package. Fig. 7 presents the response of the nonlinear helicopter model performing obstacle clearance maneuver with strong wind disturbance. From the figure, we can clearly observe that the aircraft follows the command accurately and rejects the disturbance very well. It is clear from these figures that the proposed control scheme provides satisfactory performance for nonlinear maneuver.

4.4 ADS-33 Performance Evaluation

One of the important parameters that measure the ability of the helicopter to achieve rapid and precise change in attitude when performing a sharp maneuver is the attitude quickness. The attitude quickness parameter in ADS-33 is defined in the pitch axis as the ratio between the maximum angular rate (q_{pk}) and the peak attitude angle change (θ_{pk}) [1]. The attitude quickness parameter is measured at the nominal flight condition for a series of pulse inputs with varying pulse duration.

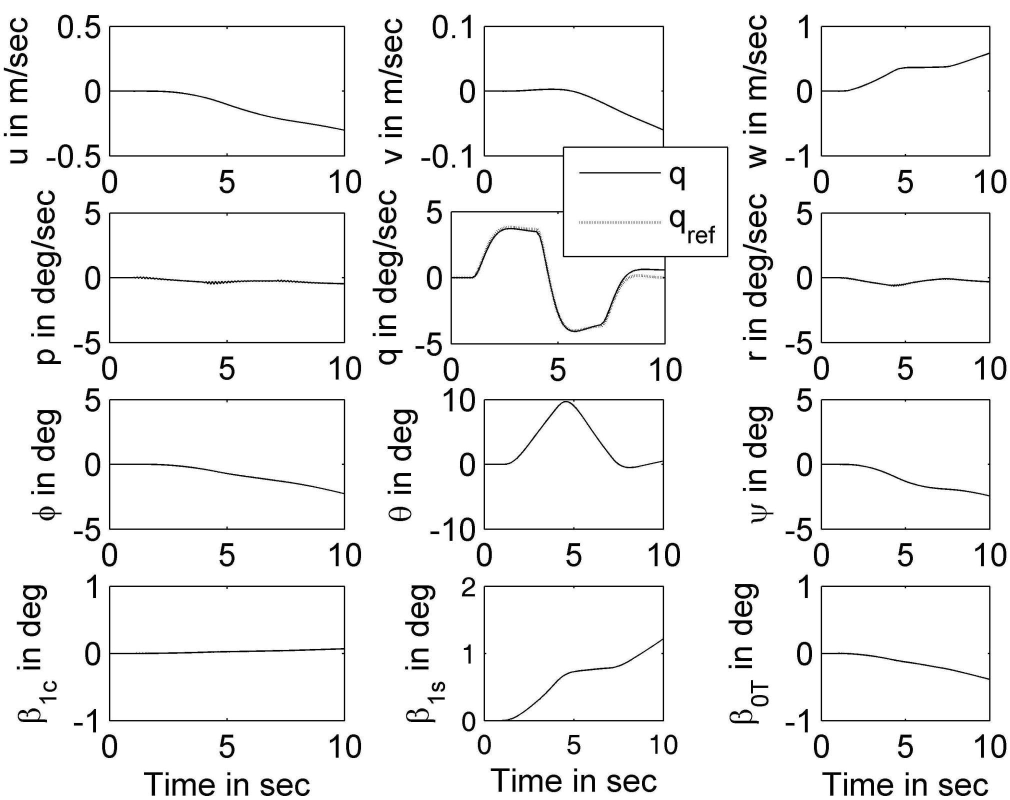

Fig. 7. Helicopter Response for Obstacle Clearance Maneuver.

Figure. 8 illustrates the attitude quickness parameter with respect to the minimum pitch attitude change $(\Delta\theta_{\min})$ for different pulse durations in a straight and level flight condition and a forward speed of 290 Kmph. The Level 1 boundary requirement is also plotted to show that the FENC scheme satisfies the ADS-33 requirements. Figure 9 shows the attitude quickness parameter with respect to the minimum roll attitude change $(\Delta\theta_{\min})$ for different pulse durations in a straight and level flight condition and a forward speed of 290 Kmph. The Level 1 criteria requirement is also plotted to show that the FENC scheme satisfies the ADS-33 requirements. The attitude quickness parameters for pitch, roll and yaw responses for the flight conditions hover, 100 Kmph, 200 Kmph and 290 Kmph are provided in Tables 2, 3 and 4 respectively. It can be seen that FENC scheme satisfies Level 1 criteria for all these conditions.

Table 2. Attitude quickness parameters for longitudinal cyclic input (2s pulse duration)

Flight condition	$\Delta\theta_{\min}$ (deg)	$q_{pk}/\Delta\theta_{pk}$ (1/sec)	Meets Level 1/Level 2/Level 3
Hover	12	0.6	Level 1
100 Kmph	7	1.1	Level 1
200 Kmph	7	0.7	Level 1
290 Kmph	8	0.7	Level 1

Table 3. Attitude quickness parameters for lateral cyclic input (2s pulse duration)

Flight condition	$\Delta\phi_{\min}$ (deg)	$p_{pk}/\Delta\phi_{pk}$ (1/sec)	Meets Level 1/Level 2/Level 3
Hover	25	2.4	Level 1
100 Kmph	14	2.0	Level 1
200 Kmph	12	2.0	Level 1
290 Kmph	15	2.0	Level 1

Table 4. Attitude quickness parameters for yaw, pedal input (2s pulse duration)

Flight condition	$\Delta\psi_{\min}$ (deg)	$r_{pk}/\Delta\psi_{pk}$ (1/sec)	Meets Level 1/Level 2/Level 3
Hover	7	2.6	Level 1
100 Kmph	9	1.9	Level 1
200 Kmph	10	1.7	Level 1
290 Kmph	7	2.4	Level 1

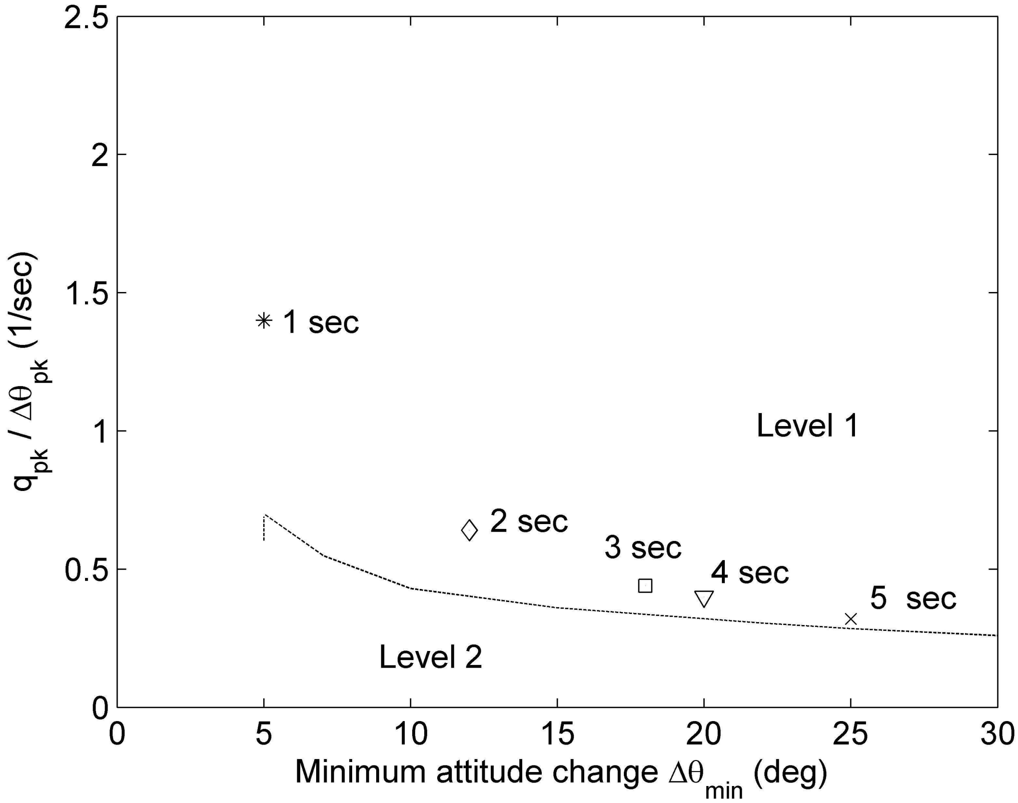

Fig. 8. Pitch attitude quickness criterion at nominal flight condition.

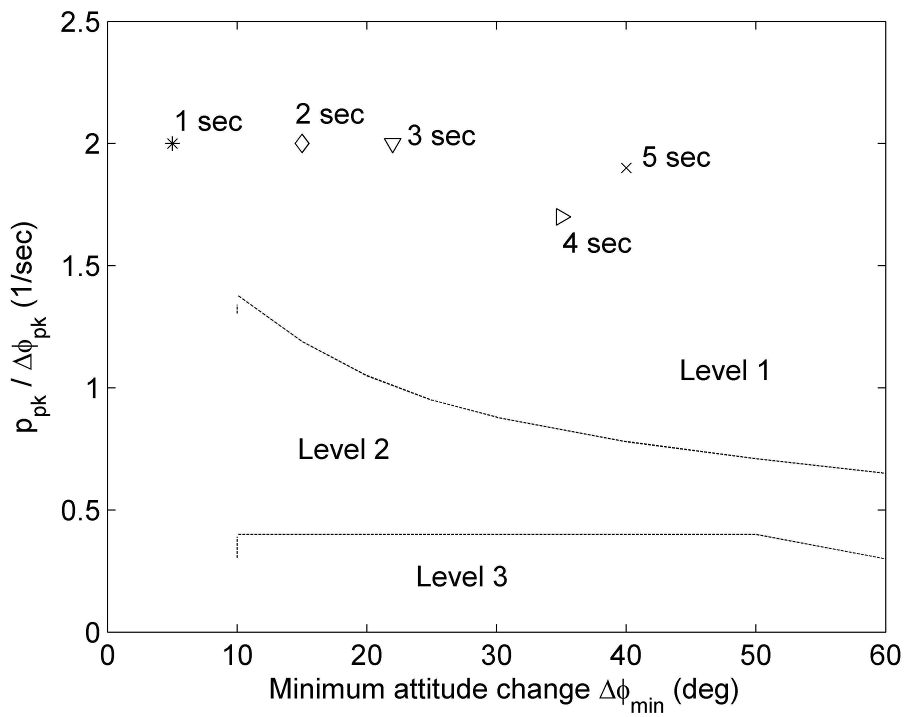

Fig. 9. Roll attitude quickness criterion at nominal flight condition.

5. CONCLUSION

In this paper, we have presented the feasibility of using an adaptive neural controller for an unstable helicopter model. A NARX algorithm is used to design a feedback error learning neural controller. An attitude command and attitude hold for the pitch axis and rate command and attitude hold systems for the roll and the yaw axes are designed. The baseline controller is designed using a full state feedback scheme at nominal flight condition. The controller compensates for unknown nonlinearities and parameter uncertainties. From the simulation results, it can be inferred that the control strategy using controller algorithm exhibits good tracking performance. The attitude quickness criterion clearly indicate that the FENC scheme satisfy the ADS-33 flying quality requirement and also robust under parameter uncertainty. The attitude quickness parameters for pitch, roll and yaw responses for the flight conditions hover, 100 Kmph, 200 Kmph and 290 Kmph are studied and are shown to meet the Level 1 requirement of ADS-33 for all these conditions.

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