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EFFECT OF FEEDBACK ON FEL-EMRAN NEURAL NETWORK FOR FAULT-TOLERANT AUTOPILOT

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ABSTRACT

Neural networks are very popular for fault-tolerant flight control. Of these, the Feedback-Error-Learning EMRAN Neural Networks (FEL-EMRAN) are widely studied both in theory and flight tests. The FEL-EMRAN controller depends on the feedback controller for learning the inverse dynamics of the plant being controlled. In this paper the effects of two distinctly diverse feedback controllers, a classical PID controller and a novel Block Back-Stepping controller called as "Diagonally Dominant Back-Stepping" controller, on the fault-tolerance capability of FEL-EMRAN are discussed. The problem of autonomous landing of a high performance aircraft under unknown actuator failures and severe wind disturbances is studied. Six types of hard over actuator failures were investigated. It was observed that the fault-tolerance capability of FEL-EMRAN improves with the sophistication of the feedback controller, but additional aids like anti-windup and phase compensation schemes were required to overcome the adverse effects of position and rate saturation of aircraft control surfaces on the process of feedback-error-learning. It is to be noted that the concept of feedback-error-learning evolved from intuition rather than the foundations of control theory. Thus, further research is needed on feedback-error-learning of neural networks from the viewpoint of fault-tolerant flight control and recent advances in neural network learning theory.

Keywords: - *fault-tolerant flight control; autolanding; actuator failures; EMRAN neural network; feedback-error-leraning; phase compensation; anti-windup; block back-stepping.*

I. INTRODUCTION

The advent of Fly-By-Wire (FBW) control systems and advances in avionics are leading to more and more automatic operations almost during the entire flight of an aircraft.. Aircraft is a highly nonlinear safety-critical system, and the use of autopilots has many advantages. It improves safety and precision of take-off and landing, improves fuel efficiency and passenger comfort, and reduces the physical and mental work load of the pilots so that they can concentrate more on other aircraft systems and tasks. However, as a system gets more complex and autonomous it will be more prone to faults and failures of its sub-systems and their components. The faults associated with an aircraft can be divided into sensor faults, actuator faults and component or structural faults. These faults lead to loss of control of aircraft and fatalities. Severe wind disturbances during landing may lead to fatalities. Therefore, several programmes were initiated for the development of fault-tolerant flight control systems [1]. The fault-tolerant control systems can be broadly divided into passive and active systems. The passive systems use robust control techniques like H ∞ control and Sliding Mode Control (SMC), and have

limited fault-tolerance capability based on their design goals. The active fault-tolerant control systems involve Fault Detection and Diagnosis (FDD) and reconfiguration of the controller. Although these methods can accommodate faults over a wider range, they have some disadvantages like inability to ensure stability of the plant during the FDD phase and accommodating unexpected faults. Therefore, several "intelligent" FTFC methods are being researched actively. The artificial neural network based FTFC methods fall under this category.

The application of artificial neural networks in flight control has been widely studied [2-3]. Neural networks can be used in several ways for controlling a plant, but the underlying principle is the same [4]. The neural network learns the inverse dynamics of the plant, either directly or indirectly, so that the system being controlled can be made to follow a reference trajectory. In the Direct-Inverse-Learning (DEL) method serious robustness problems may arise due to the absence of feedback in the control mechanism. This problem can be overcome in Feedback-Error-Learning (FEL). The FEL architecture, shown in Fig. 4, comprises of a feed-forward neural controller and a

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conventional feedback controller. The feedback controller can be any conventional controller like PID, LQR, SMC or H ∞ . The total control effort, u , is the sum of the output of the neural network controller, unn , and the feedback controller, u fc . The error between the aircraft output and the reference signal is used to vary the parameters of neural network and generate the output unn . In course of time, the neural network learns the inverse dynamics of the plant, dominates the total control effort. The inclusion of feedback increases the robustness of the combined controller. Since the neural network uses online learning, no prior training is required. It has been proven in theory and flight tests that the Extended Minimal Resource Allocation Neural Networks (EMRAN) are most suitable for aerospace applications [5].

The landing phase of flight is hazardous due to the proximity of aircraft to the ground and limited time available to the pilot for recovery in the case of failures. Boeing's safety reports indicate that about 41% of the commercial aircraft accidents occurred during the final approach and landing phases. Of these, 45% of the accidents were due to wind disturbances, and the remaining 55% were due to failure of sensors or actuators, structural damage to aircraft, and piloting errors [6].

Thus, the problem of auto-landing of an aircraft, under unknown actuator failures and severe wind disturbances, using a Feedback-Error-Learning Minimal Resource Allocation Neural Network (FEL-EMRAN), is discussed in this paper. Two distinct types of feedback controllers are used to train FEL-EMRAN. One is a simple classical PID controller and the other a sophisticated controller, called "Diagonally Dominant Back-Stepping" (DDBS)

Six types of stuck-actuator failures in conjunction with severe wind disturbances were investigated: failure of either left or right elevator, failure of either left or right aileron, failure of rudder, simultaneous failure of both ailerons, simultaneous failure of left-elevator and left- or right-aileron and simultaneous failure of right-elevator and left- or right aileron. It was observed that the fault-tolerance capability of EMRAN with DDBS feedback controller was superior to that with a simple PID controller, but only with aid from phase compensation and anti-windup schemes to enhance feedback-error-learning [8]. The results, although highly satisfactory, indicate that the FEL architecture using neural networks has to be investigated further from the view point of fault-tolerant flight control, and recent advances in neural network learning theory [9].

The organization of the rest of the paper is as follows:

Section II describes the auto-landing problem whilst Section
   1. discusses the design of FEL-EMRAN controller with PID or DDBS feedback controller. Section IV presents the auto-landing simulation results. Section V summarizes the conclusions drawn from this study and the plans for future work.

II.   AUTOLANDING PROBLEM

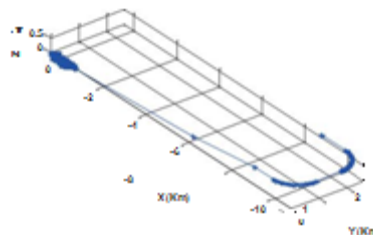The flight path for autonomous landing of the aircraft is shown in Fig. 1 [3, 8].

Fig 1. Autolanding Trajectory

Starting with a wings-level flight at an altitude of 600 m, the aircraft executes two coordinated level turns followed by a glide slope descent, flare and touchdown on the runway. To count the landing as successful, the aircraft has to land within a rectangular area or "Pill Box" measuring 500 m X 10 m on the runway.

The wind disturbances, shown in Fig. 2, are modeled on the Dryden spectrum. Wind turbulence is assumed to be present along the horizontal axis whilst micro bursts along the lateral and vertical axes.
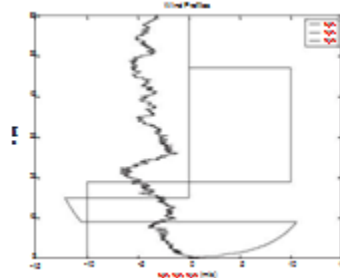

Fig. 2 Wing Profile during Autolanding

A. Aircraft Model and Actuator Failure Cases

MATLAB and Simulink (R2012a version) software was used to develop a 6 DOF nonlinear model of a typical fighter aircraft, and simulate auto-landing under severe wind disturbances and actuator failures. The aerodynamic data of the aircraft was modified to enable independent deflection of left and right elevators or ailerons [3, 8]. Nonlinear first-order models of hydraulic actuators with a time constant of 50 ms, and 60 deg/s rate limit were used in the simulations. The deflections of the control surfaces were restricted to: elevators (-25 to +25 deg), ailerons (-20 to +20 deg), and rudder (-30 to +30 deg). It was assumed that the control surfaces can get stuck at any angle anywhere in their full range of deflections. Further, to create worst case scenarios, the control surfaces were assumed to fail at the level turn and descent just before landing. As mentioned in Section I, six types of actuator failures were simulated.

B. Off-line Simulation of Fault Tolerance Ranges

The dynamics of modern high performance aircraft are highly nonlinear and coupled. Therefore, it may not be possible to safely land the aircraft within the "Pill Box" under failures over the entire ranges of deflection of the control surfaces. Therefore, a fault-tolerance feasibility for all the six types of actuator failures was simulated off-line, before assessing the fault-tolerance capability of the FEL-EMRAN controller. It is assumed that the accommodation of fault is possible if, under stuck-actuator failures, it is possible to trim the aircraft in wings-level flight, level turning and level descent. A typical fault-tolerance envelope for the case of simultaneous failure of left-elevator and left-aileron is shown in Fig.3.
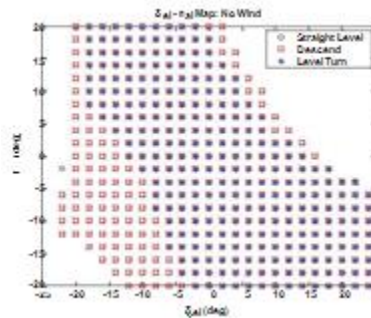

Fig. 3 Fault Tolerance Feasibility Envelope for Simultaneous Failure of Left-Elevator and Left-Aileron

III.   FEL-EMRAN CONTROLLER

In the present study, the original EMRAN algorithm is modified to generate two types of feedback-error-learning or inversion-based control schemes [10, 11]:

, Conventional FEL Control Strategy - EMRAN1, and

, Estimation Before FEL Control Strategy - EMRAN2

The Nonlinear Dynamic Inversion (NDI) principle inherent the FEL neural controllers can be explained using the pitch acceleration (q) and rate of change of angle of attack (α) dynamics of aircraft:

$$q = f_1(q, \alpha, \delta_e)$$
$$\alpha = f_2(q, q) \qquad\qquad (1)$$

where, δ_e is the elevator deflection, and $f_1, f_2 \in R$ are smooth functions with bounded first derivatives. In the integrator backstepping algorithm, first the desired pitch rate

4) $_d$ is computed by inverting the equation for α , for a given α and a desired angle of attack rate α_d :

$$q_d = f_2^{-1}(\alpha_d, \alpha) \qquad\qquad (2)$$
where, $\alpha_d = G_\alpha (\alpha_d - \alpha)$ G_α is
            and the   feedback gain.

Next, for a given q_d and α , the desired elevator deflection is computed by inverting the equation for q :

$$\delta_e = f_1^{-1}(q_d, \bar{\alpha}, q_d) \qquad\qquad (3)$$
wher $q_d = G_q (q_d -$ is   the   feedback
e, $q)$ and G_q gain.

EMRAN1: In the implementation of EMRAN1, only those parameters of the neural network, such as centers, widths and weights, are updated within a given radius of the current input. The various tuning parameters of the network are obtained using the Genetic Algorithm under a variety of actuator failure cases. Parameter updates are performed using

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where, $\alpha_d = G_\alpha (\alpha_d - \alpha)$ G_α is
            and the   feedback gain.

Next, for a given q_d and α, the desired elevator deflection is computed by inverting the equation for q :

$$\delta_e = \frac{1}{f_1 \ (q_d, \ , q_d)} \ \overline{\alpha} \qquad (3)$$

wher $q_d = G_q \ (q_d - q)$ is the feedback
e, and G_q gain.

EMRAN1: In the implementation of EMRAN1, only those parameters of the neural network, such as centers, widths and weights, are updated within a given radius of the current input. The various tuning parameters of the network are obtained using the Genetic Algorithm under a variety of actuator failure cases. Parameter updates are performed using

It can be noted from the above equations that EMRAN2, instead of the simple desired state derivatives (α_d , q_d), uses these derivatives with a correction term as shown in (5):

$$[\{\alpha_d - G_\alpha \ (\alpha - \alpha_d)\}, \{q_d - G_q (q - q_d)\}] \qquad (5)$$

The first term in the above equation is a feed forward that ensures tracking of the desired trajectory. The second term is a feedback that minimizes deviations from the desired trajectory

It is to be noted that learning of the inverse function is achieved using (2) and (3), whilst (4) enables the calculation of the control signal. In the present study, EMRAN1 controller was implemented with the basic PID feedback controller, and EMRAN2 was implemented with the DDBS feedback controller, as discussed in the following sub-sections.

A. Simple PID Feedback Controller
A schematic of EMRAN controller with a classical PID feedback controller is shown in Fig. 4. A linear model of the aircraft at the flight condition (h = 600m, V=82.6 m/s) was used to design separate PID controllers for the longitudinal and lateral-directional axes. Similarly, separate EMRAN1 neural controllers were designed for these axes, as shown in Figs. 5 and 6. For the longitudinal-EMRAN block, the reference signal is the desired pitch rate (q_d) whilst for the

lateral-EMRAN block, the roll rate (p_d) is the reference signal. The estimated sideslip angle ($\hat{\beta}$) is calculated using the relation $\hat{\beta} = \chi - \hat{\alpha} \varphi - \psi$, where $\hat{\alpha} \approx \theta - \gamma$, $(\varphi , \theta , \psi)$ are Euler angles, α is the AoA, γ and χ are the flight path angle and the ground track angle respectively.
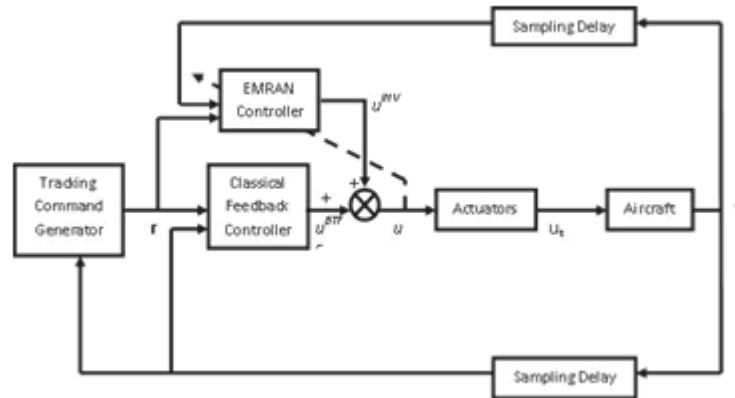

Fig 4. Schematic of EMRAN Controller with Classical PID Feedback controller
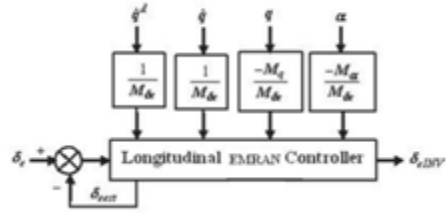
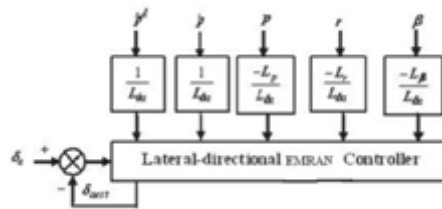*Fig. 5 Longitudinal EMRAN Controller*

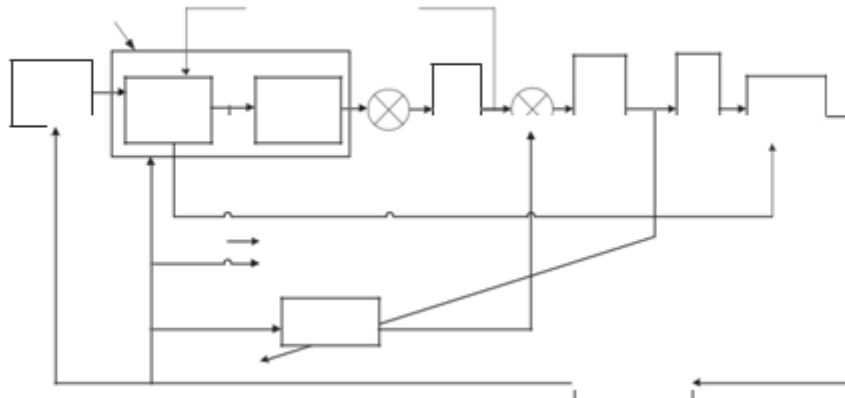*Fig. 6 Lateral-Directional EMRAN Controller*

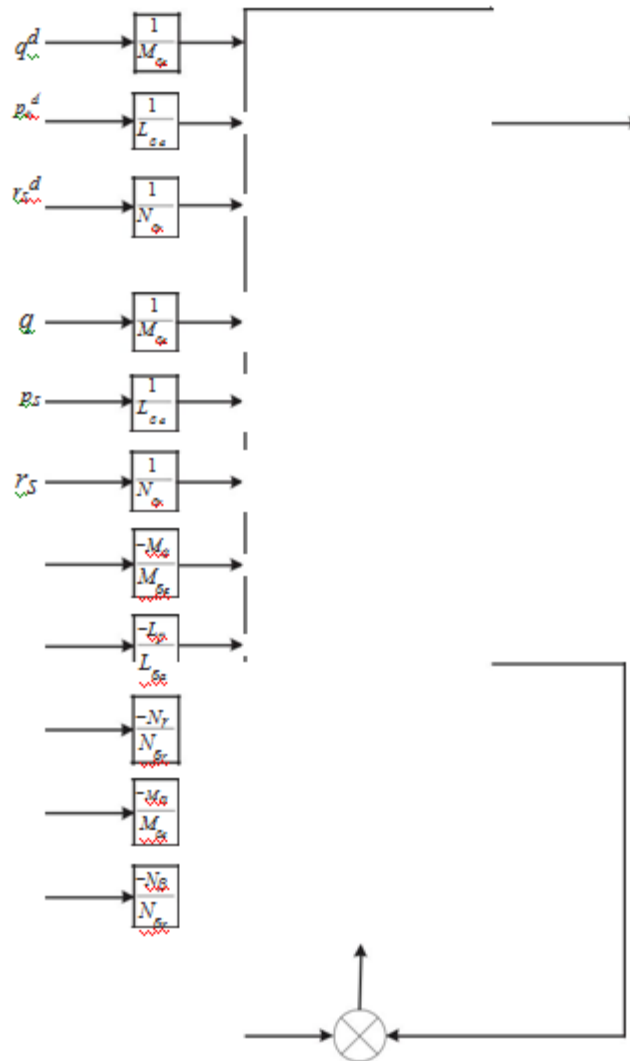*Fig. 7 Schematic of EMRAN Controller with the DDBS Feedback Controller*

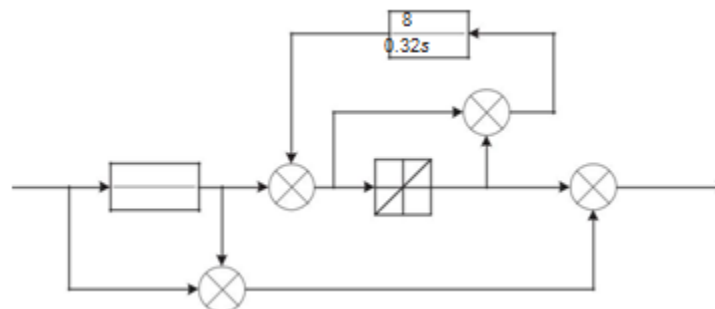*Fig. 8 EMRAN2 Controller Block Schematic*

Fig. 9 SAAB Phase Compensator for Alleviation of Actuator Rate Limiting

The tracking command generator shown in Fig. 4 generates the reference commands (altitude, velocity and the deviations from the desired track) required for autolanding. A delay equivalent to one sampling rate is introduced in the feedback loops to account for computational delays.

B. The DDBS Feedback Controller

The novel Diagonally Dominant Back-Stepping (DDBS) controller is a subtly modified version of the conventional Block Back-Stepping (BBS) controller [11]. In the design of the DDBS, a mixed axis system was used to describe the aircraft body-axis angular rates (p, q, r), the wind axis angle rates (μ, α, β), and the velocity vector rates (μ, α, β) [7].

The 3X3 matrices describing these dynamics can be reduced to diagonally dominant forms. Then, the DDBS controller can be designed using linear controller design methods. A single coupled linear model of aircraft dynamics was used to design the innermost loop control laws in the DDBS controller. Hence a unified block of EMRAN2 was implemented with the DDBS feedback controller. A schematic of the EMRAN controller with the DDBS controller as the feedback is shown in Fig. 7. A schematic of EMRAN2 implementation is shown in Fig.8.

C. Sliding Model Controller

It was observed that stuck-actuator failures were causing large transients in the longitudinal response. Hence, a simple first order Sliding Mode Controller (SMC) was implemented in the longitudinal axis to overcome these large transients, and enable the neural controller learn the inverse dynamics of the plant at a moderate rate.

D. Anti-windup and Phase Compensation Schemes

The feedback-error-learning architecture cannot accurately capture the abrupt changes in aircraft dynamics due to position or rate saturation of the control surfaces. Thus, to enhance the fault-tolerance capability of the FEL-EMRAN controller, in conjunction with the DDBS feedback controller, simple anti-windup and phase compensation schemes were implemented. The SAAB phase compensator implemented in the controller is shown in Fig. 9. It was interesting to note that better phase response can be achieved by placing the compensator ahead of the actuator.

IV.   RESULTS OF AUTOLANDING SIMULATION

Auto-landing of the aircraft under the six types of unknown actuator failures and severe wind disturbances was simulated for various positions of stuck control surfaces, covering their full deflection range. These simulations were done both for the case of PID feedback controller and the DDBS feedback controller. The simulation results for the case of simultaneous failure of left-elevator and left -aileron are shown in Figs. 10 and 11 for the PID and DDBS feedback controllers respectively. It can be noted that the fault-tolerance performance of FEL-EMRAN with DDBS feedback is far better than the performance with PID feedback. It was observed that the superior fault-tolerance with DDBS feedback could only be achieved with the aid of anti-windup and phase compensation schemes. Without these aids, the fault-tolerance of EMRAN+DDBS controller degenerates.
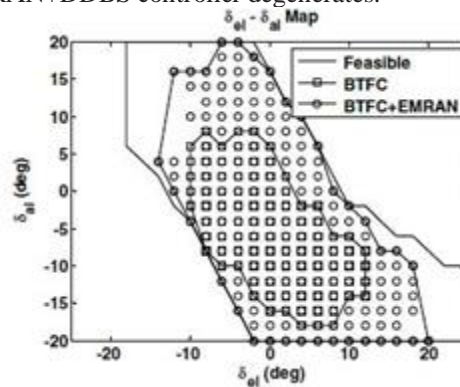

Fig. 10 Fault-tolerance Envelope of EMRAN Controller with Classical PID Feedback Controller for Simultaneous Failure of Left-Elevator and Left-Aileron.
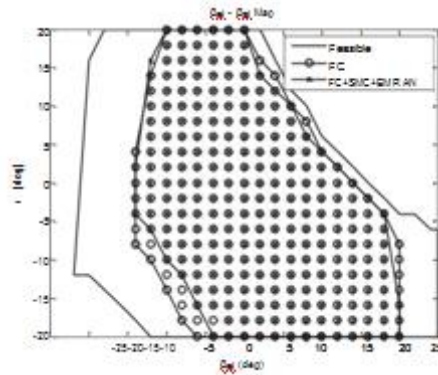
Fig. 11 Fault-tolerance envelope of EMRAN Controller with DDBS Feedback Controller for Simultaneous Failure of Left-Elevator and Left-Ailerron.

Typical auto-landing trajectories in the case of double control surface failure (left-elevator and right-aileron) are shown in Fig. 12. It can be observed that the autolanding is successful with the aircraft landing within the Pill-Box. The increase in the number of neurons, and the variations of the parameters of the first neuron, with time, for the case of the double control surface failure are shown in Fig. 13.
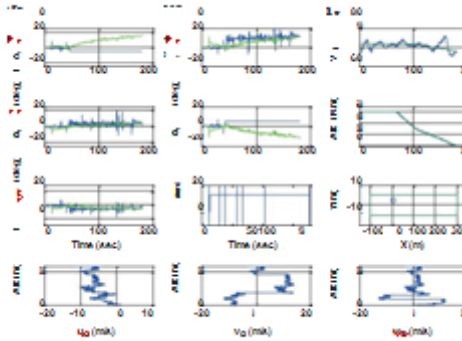

Fig. 12 Autolanding with Left-Elevator stuck at -5 deg. And Right-Aileron stuck at +5 deg.
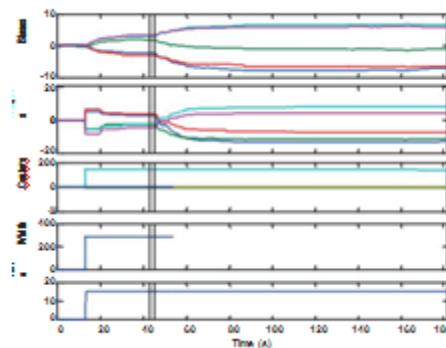

Fig. 13 Variation of the parameters of the first neuron (Left-Elevator stuck at +12 deg and Left-Aileron stuck at -4 deg)

V.   CONCLUSIONS AND FUTURE WORK

The fault-tolerance performance of a feedback-error-learning EMRAN neural controller for autolanding of an aircraft has been studied. Autolandings were simulated for six types of unknown hard over actuator failures in conjunction with severe wind disturbances. A classical PID controller and a novel Block Back-Stepping controller called as "Diagonally Dominant Back-Stepping" (DDBS) controller were implemented as feedback controllers for the EMRAN neural controller. It was observed that the fault-tolerance capability of the EMRAN controller improves with the sophistication of the feedback controller. Further, it was observed that the improved performance with the DDBS controller could only be achieved with the aid from anti-windup and phase-compensation schemes to overcome the adverse effects due to position and rate saturation of the control surfaces. Without these augmentation schemes the FEL-EMRAN was degrading the fault-tolerance performance of the DDBS controller, and failing to land the aircraft in the pillbox in some failure cases. From these observations, it is concluded that further research is needed on feedback-error-learning schemes from the perspective of fault-tolerant flight control and recent advances in neural network learning theory [12 - 14]. It is to be noted that the concept of feedback-error-learning evolved from intuition rather than the foundations of control theory. Also, a single neuron which is static may exhibit unpredictable dynamic characteristics when placed in a closed-loop for feedback-error-learning.

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