# Control of aircraft maneuvers using neural network

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In this work, the control method required to fly autoguided aircraft along predetermined trajectories by using neural network technique is presented. Three control algorithms are analyzed: Off-line trained neural network, modified neural network with feedback on the network itself and Modified neural network with linear quadratic feedback on the system. Four motions in vertical plane and in three dimensions were studied: Climbing rising, vertical zigzag, circular loop and approximated elliptical loop maneuver. The robustness of neural network performance is tested by adding uncertainties in the model. The results indicate that the three-layer network is reliable and strong enough to represent the inverse dynamic of the aircraft. It can execute the desired trajectories with an error less than 2%.

في هذا البحث تم دراسة طريقه للتحكم في مسارات الطائرات السابق تحديدها وذلك باستخدام.ثلاث شبكات عصبية للتحكم تم اختيارها: شبكه عصبيه تم تمرينها مسبقا، شبكه عصبيه معدله بتغذية رجعيه علي نفسها وأخيراً شبكه عصبيه معدله بتغذية تربيعية خطية. تم دراسة أربعه مسارات مفروضة في المستوي الرأسي و ثلاث مسارات مفروضة في الفراغ وهي عبارة عن: ارتفاع رأسي ، ارتفاع رأسي متعرج، دوران في مستوى رأسي و دوران في مستوى رأسي في شكل قطع ناقص . بعد ذلك تم اختبار أداء الشبكةعن طريق عمل خطأ في النظام. ولقد أظهرت النتائج أن استخدام شبكه عصبيه مكونه من ثلاث طبقات ذات موثقيه وقدره لعمل نموذج عكسي للطائرة. ويمكن الحصول علي المسار المطلوب في حدود خطأ لا يزيد عن ٢%.

**Keywords**: Neural network, Inverse simulation, Trajectories and quadratic feedback

## 1. Introduction

A wide range of autopilot and guidance systems has been designed to perform prescribed maneuvers within close tolerances. The objective of control commands, derived from error signals via a guidance algorithm, is to decrease the differences between the measured and the desired flight conditions. As a consequence, the assumed trajectory or maneuver can be realized more or less precisely.

An alternative approach known as inverse simulation is adopted to determine the control actions required by the modeled vehicle to fly a specified maneuver [1, 2]. This approach is recently receiving wide interest, particularly in its application to the solution of aerospace problems involving precision maneuvering. The requirements imposed on motion are treated as program constraints on the system and from a program of motion. Consequently, the resultant motion of the aircraft is considered as a constrained motion (or program motion) of the controlled system [3, 4]. The neural network approach is applied for modeling and control of dynamic problem [5-7]. Also neural network is applied for system identification for flight modeling and control [8-11].

The purpose of this study is to investigate the implementation of neural network technique to solve the inverse problem of the dynamic of flying vehicles. The desired neural network should be capable to produce the control actions of the aircraft precisely and to perform any predefined maneuvers.

## 2. Aircraft model

The model for the longitudinal motion can be written as.

$$\dot{x}(t) = Ax(t) + Bu(t) \,. \tag{1}$$

The coefficient of the state matrix *A* are the aerodynamic stability derivatives, referred to airplane body axes, in concise form. The coefficients of the input matrix *B* are the control derivatives also in concise form.

$$\begin{bmatrix} \dot{u} \\ \dot{w} \\ \dot{q} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} x_u & x_w & x_q & x_\theta \\ z_u & z_w & z_q & z_\theta \\ m_u & m_w & m_q & m_\theta \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} u \\ w \\ q \\ \theta \end{bmatrix} + \begin{bmatrix} x_\eta & x_\tau \\ z_\eta & z_\tau \\ m_\eta & m_\tau \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \eta \\ \tau \end{bmatrix}. \tag{2}$$

Where $u$ is axial velocity, $w$ is normal velocity, $q$ is pitch rate, $\theta$ is pitch angle, $\eta$ is elevator angle and $\tau$ is thrust. The output equation is

$$y(t) = Cx(t). \tag{3}$$

Where $C$ is the identity matrix.

Eqs. (2 and 3) represent the longitudinal small perturbation motion of the aeroplane in state space form.

The lateral equation for small perturbation, referred to body axes, may be treated in exactly the same way to obtain the lateral state equations as given in eq. (1)

$$\begin{bmatrix} \upsilon^\circ \\ P^\circ \\ r^\circ \\ \phi^\circ \end{bmatrix} = \begin{bmatrix} y_\upsilon & y_p & y_r & y_\phi \\ L_\upsilon & L_P & L_r & L\phi \\ n_\upsilon & n_p & n_r & n_\phi \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} \upsilon \\ P \\ r \\ \phi \end{bmatrix} + \begin{bmatrix} y_\xi & y_\zeta \\ I_\xi & I_\zeta \\ n_\xi & n_\zeta \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \xi \\ \zeta \end{bmatrix}. \tag{4}$$

Where $C$ is the identity matrix, $\upsilon$ is lateral velocity, $p$ is roll rate, $r$ is yaw rate, $\phi$ is roll angle, $\xi$ is aileron angle and $\zeta$ is rudder angle.

Eqs. (2 to 4) are based on the following assumptions: The aeroplane is a rigid body and the axis system is co-located with the cg. In the body, the aeroplane is symmetric about oxz and the mass is uniformly distributed, the aeroplane is assumed to be flying in steady trimmed rectilinear flight (zero roll, side slip and yaw angles). Small perturbation and stable disturbed atmospheric are also assumed. The thrust is controlled by throttle lever angle.

## 3. Case study

Ling-Temco-Vought A-7A Corsair II aircraft continuous longitudinal and lateral model is obtained from Taper (1969) (as shown in Cook, M.V.)[12]. Discrete model are generated every 0.05 second for both longitudinal and lateral equations of motion using Matlab program and Simulink technique.

The main objective of the direct simulation is to obtain the input-output data pattern for different trajectories required to train the neural network. Selecting different elevators and rudder angles results in different aircraft trajectories. The inputs to the system are the selected elevator, rudder and bank angles. The outputs are the velocity and the displacements of the aircraft, which represent the output trajectory. The elevator may take the form of step input or sinusoidal input with different amplitudes and frequencies as illustrated in table 1.

## 4. Application of neural network

Artificial Neural Network (NN) can be applied to work as an inverse model for aircraft. A multi-layer feed-forward network trained off-line was used. Different training algorithm and number of neurons in hidden layer are also changed to obtain the optimum neural network structure (minimum training time with corresponding error). For the longitudinal motion, the input layer consists of tansigmoid threshold function with four neurons, the second layer is also tansigmoid and the number of neurons is varied from two to ten. The output layer consists mainly of single neuron to represent the output variable, which is the elevator deflection. For both longitudinal and lateral trajectories, the number of neurons in the input, hidden, and output layers are 4, 25 and 3, respectively. Using the Matlab program with Levemberg-Marquardt training algorithm trainlm a

Table 1
Elevator range for longitudinal maneuvers

| Maneuver | Input | Amplitude (rad) | Frequencies (rad/sec) |
|---|---|---|---|
| Climbing | Step | 0.0174532 | |
| Vertical zigzag | Sine wave | 0.05 | 0.01 |
| Straight loop | Sine wave | 0.08 | 0.07 |
| Elliptical loop | Sine wave | 0.115 | 0.15 |

suitable network are designed. First the network was trained to perform each maneuver separately. Finally it was trained to realize all the desired maneuvers. In this case the data pattern lateral includes 8*8008 inputs and 2*8008 outputs.

### 4.1. Feed forward aircraft control with NN

A feed forward control of the aircraft trajectories can be applied upon using the trained network as an inverse model. The inputs to the network are the desired trajectories. The trajectory is defined by the components of velocities and displacements x- and z-directions. The output of the network is the elevator deflection, which represents the control input to the system. The outputs of the aircraft dynamic model are the actual velocities and displacements of the aircraft in x-and z-directions as well as the pitch angle and pitch rate.

### 4.2. Feedback model

Two methods are suggested to modify the aircraft inverse model to sustain the abnormal conditions such as mach number change or model damage.

### 4.3. Modified neural network model with feedback on the network itself

Neural network may be reconstructed such that the inputs to the network are the desired trajectory, aircraft velocities and a Delayed output trajectory. Increasing the number of input data may increase the

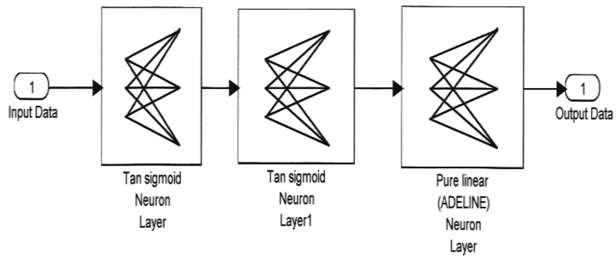


Fig.1. Neural network structure.

strength of the network [13]. The new system block diagram during direct simulation such that the output trajectory and the delayed trajectory are stored in the output data file fig. 2 shows the block diagram of the aircraft as controlled with NN with feedback on the network.

### 4.4. Modified neural model with linear quadratic feedback on the system

A second alternative modification is suggested by using state feedback on the aircraft system. The feedback gain matrix "K" is designed based on linear quadratic optimal control (riccati equation) as shown in fig. 3.

## 5. Results

The network with different number of neurons in the hidden layer is trained to attain certain error target represented by the sum squared error. The number of epochs that satisfies the target error is directly proportionally to the computer time needed for training processing. Table 2 represents the

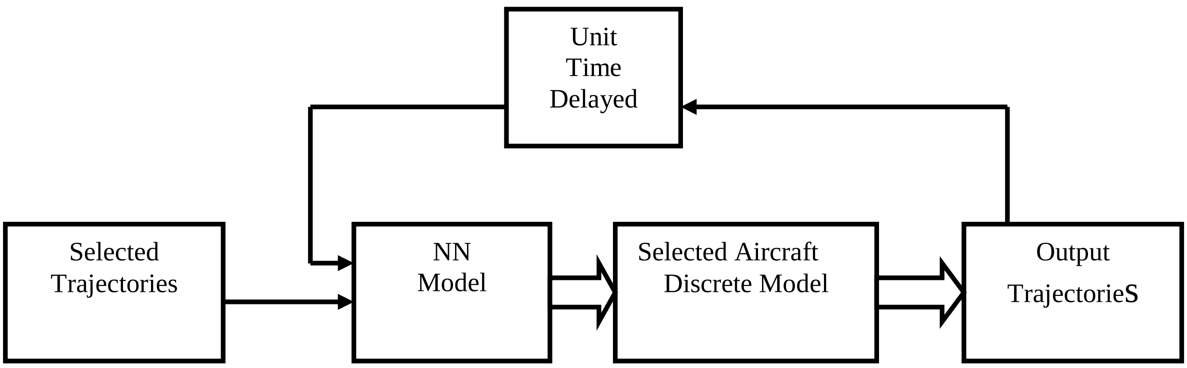


Fig. 2. Control of aircraft trajectory using NN model with a feedback on the network itself.

relation between the sum square error (from 10% to 1%), the number of neurons in hidden layers (from 2 to 10) and the corresponding training time i.e. numbers of epochs. From table 2, it can be noticed that the optimum number of neurons in hidden layer lies between four to six for sum square error between 10% to 1%. The decrease in the sum of squared error increases the training time. Although the best network structure, for 1% sum squared error may include four or six neurons in the hidden layer, but larger number of neurons is useful to increase the strength of the network.

Simulation conducted using the off-line trained network shows that the aircraft can execute the predetermined trajectories successfully especially for climbing and vertical-zigzag as shown in figs. 4 - 6. The maximum error in tracking both the vertical circular is less than 2% as long as the loops are performed within the trained zone. The feedback on the neural network itself has adverse effects on the results. The maximum error increases to 6% for straight-rising maneuver, 10% for vertical zigzag maneuvers and not recommended for the other maneuvers because the output results are out of maneuvers range. The linear quadratic feedback on the system improves the tracking of the desired maneuvers.

The second main object in this work is helping the aircraft to sustain the abnormal flight condition such as mach number change or model damage. When an error was imposed in the model and upon implementing the off-line trained network, the elliptical loop maneuvers is insignificantly affected. Meanwhile, for vertical rising and vertical zigzag motion the network renders maximum errors of 3% and 4.5% as the modeling errors increases from 10% to 40%. Errors are included in the *B* matrix of aircraft model and the results are depicted in figs. 7 to 9.

Table 2
Number of epochs needed for certain number of neurons in the hidden layer to attain a predefined error

| Sum square errors | No. of neurons | | | | |
|---|---|---|---|---|---|
| | $S_2=2$ | $S_2=4$ | $S_2=6$ | $S_2=8$ | $S_2=10$ |
| 0.1 | 20 | 18 | 16 | 22 | 21 |
| 0.05 | 22 | 20 | 18 | 24 | 23 |
| 0.02 | 28 | 25 | 25 | 29 | 30 |
| 0.015 | 31 | 28 | 31 | 31 | 32 |
| 0.01 | 200 | 180 | 180 | 600 | 800 |

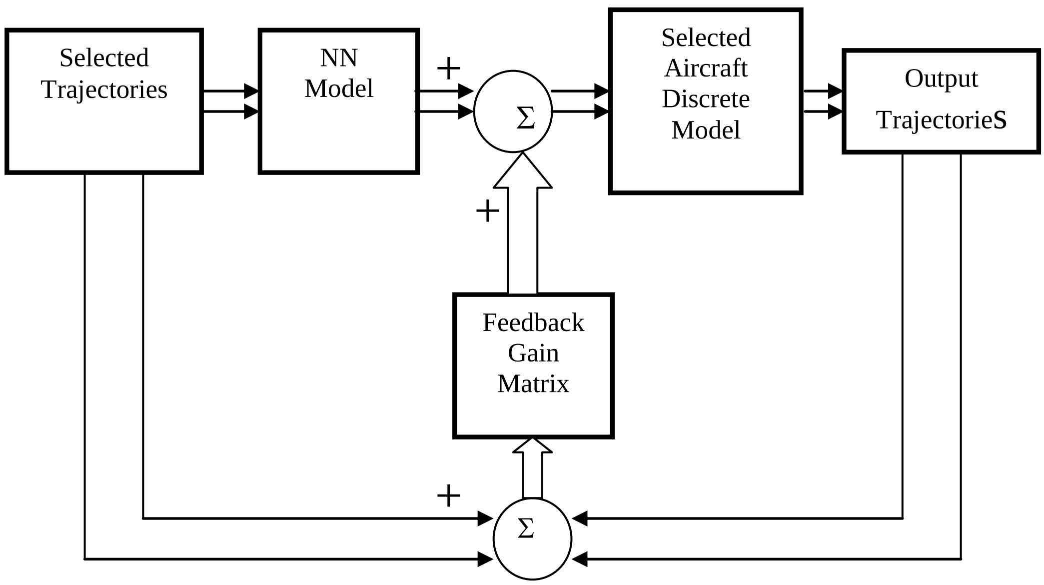


Fig. 3. NN Feed-forward control and quadratic optimal feed back control.

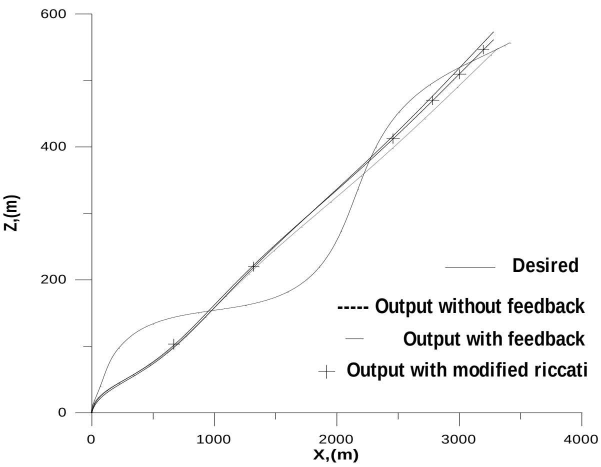


Fig. 4. Vertical-rising maneuver with modified model.

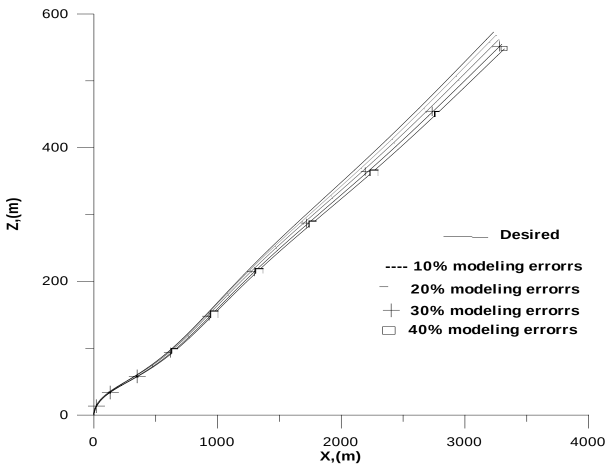


Fig. 7. Climbing maneuver with different modeling error.

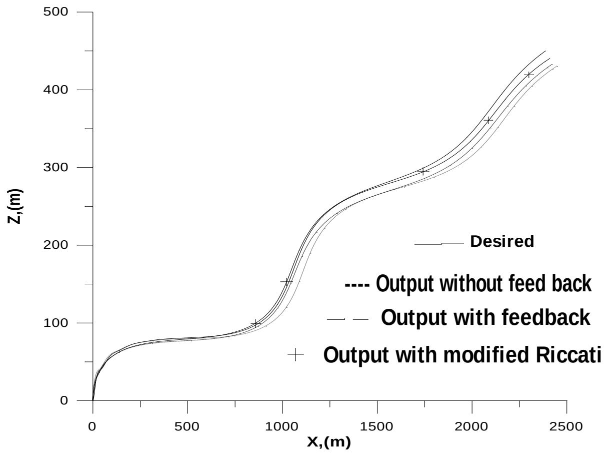


Fig. 5. Vertical –zigzag maneuver with modified model.

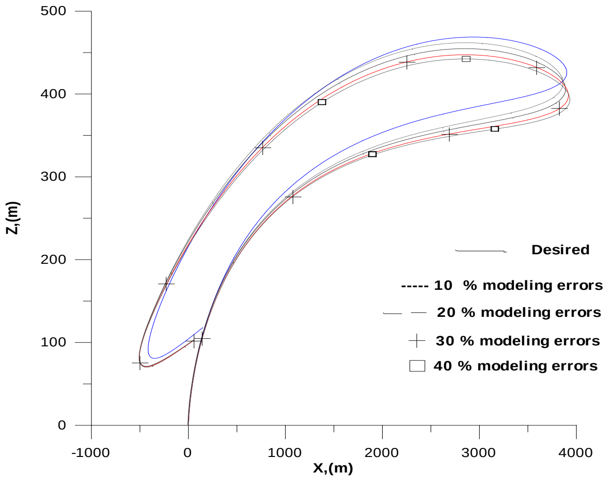


Fig. 8. Vertical loop maneuver with different modeling error.

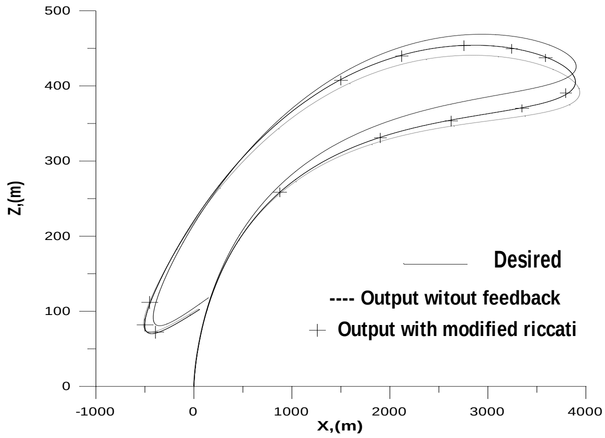


Fig. 6. The vertical-loop maneuver with modified model.

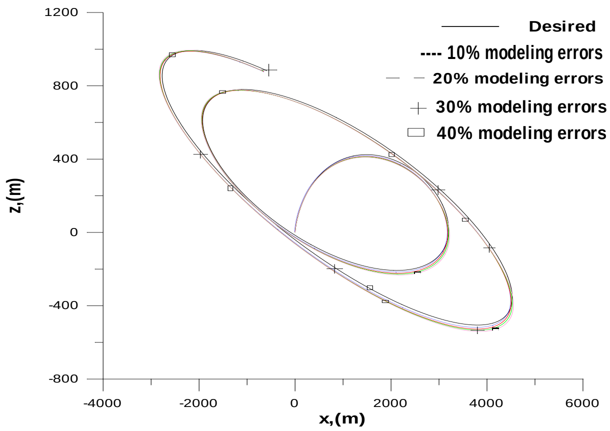


Fig. 9. Elliptical loop maneuver with different modeling errors.

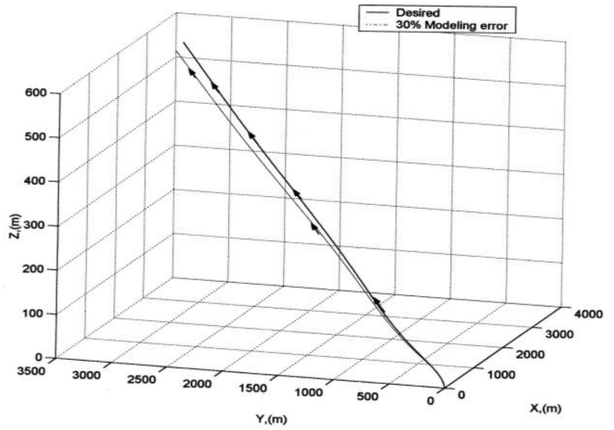


Fig. 10. Climbing 3-D maneuver with 30% modeling error.

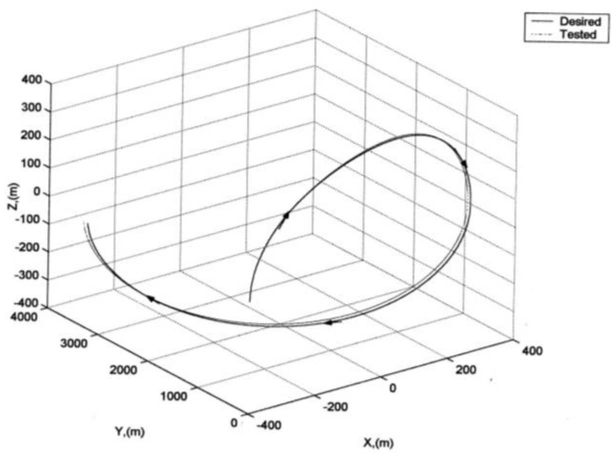


Fig. 11. Vertical-loop 3-D tested maneuver.

The time elapsed in training the neural network for 3-D maneuvers is longer than the training time for 2-D maneuvers, assuming the same sum of the squared error. During recall mode the output results for 3-D looping, are in good agreement with the desired trajectories.

## 6. Conclusions

It can be concluded that the three-layer network is reliable and strong enough to represent the inverse dynamics of the aircraft. The number of neurons in the hidden layer is the most important factor that affects the sum of the squared error and the training time. The off-line trained network was able to execute the predescribed trajectories successfully. The linear quadratic feedback on the system improves the tracking of the desired maneuvers. Meanwhile the feedback on the neural network itself has adverse effects. The found to be implementation of neural network is feasible in the presence of model uncertainties.

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