A NEW APPROACH TO NONLINEAR MODELING OF HIGHLY MANEUVERABLE AIRCRAFT USING NEURAL NETWORKS

Saghafi F., Heravi B. M.

Department of Aerospace Engineering
Sharif University of Technology
Tehran, Iran
Emails: saghafi@sharif.edu; heravi@mehr.sharif.edu

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Abstract

Artificial Neural networks offer viable solution to identification and modeling of aerospace dynamic systems. This paper proposes a new approach to the nonlinear modeling of agile aircraft which is applicable to develop flight simulators. In contrary to classical methods, neural-network-based modeling of aircraft dynamics does not require any aerodynamic or propulsion model and a few flight test measured data suffice. The obtained model is shown valid for arbitrary pilot inputs within a region of mach-altitude around the pre-specified flight condition.

1 Introduction

In the last decade, many researches have been carried out in the field of neural-network-based identification of aircraft dynamics. In most of which, the neural network is applied to approximate inversed or forward dynamics of aircraft by adaptively canceling inversion or modeling error through online learning [1-4]. However, due to general approximation and generalization capabilities, neural networks are potentially applicable to nonlinear modeling of aircraft dynamics for simulation applications.

Nonlinear aircraft simulations are used in pilot training, dynamic analysis, guidance and trajectory studies and many other tasks. The classical methods of modeling aircraft flight dynamics are very much dependent on and limited to aerodynamic data. This kind of data are often not enough accurate, costly to determine or even, in some cases, not available.

Recurrent neural networks are proved to be effective for the task of nonlinear dynamic system identification without needing any a priori knowledge about the plant. Hence, a neural network trained with experimental data is expected to be eligible to substitute the conventional Newton's-law-based aircraft dynamic model.

For this purpose, the neural network must be able to work completely offline without the presence of error feedback signal and generalize well for any pilot inputs. No aerodynamic, propulsion or configuration data would be needed to develop such a neural model and a few flight test data obtained by IMU (Inertial Measurement Unit) suffice. An IMU is a device composed of three accelerometers measuring three translational accelerations and three rate gyros measuring three rotational rates

In a few recent researches, neural networks are applied to estimate the aerodynamic forces and moments acting on aircraft [5] and for the modeling of linearized lateral dynamic response of aircraft [6,7]. In this paper, a new neural approach is proposed for modeling of fully coupled nonlinear six-degree-of-freedom dynamics of highly maneuverable aircraft.

To validate the approach, a highly

maneuverable fighter, the F-16 Fighting Falcon, was chosen. Since, if the method is proven for an agile aircraft with highly coupled nonlinear dynamics, it will be expected to work well for the aircraft with less complicated dynamic behaviour like transport airplane.

2 Nomenclature

a^1, a^2: Output vector of hidden and output layers

P: Input vector of neural network

$IW, LW, CW^1, CW^2, b^1, b^2$: Weight matrix of input to hidden layer, hidden to output layer, context layer, self-feedback and bias vectors of hidden and output layers

$\tan sig$, $purlin$: Tangent sigmoid and pure linear transfer functions

$\delta_E, \delta_A, \delta_R$: Elevator, aileron and rudder deflections

p, q, r: Pitch, roll and yaw rates

$\dot{u}, \dot{v}, \dot{w}$: Translational accelerations in body axes

$\alpha, \beta, \bar{q}$: Angle of attack, side slip angle, dynamic pressure

S, b, c: wing area, wing span and mean aerodynamic chord

$C_x, C_y, C_z, C_p, C_q, C_z$: Dimensionless aerodynamic coeffs.

$Cx_q, Cy_p, Cy_r, Cz_q, Cl_p, Cl_r, Cz_q, Cm_q, Cn_p, Cn_r$: Damping derivatives

$Cl_{\delta A}, Cl_{\delta R}, Cn_{\delta A}, Cn_{\delta R}$: Control derivatives

$I_{11}, I_2, I_{33}, I_{13}$: Elements of moments of inertia matrix

$[f_{a,p1}]^B, [m_B]^B$: Total aerodynamic and propulsion force and moment vectors in body axes

l_R: Engine angular momentum

3 Data Generation

In order to design a neural-network-based simulator, it is necessary to apply real flight test data as training and validating data; however, to prove the concept, the data extracted from a conventional aircraft simulator is enough for the study of the general idea. The differences between simulator and real data are mostly caused by modeling simplifications, noise and measurement errors. Once the neural network is able to predict an aircraft simulator dynamic behavior, it is most likely to achieve the same results for a real aircraft dynamics. Therefore, in this work, the training and validating data is generated by a conventional simulator.

The simulator is a full nonlinear six-degree-of-freedom model of the F-16 dynamics. To improve the accuracy, gravitational acceleration is calculated with respect to altitude and standard model atmosphere is applied. Pilot inputs are elevator, rudder and aileron deflections while throttle setting is not included.

The aerodynamic is modelled by calculating the non-dimensional forces and moment coefficients which , as presented in the following formula, vary nonlinearly with angle of attack and side slip (α, β), angular velocities (p,q,r) and control surface deflections (δ_E, δ_R and δ_A). In these equations, any of damping and control derivatives is found by interpolating through tabular aerodynamic data [8].

$$\begin{gathered}
Cx = Cx_q(\alpha)q + Cx(\alpha, \delta_e) \\
Cy = Cy_p(\alpha)p + Cy_r(\alpha)r + (-0.02\beta + 0.00287\delta_{\mathrm{r}} + 0.0105\delta_{\mathrm{a}}) \\
Cz = Cz_q(\alpha)q + \mathrm{S}(\alpha)(1 - (\frac{\beta}{57.3})^2) - 0.19(\frac{\delta_{\mathrm{e}}}{25})) \\
Cl = Cl_p(\alpha)p + Cl_r(\alpha)r + Cl_{\delta a}(\alpha,\beta)\delta_a + Cl_{\delta r}(\alpha,\beta)\delta_r + Cl(\alpha,\beta) \\
Cm = Cm_q(\alpha)q + Cm(\alpha, \delta_e) \\
Cn = Cn_p(\alpha)p + Cn_r(\alpha)r + Cn_{\delta a}(\alpha,\beta)\delta_a + Cn_{\delta r}(\alpha,\beta)\delta_r + Cn(\alpha,\beta)
\end{gathered} \tag{1}$$

$$\begin{gathered}
[f_{a,p}]^B = \begin{bmatrix} f_{a,p1} \\ f_{a,p2} \\ f_{a,p3} \end{bmatrix} = \begin{bmatrix} \bar{q}SC_x + f_p \\ \bar{q}SC_y \\ \bar{q}SC_z \end{bmatrix} \\
[m_B]^B = \begin{bmatrix} m_{B1} \\ m_{B2} \\ m_{B3} \end{bmatrix} = \begin{bmatrix} \bar{q}SbC_l \\ \bar{q}ScC_m \\ \bar{q}SbC_n \end{bmatrix}
\end{gathered} \tag{2}$$

Applying Euler and Newton laws leads to the six following first order coupled nonlinear ordinary differential equations [9] which are numerically solved for p,q,r and u, v, w by 4th order Runge-kutta method.

$$\dot{p} = \frac{1}{I_{11}I_{13} + I_{13}^2}\left\{ \left[(I_2 I_{33} - I_{33}^2 - I_{13}^2)r - I_{13}(I_{33} + I_{11} - I_2)p - I_{13}l_R\right]q + I_{33}m_{B1} - I_{13}m_{B3}\right\}$$

$$\dot{q} = \frac{1}{I_2}\left\{ \left[(I_{33} - I_{11})p - l_R\right]r + I_{13}(p^2 - r^2) + m_{B2}\right\}$$

$$\dot{r} = \frac{1}{I_{11}I_{13} + I_{13}^2}\left\{ \left[(-I_2 I_{11} + I_{11}^2 + I_{13}^2)p - I_{13}(I_{33} + I_{11} - I_2)r + I_{11}l_R\right]q + I_{11}m_{B3} - I_{13}m_{B1}\right\}$$

$$\dot{u} = rv - qw + \frac{f_{a,p1}}{m} + 2(q_1 q_3 - q_0 q_2)g$$
$$\dot{v} = pw - ru + \frac{f_{a,p2}}{m} + 2(q_2 q_3 + q_0 q_1)g$$
$$\dot{w} = qu - pv + \frac{f_{a,p3}}{m} + (q_0^2 - q_1^2 - q_2^2 + q_3^2)g \quad (3)$$

As is implied in the previous equations, quaternions are used to calculate the aircraft attitudes. Differential equations of quaternions are as follows [9].

$$\begin{Bmatrix} \dot{q}_0 \\ \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \end{Bmatrix} = \frac{1}{2} \begin{bmatrix} 0 & -p & -q & -r \\ p & 0 & r & -q \\ q & -r & 0 & p \\ r & q & -p & 0 \end{bmatrix} \begin{Bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{Bmatrix}. \quad (4)$$

4 Neural Network Architecture

Elman network is a kind of recurrent neural network that is suitable for the modeling of time varying systems. In its original architecture, the context units consist of internal state history and the hidden layer units have the task of mapping both an external input and also the previous internal state to the output target. This makes Elman network capable in identifying the temporal outputs of dynamic systems [10]. Although, Elman network with enough context layer units can represent an arbitrary n^{th} order system, its dynamic memory capacity will increase if it is modified by introducing additional self-feedback connections to the context units [11]. The modified Elman neural network architecture used in this work is shown in Fig. 1.

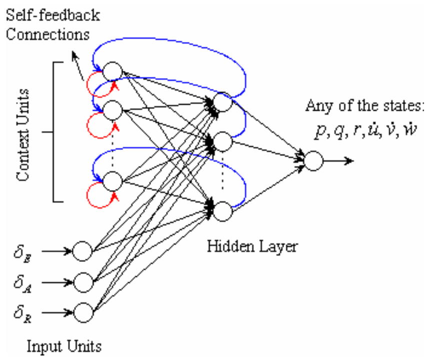

Fig. 1. Modified Elman Network Architecture

All feedback and feedforward connections are weighted and determined in the training process. Self-feedback connections in the context units strengthen the role played by internal states history in the modeling process. This makes the neural model capable to more accurately predict the target dynamics especially when inputs are constant for a period of time and the output behaviour is dominated by previous states. All these, makes the modified Elman network ideal for aircraft neural network modeling [7]. Governing equations for this network structure is as follows.

$$a^1(k) = tansig\left(IW \times P + b^1 + CW^1 \times a^1(k-1) + CW^2 \times a^1(k-2)\right)$$
$$a^2(k) = purlin(LW \times a^1(k) + b^2) \quad (5)$$

$$P = \left[\delta_E^{\,T} \quad \delta_A^{\,T} \quad \delta_R^{\,T}\right]^T \quad (6)$$

Six individual modified Elman neural networks are designed and trained to predict the six aircraft states: roll, pitch and yaw rates and three translational accelerations (Fig. 2). These states can be directly measured by rate gyros and accelerometers in a flight test.

Genetic algorithm is applied in the training process to find the global optimum set of weights and biases that minimizes the mean squared error between neural network output and the target data obtained by the flight simulator. In comparison with gradient-based techniques (like error-backpropagation), Genetic algorithm offers superior solution in complex optimization problems like training neural networks. This is due to the fact that gradient searches may be trapped in one of the local minima, hence obtaining the global optimum is not guaranteed, while genetic algorithm performs a universal random search which leads to the global optimum solution with the cost of longer computation time [12].

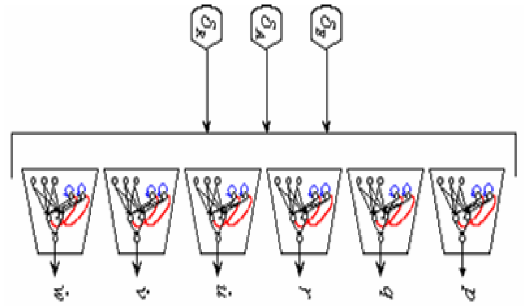

Fig. 2. MISO System of Neural Networks

5 Training and Validating Inputs

Training inputs are three 3211 elevator, rudder and aileron deflections, all started at trimmed flight condition in Mach 0.5 and 20'000 feet altitude. 3211 is a conventional input for aircraft parameter estimation and has been shown to be very effective in exciting aircraft dynamical modes [13]. Any of the three inputs (shown in Fig. 3) is fed to the network while the other two are constant at their trim values and the mean squared error between the network output and the expected ones is calculated. The cost function that is to be minimized by genetic algorithm is as follows.

$$J = MSE_{Elevator} + MSE_{Rudder} + MSE_{Aileron}$$

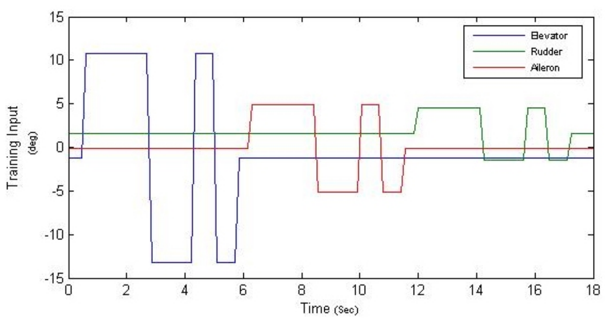

Fig. 3. Training Input Signals (3211)

When the training is accomplished and J reaches to an acceptable value, validating tests are performed to show that the trained network is able to generalize for new and combined pilot inputs generating various manoeuvres.

Both training and validating inputs must be selected in such a way that flight condition does not leave the design point Mach-altitude region and also must prevent generating unrealistic data by the simulator in the conditions in which its mathematical model is not valid.

6 Results

Training results for all six states are shown in figure 4; where, target - the data generated by the conventional simulator - is compared to the neural network output. Training squared error for each state is shown below the corresponding state. This figure indicates that the proposed network is able to learn the dynamic behavior of the F-16 aircraft for in-sample (training) data.

Fig. 5 shows the validating results obtained by exciting the neural networks with new inputs; with which the aircraft does various maneuvers (climb, descent and turn) in forty seconds. To make a comparison, conventional simulator results is also included in the same figure (marked as the real data). As figure 5 demonstrates, the trained networks with 3211 input signals generalize well for arbitrary inputs. Mean squared error of validating and training results for all six neural networks are summarized in Table 1.

Table 1. Training and Validating Mean Squared Errors

States	Training Mean Squared Error	Validating Mean Squared Error
p	$(rad/sec)^2\ 4.82\times10^{-4}$	$(rad/sec)^2\ 9.40\times10^{-4}$
q	$(rad/sec)^2\ 2.07\times10^{-6}$	$(rad/sec)^2\ 4.21\times10^{-5}$
r	$(rad/sec)^2\ 1.59\times10^{-4}$	$(rad/sec)^2\ 0.31\times10^{-3}$
$\dot{u}$	$(Ft/sec^2)^2\ 0.287$	$(Ft/sec^2)^2\ 7.54$
$\dot{v}$	$1.14\ (Ft/sec^2)^2$	$14.36\ (Ft/sec^2)^2$
$\dot{w}$	$0.343\ (Ft/sec^2)^2$	$8.26\ (Ft/sec^2)^2$

Since aircraft dynamic responses to pilot commands are influenced by altitude and Mach number, the neural network model is expected to be valid for a Mach-altitude region around the designed point (Mach 0.5 and 20'000 feet altitude). The error caused by Mach-altitude effect on trained neural network is shown in figures 6-8. In figure 6, neural network yaw rate response is compared to real data generated by the conventional flight simulator in different speeds and altitudes. Figures 7 and 8 show the mean squared errors of yaw rate and $\dot{v}$ networks versus a range of 2000 to 47'000 feet altitude and 0.4 to 0.9 Mach number. It is found that the proposed neural dynamic model is valid for a range of 5000 ft altitude and 0.1 Mach number in which the error remains acceptable.

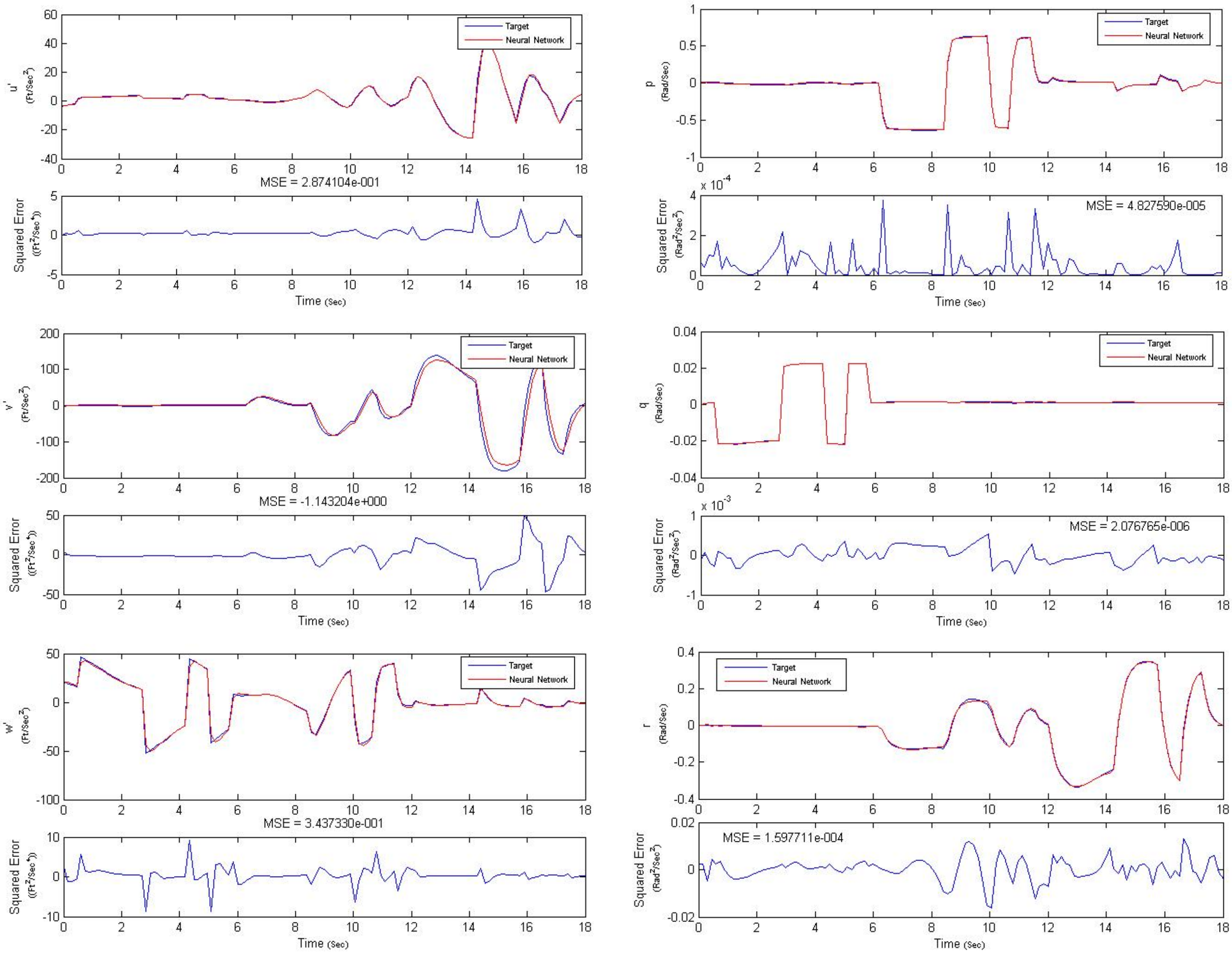

Fig. 4. Training Results

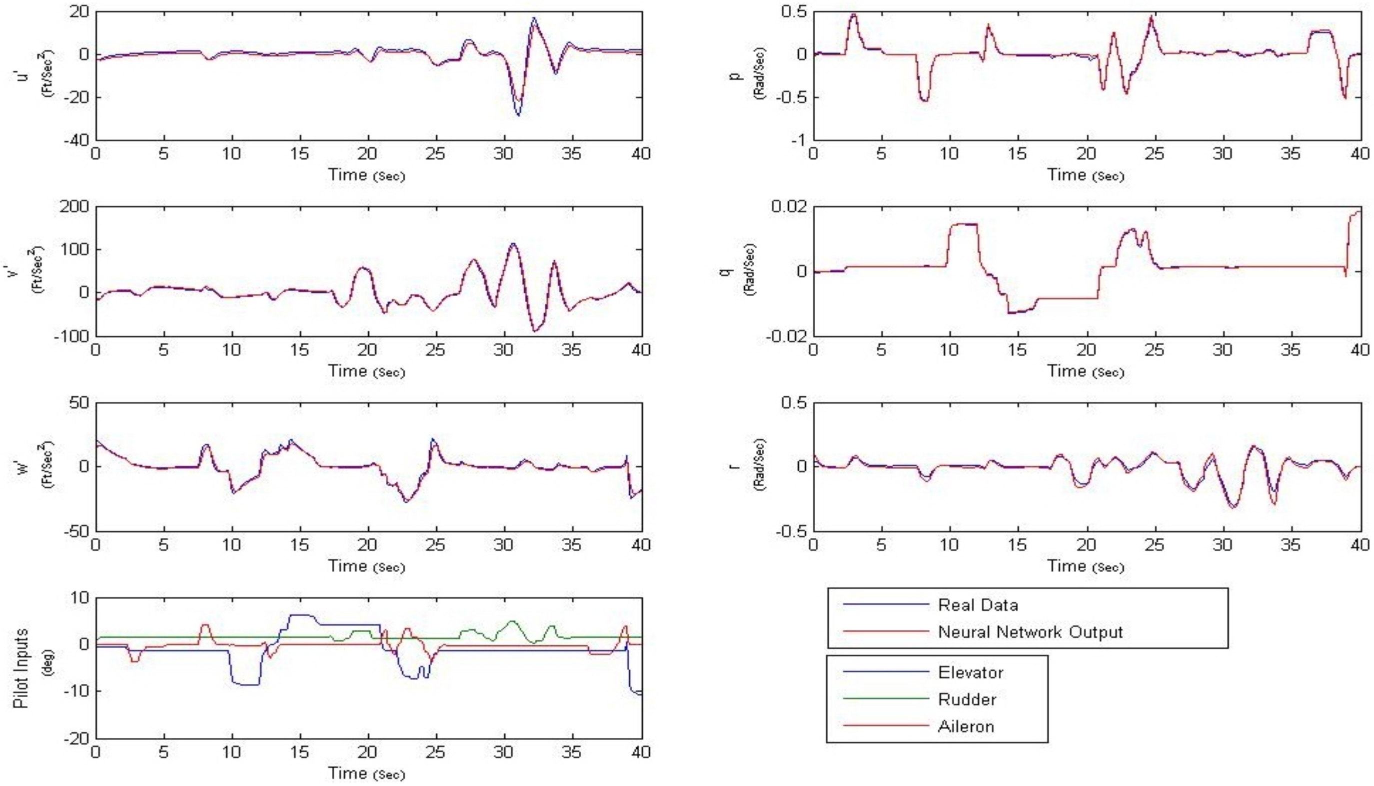

Figure 5: Validating Results

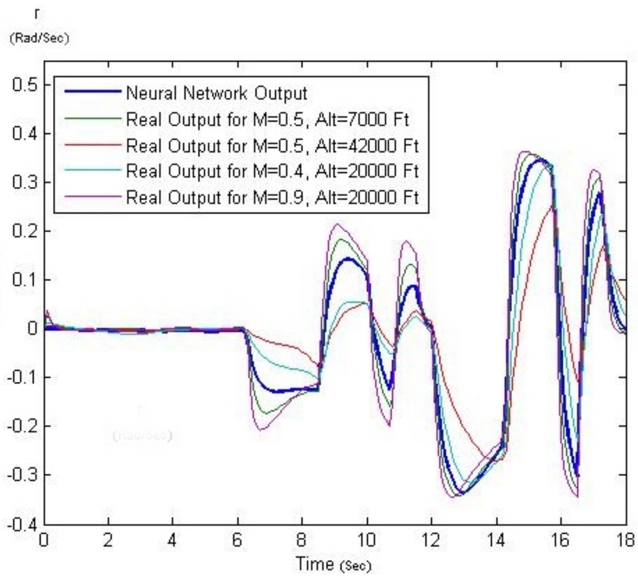

Fig. 6. Mach and Altitude Effect on Yaw Rate Response

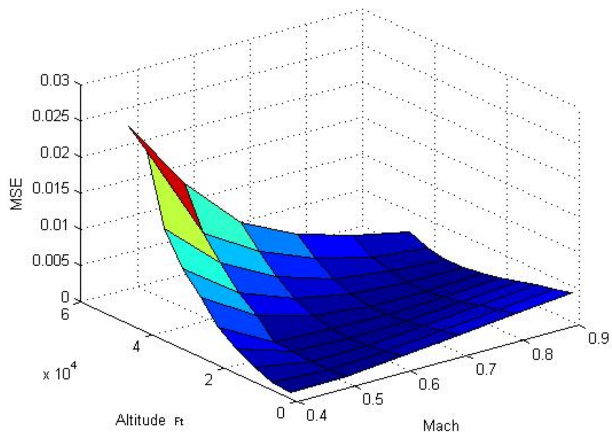

Fig. 7. Mean Squared Error of Yaw Rate Network versus Mach and Altitude

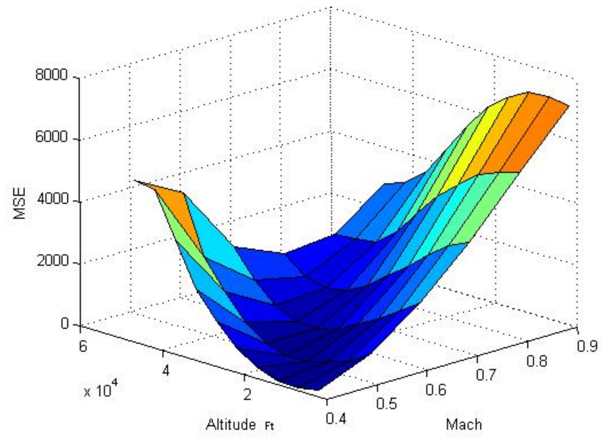

Fig. 8. Mean Squared Error of Lateral Acceleration ($\dot{v}$) Network versus Mach and Altitude

6 Conclusions

It is shown that neural networks are able to well predict the dynamic behaviour of highly manoeuvre aircraft which is helpful in developing flight simulators. Six modified Elman networks were trained to model the F-16 dynamics for a pre-specified Mach and altitude. The obtained network generalization for new inputs and different manoeuvres was found quite acceptable. Further investigation is performed to find out the valid region around the design point (Mach 0.5 and 20'000 feet altitude). Developing the neural network to model aircraft dynamic for the entire flight envelope (Mach-altitude) is currently carried out and some satisfactory results have been obtained which will be published in the near future.

7 References

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