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Neural Network Based Altitude-Hold Autopilot Control of an Aircraft

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Abstract

Since the nature of mathematical model of an aircraft is extremely nonlinear and controlling the state variables have always been highly challenging tasks for the researchers, therefore, this paper presents an ANN (Artificial Neural Network) based control architecture to control the longitudinal dynamics of an aircraft by controlling the longitudinal motion of the aircraft. The proposed controller serves as an altitude-hold autopilot system which holds the aircraft at a desired altitude as assistance to the pilot. Using sigmoid activation function with multilayer network and back-propagation supervised learning; the NN (Neural Network) plant model is trained offline. The control algorithm is based on NN model predictive control architecture where the controller first predicts the future plant behavior for the given range of control inputs using NN plant model and then using optimization algorithm a set of potential control inputs are computed to optimize the future plant responses. The proposed model is tested for 500 and 1000 ft step inputs and a pulse input ranging from 0-1000 ft. The simulation results show that the model is working under altitude-hold autopilot mode smoothly without any overshoot and steady-state error.

Key Words: *Boeing 747, Altitude-Hold Autopilot, Longitudinal Control, Artificial Neural Network, Back-Propagation.*

I. INTRODUCTION

The evolution of the airplanes from piston-engine airplanes to jets has triggered the advancement of the designing and development of heavier-than-air flying machines is a complex and convoluted task and plays an important role in the growth of civil and military aviation. Modern aircrafts are built with various automatic flight control systems that aid the pilots in a flight. On the one hand, the most common reason for plane crashes is human error, so it can be consoling to know that aircraft systems are designed to be automatized, reflexive, and intelligent.

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An aircraft automatic pilot system controls the aircraft without the pilot directly maneuvering the controls. The autopilot maintains the aircraft's attitude and/or direction and returns the aircraft to that condition when it is displaced from it. Automatic pilot systems are capable of keeping aircraft stabilized laterally, vertically, and longitudinally. Development of artificially intelligent systems sophisticated enough to control various modes and can achieve several flight tasks. One of the major tasks of the autopilot is to hold the specific altitude. These conventional autopilot systems are controlled by artificial intelligence-based systems and designed by mathematical models to control the maneuvering of an aircraft. Some of the challenges faced by researchers during the mathematical modelling and the controller design for an aircraft are discussed below.

- Autopilot is one of the essential functions for aircraft controls. Autopilot system's performance directly affects the mission success and performance of aircraft [1].
- In recent times it is the most important realization of aeronautic engineers that much more improvements are required in efficiency of autopilot systems [2].
- The design of an aircraft control system is a very challenging control problem because of many reasons. Some are listed below:
- The dynamics of the aircraft are highly non-linear.
- The parameters of the aircraft change with environment as well as operating conditions.

There are a number of aircraft control systems. These include lateral control, altitude control, speed control and safe landing control etc. A lot of literature has been investigated for aircraft control systems, some adaptive strategies are:

- AI (Artificial Intelligence) based adaptive control design of autopilot system for nonlinear UAV (Unmanned Aerial Vehicle) [3].
- Self-tuning fuzzy PID (Proportional Integral Derivative) controller design for aircraft pitch control [4].
- Gain scheduling control [5].

Literature is available on altitude-hold autopilot control of an aircraft. Some of the control algorithms which have been used as altitude-hold autopilots are as under:

- PID Controller [6].
- SAS (Stability Augmentation System) [7].
- Two-time-scale cascade decomposition [8].
- Sliding mode controller along with feedback linearization [9].

The main problem of the above linear techniques is that they require an accurate mathematical model which is usually not available. It is therefore a need of time to investigate those techniques which do not rely upon mathematical model. One of the pilot's many tasks is to hold the specific altitude. A well-trained pilot can control the altitude manually but requires a very sharp eye on the control of aircraft. It is a real time control affected by many external factors and all techniques are based on linear systems. So, for realistic nonlinear systems, a best choice is ANN based control systems. We intend to develop a FFANN (Feed-Forward Artificial Neural Network) with three layers which is trained to behave as an autopilot, and hold the required altitude for specific time.

I.1 Objectives

The specific objectives of this research study are as follows:

(1) Selection of mathematical model of an aircraft for generation of data for training of the proposed altitude-hold autopilot.
(2) Simulation of the model in MATLAB/SIMULINK and analysis of the system.
(3) Development of ANN controllers as altitude hold autopilot
(4) Testing of the closed loop system with simulation studies.

I.2 Methodology to Achieve the Control Objectives

The methodology to achieve the aforementioned objectives is based on the selection of a mathematical model for the longitudinal dynamics of an aircraft from the literature review. The model will be first validated and then it will be used for the generation of data for the ANN. Once the sufficient data is generated, it will be then used to train the ANN structure. Precisely, a back propagation neural network structure on supervised learning method will be trained by optimizing its weights. Later this trained structure will be used in the ANN controller for the altitude-hold autopilot system. The proposed aircraft model will be tested for different transient and steady state conditions to evaluate its stability. The vital role of this ANN control algorithm is to generate a suitable signal for the elevator surface of the aircraft to maintain a constant altitude.

The description of the proposed research study, literature review, derived objectives of this study and workable methodology have been presented in the above section. In Section 2, the mathematical model for the longitudinal dynamics of an aircraft is presented. Section 3 covers the generic algorithm of artificial neural network along with back-propagation which will be used to train the data generated from the mathematical model of the aircraft. The control law for the altitude-hold autopilot is developed in Section 4. The simulation results developed in MATLAB and SIMULINK are presented and discussed in Section 5. Finally, the contribution of this research study and outcome is discussed in the conclusion in Section 6.

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II. LONGITUDINAL DYNAMICS MODELLING OF AN AIRCRAFT

An airplane is a powered, fixed-wing aircraft that is propelled forward by thrust from a jet engine, propeller or rocket engine. An aircraft needs a power source to provide the thrust necessary to obtain lift. Basic principle of every airplane is almost the same, whether the most advanced high-performance jet or the simplest aircraft. Aircraft can move within its fixed determined axes in two ways. It can translate, that is changing location, from one point to another point or can rotate, and that is changing its attitude.

Control system engineering plays a significant role in designing high-performance airplane. The motion of an aircraft is particularly complex because the rotations and translations are coupled together; a rotation affects the magnitude and direction of the forces which in turn affects translations. In this study Boeing 747 is considered for the analysis of the altitude-hold autopilot system. As per the first objective of the study, the mathematical model of the aircraft (Boeing 747) from [10] has been selected for the generation of data for training of the proposed altitude-hold autopilot based on artificial neural networks. Fig. 1 shows the schematic diagram of Boeing 747 with the coordinate frames which move with the aircraft. It is important to mention here that since this study is focusing on the altitude-hold autopilot system, therefore, only longitudinal equations of motion are considered.

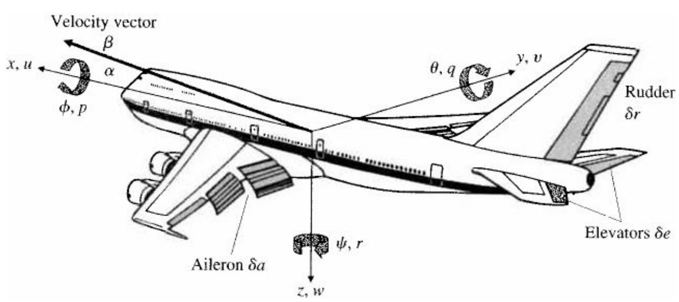

FIG. 1. REFERENCE FRAMES OF AN AIRCRAFT [10]

Where x, y, z are position coordinates, u, v, w are velocity coordinates, p is roll rate, q is pitch rate, r is yaw rate, ϕ is roll angles, θ is pitch angle, ψ is yaw angle, β is side-slip angle, and α is angle of attack.

The generic mathematical model of Boeing 747 is an eighth order model; comprising of both longitudinal and lateral motion. The longitudinal motion is based on axial (X), vertical (Z), and pitching (θ,q) motion whereas the lateral motion contains rolling (ϕ,p) along with yawing (r,β) movement as shown in Fig. 1. The longitudinal motion is driven by the elevator surfaces and the engine throttle and the lateral motion is

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controlled by ailerons and rudder control. The coupled equations of motion for the translational motion and rotational motion are given in Equations (1-2), respectively. The reader is referred to [10] for the derivation of Equations (1-2). However, these equations are nonlinear in nature and the linearization of Equations (1-2) is carried out in Section 2.1.

$$\begin{aligned}
&m(\dot{U} + qW - rV) = X - mg\sin\theta + \kappa T\cos\theta \\
&m(\dot{V} + rU - pV) = Y - mg\cos\theta\sin\varphi \\
&m(\dot{W} + pV - qU) = Z + mg\cos\theta\cos\varphi - \kappa T\sin\theta
\end{aligned} \tag{1}$$

$$\begin{aligned}
&I_x\dot{p} + I_{xz}\dot{r} + \left(I_z - I_y\right)qr + I_{xz}\,qp = L \\
&I_y\dot{q} + \left(I_x - I_z\right)pr + I_{xz}\left(r^2 - p^2\right) = M \\
&I_z\dot{r} + I_{xz}\,\dot{p} + \left(I_y - I_x\right)qp + I_{xz}\,qr = N
\end{aligned} \tag{2}$$

Where m is mass of the aircraft, [U,V,W] is body axis components of the velocity of the center of mass (cm),

$$\beta = \tan^{-1}\left(\frac{V}{U}\right)$$

$[U_0, V_0, W_0]$ = reference velocities
[p, q, r] = the body-axis components angular velocity of the aircraft
[X, Y, Z]= the body-axis aerodynamics forces about the cm.
[L, M, N] = the body-axis aerodynamics torque about the cm.
g_0= the gravitational force per unit mass
I_i= the inertia in body axes
$(\theta, \varnothing)$ = the Euler pitch and angle of the aircraft body axes with respect to horizontal.
V_{ref}= reference flight speed
T= Propulsive thrust resultant
κ= the angle between thrust and body x-axis.

II.1 Linearization of the Equations of Motion

These equations can be linearized with the following assumptions; $\dot{U} = \dot{V} = \dot{W} = \dot{p} = \dot{q} = \dot{r} = 0$, which implies to the steady state, straight, level, and constant speed flight. In addition, if the turning in any axis is ignored then we have $p_0 = q_0 = r_0 = 0$ and when the wings are level then ϕ =0. Moreover, due to the presence of an angle of attack to provide some lift to balance the aircraft's weight θ_0 and $W_0 \neq 0$. We further define

$$\begin{aligned}
&U = U_o + u \\
&V = V_o + v
\end{aligned} \tag{3}$$

$W = W_o + w$

Components of steady state velocity body axis can be expressed as

$$\begin{aligned} U_o &= V_{ref}\cos(\theta_o) \\ V_o &= 0\ (\beta_0 = 0) \\ W_o &= V_{ref}\sin(\theta_o) \end{aligned} \tag{4}$$

With these conditions, equilibrium equations can be redefined as

$$\begin{aligned} 0 &= X_0 - mg_o\sin\theta_o + \kappa T\cos\theta_o \\ 0 &= Y_0 \\ 0 &= Z_0 + mg_o\cos\theta_o - \kappa T\sin\theta_o \\ 0 &= L_0 \\ 0 &= M_0 \\ 0 &= N_0 \end{aligned} \tag{5}$$

With the following assumptions.

$$\begin{aligned} &(v^2, w^2) << u^2 \\ &(\phi^2, \theta^2) << 1, \\ &\left(p^2, q^2, r^2\right) << \frac{u^2}{b^2} \end{aligned} \tag{6}$$

Where b is wingspan

Since, in this study longitudinal motion is considered, therefore, only the longitudinal equations of motion are selected for the development of altitude-hold autopilot system. The uncoupled fourth-order set of linearized longitudinal dynamics representing the perturbation in longitudinal (U,W,θ, and q) motion can be represented as

$$\begin{bmatrix} \dot{u} \\ \dot{w} \\ \dot{q} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} X_u & X_w & -W_0 & -g_0\cos\theta_0 \\ Z_u & Z_w & U_0 & -g_0\sin\theta_0 \\ M_u & M_w & M_q & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} u \\ w \\ q \\ \theta \end{bmatrix} + \begin{bmatrix} X_{\delta e} \\ Z_{\delta e} \\ M_{\delta e} \\ 0 \end{bmatrix} \delta e \tag{7}$$

Where u is forward velocity perturbation in the aircraft in x-direction, w is velocity perpetuation in the z-direction, q is angular rate about the positive y-axis, or pitch rate, θ is pitch angle perturbation from the reference θ_0 value, $X_{u,w,\delta e}$ is partial derivatives of aerodynamics force in x-direction with respect to perturbation in u,w, and δe (X,Z,M are stability derivatives and are defined from wind tunnels and flight tests), $Z_{u,w,\delta e}$ is partial derivatives of aerodynamics forces in z-direction with respect to perturbation in u, w, and δe, $M_{u,w,q,\delta e}$ is partial derivatives of aerodynamics moment with respect to perturbation in u, w, q, and δe, and δe is movable tail-selection or "elevator" angle for pitch control.

In order to capture the altitude variation, Equation (8) is added to the longitudinal equation of motion, i.e. in Equation (7). In should be noted that Equation (9) is the linearized form of Equation (8).

$$\dot{h} = V_{ref} \sin\theta - w\cos\theta \tag{8}$$

$$\dot{h} = V_{ref}\theta - w \tag{9}$$

For the purpose of illustration as given in [10], in horizontal flight of Boeing 747 with a weight of 637,000 lb the longitudinal perturbation equations of motion at 20,000 ft with nominal speed of 830 ft/sec can be expressed as follows:

$$\dot{x} = Fx + G\delta e \tag{10}$$

$$\begin{bmatrix} \dot{u} \\ \dot{w} \\ \dot{q} \\ \dot{\theta} \\ \dot{h} \end{bmatrix} = \begin{bmatrix} -0.00643 & 0.0263 & 0 & -32.2 & 0 \\ -0.0941 & 0.624 & 820 & 0 & 0 \\ -0.000222 & -0.00153 & -0.668 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & -1 & 0 & 830 & 0 \end{bmatrix} \begin{bmatrix} u \\ w \\ q \\ \theta \\ h \end{bmatrix} + \begin{bmatrix} 0 \\ -32.7 \\ -2.08 \\ 0 \\ 0 \end{bmatrix} \delta e$$

(11)

The parameters of matrix F and G are same as given in [10]. Here the desired output of the altitude hold autopilot can be defined as:

h = Hx(12)

$$h = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u \\ w \\ q \\ \theta \\ h \end{bmatrix} \tag{12}$$

A frequently used concept to analyze and design a control system is the transfer function. This helps in analyzing the stability of a system under various input conditions. The open loop transfer function for the system given in the Equation (11) can be obtained as [10].

$$\frac{h(s)}{\delta e(s)} = \frac{32.7(s+0.0045)(s+5.645)(s-5.61)}{s(s+0.003 \pm 0.0098j)(s+0.6463 \pm 1.211j)} \tag{13}$$

Altitude-hold autopilot control tasks is not straight forward and carried out in more than one feedback loops as shown in Fig. 2. The inner loop is relating the pitch rate q to δe to improve the damping of the aircraft. Damping can be further improved if the pitch angle θ is added in the same inner feedback loop [10].

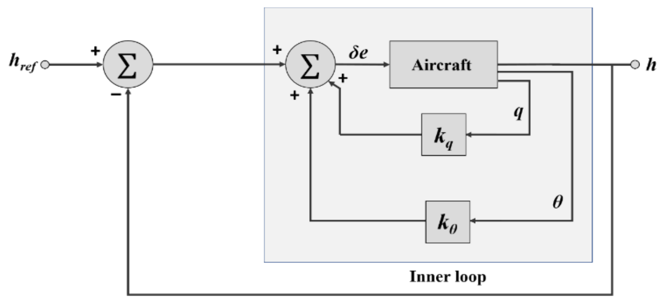

FIG. 2. ALTITUDE-HOLD AUTOPILOT FEEDBACK CONTROL SYSTEM OF AN AIRCRAFT [10]

The effectiveness of inner-loop is essential to make the outer-loop successful which is based on altitude h feedback system. With the given inner-loop the modified transfer function from elevator angle δe to the altitude h can be expressed as

$$\frac{h(s)}{\delta e(s)} = \frac{32.7(s+0.0045)(s+5.645)(s-5.61)}{s(s+2.25 \pm 2.29j)(s+0.0105)(s+0.0531)} \tag{14}$$

As per methodology given in Section 1.2, in Fig. 3 response of the inner-loop has been validated against the 2° (0.035-rad) step command in θ as given in Fig. 3 [10]. This ensures that the proposed model can be used for the generation of data for ANN architecture.

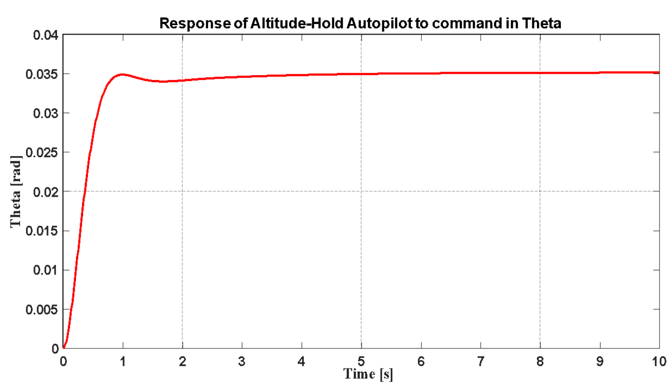

FIG. 3. STEP INPUT COMMAND IN Θ IN THE INNER-LOOPFOR THE AUTOPILOT ALTITUDE-HOLD

For the outer feedback loop, a PID controller is used in this study to achieve the desired altitude. The transfer function of the overall system, with both inner and outer loops, can be defined as:

$$\frac{h(s)}{\delta e(s)} = \frac{-0.1392s^5 - 0.01114s^4 + 4.408s^3 + 0.1985s^2 + 0.002199s + 6.279e-06}{s^6 + 4.424s^5 + 14.28s^4 + 5.301s^3 + 0.2063s^2 + 0.002199s + 6.279e-06} \tag{15}$$

Equation (15) will be used for the generation of required data for the ANN to maintain the desired altitude during autopilot altitude-hold mode. The following section presents the generic architecture of the ANN.

III. ANN AND BACK PROPAGATION ALGORITHM

ANN is a computational model based on the structure and functions of biological neural networks. It is like an artificial human nervous system for receiving, processing, and transmitting information. A simple artificial neuron having a single input layer (x) and output layer (y) is called a perceptron. The inputs given to a perceptron are processed by summation function and followed by activation function to get the desired output [11] as shown in Fig. 4. The significant features of the ANNs for the intelligent control's advantage are that they do not require programming and learn from experience, their processing speed is high and can be implemented in real-time condition, their capacity to generalize from given training data to unseen data; most importantly they fail with prior warning rather than abruptly.

The fundamental architecture of a single artificial neuron comprises of a weighted summer and an activation (or transfer) functions as shown in Fig. 4.

Where $x_1 \ldots x_j$ are inputs, $w_{i1} \ldots w_{ij}$ are weights, b is a bias, f is the activation function, y is the output.

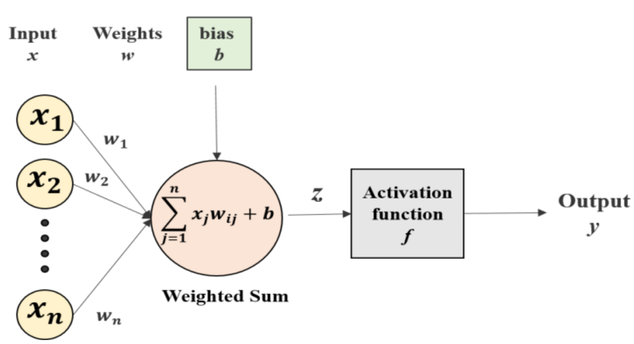

FIG. 4. STRUCTURE OF SINGLE LAYER PERCEPTRON (BIOLOGICALLY A NEURON)

Then the weighted sum z can be defined as:

$$z = \sum_{j=1}^{n} x_j w_{ij} + b \tag{16}$$

Where the output y can be expressed as:

$$y = f(W^T X + b) \tag{17}$$

Where

$$z = W^T X + b \; z \tag{18}$$

The activation function (f) has different types but the most popular one is the sigmoid activation function as represented in Equation (19) and shown in Fig. 5.

$$f(x) = \frac{1}{1+e^{-x}} \tag{19}$$

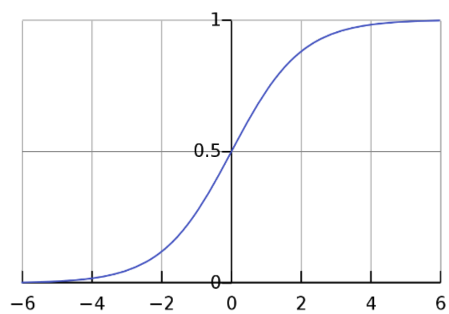

FIG. 5. ACTIVATION FUNCTION (SIGMOID)

Usually, there are two types of perceptron; single layer and multilayer. A MLP (Multilayer Perceptron) consists of input layer, hidden layer (one or more than one hidden layer) and output layer as shown in Fig. 6. The single layer is limited to only learn linearly separable patterns, whereas, the multilayer which is also called FFNN can have more processing power depending upon the number of hidden layers [12].

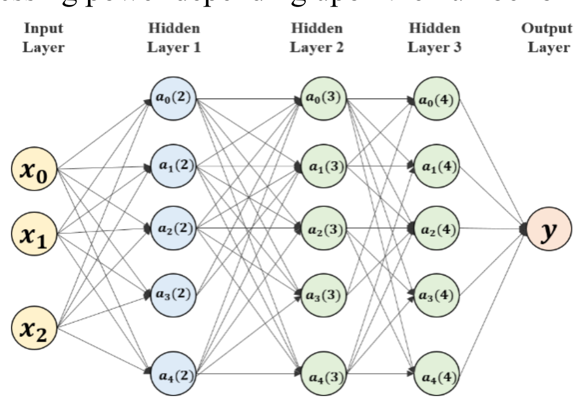

FIG. 6. A MULTILAYER PERCEPTRON

Learning of a NN can be defined as the process of tuning or regulating the weights and biases such that for the potential input signal the required output can be acquired. There are two methods of learning which has been discussed in the literature [13].

(i) Supervised Learning: In the supervised learning, a data which consists of inputs commands and its corresponding output responses is provided to train the neural network plant model. During this training process the weights are adjusted until the error between desired output and actual output reaches a minimum value. This is mostly used for dynamics system where feedback control system is required.

(ii) Unsupervised Learning: On the contrary, unsupervised learning method is based on the open-loop control algorithm where the plant state doesn't need any adjustment based on feedback approach. Such method is used for image recognition, image compression, speech recognition, etc.

For controlling the altitude control, we are using back-propagation supervised learning of artificial neural networks using gradient descent. Its uses error function which will calculate the gradient of the error function with respect to the weights of the neural network. For MLFFP (Multilayer Feed-Forward Perceptron) have input layer, output layer and hidden layers-where all the computations are done.

If network has a units in layer i and b units in layer i+1, then w_i will be of dimension b×(a+1). Here we are taking bias as x_0 and a_0, respectively. Vector-X reposting the nodes of input layer and Vector-A representing the hidden layer, where

$$X = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} A = \begin{bmatrix} a_0(1) \\ a_1(2) \\ a_2(3) \\ a_3(4) \end{bmatrix} w^1 = \begin{bmatrix} w_{10} & w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} & w_{24} \\ w_{31} & w_{32} & w_{33} & w_{34} \end{bmatrix}$$

The Equations (16-17) and by generalizing the multiple hidden layers and multiple nodes in each of the layer we can represent the MLFFP as follows:

$$y = \left\lfloor f\left(\sum_m w_m^l \left[\ldots f\left(\sum_j w_{kj}^2 \left[f\left(\sum_i w_{ji}^1 x_i + b_j^1\right) + b_k^2 \right]\right) \ldots \right]_m + b_n^l \right)\right\rfloor_n \tag{20}$$

We measure how good this output $\hat{y}$ by using cost function C and desire result in output layer y called MSE (Mean Squared Error). Loss function is calculated for the entire training dataset and their average is called the Cost function C.

$$C = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}\right)^2 \tag{21}$$

Basic purpose of the back propagation is to bring the error function to minimum. For further derivation of the back propagation algorithm, the readers are referred to [14-15].

IV. CONTROL ALGORITHM FOR THE ALTITUDE-HOLD AUTOPILOT SYSTEM

The ANN architectures have been explained in the previous section. In this section the control algorithm for the altitude-hold autopilot system will be presented. In literature, a variety of ANN architectures for prediction and control have been used such as model predictive control [16], model reference adaptive control [17], and feedback linearization control [18]. Figs. 7-9 show the individual ANN architectures of these three controllers, respectively. It is widely known that the MLP-NN can be efficiently used with these controller for a wide range of applications of the dynamic systems [14]. However, in this study NN model predictive control architecture (Fig. 7) is used for the training of aircraft data.

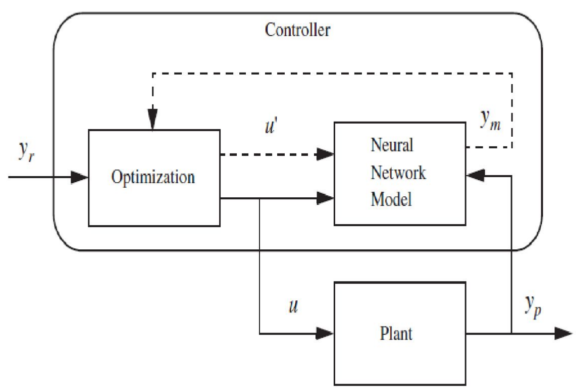

FIG. 7. NEURAL NETWORK MODEL PREDICTIVE CONTROL

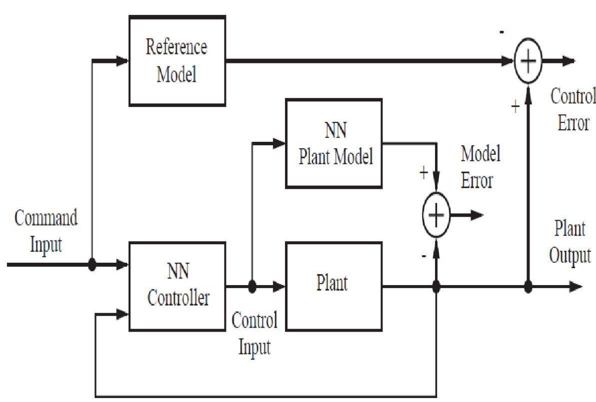

FIG. 8. NEURAL NETWORK REFERENCE MODEL CONTROL ARCHITECTURE

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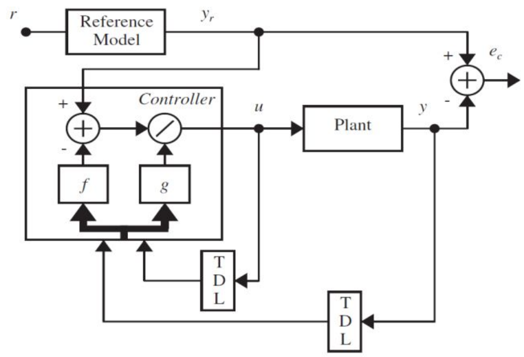

FIG. 9. NEURAL NETWORK FEEDBACK LINEARIZATION CONTROL

Each of these control architectures has its advantages and limitations. A comparison of these three controllers is given in [11,14] and based on the findings of this literature study NN model predictive control architecture is used in MATLAB/SIMULINK environment. Fig. 10 shows the block diagram of the overall model to work as an altitude-hold autopilot system. ANN controller block is used with the aircraft model (Equation (15) where the controller first predicts the future plant behavior for given range of control inputs using NN model. In the second stage a set of control inputs are determined using an optimization algorithm which optimize the future plant responses. Here, the NN plant model, using any desired activation function, any MLPNN and back-propagation training, is trained offline. Finally, the optimized control inputs are given to the actual plant model. The proposed aircraft model is analyzed for different step inputs and during the transient and steady-state maneuvers. The next section presents the results and discussion based on the model and control algorithm discussed in the above sections.

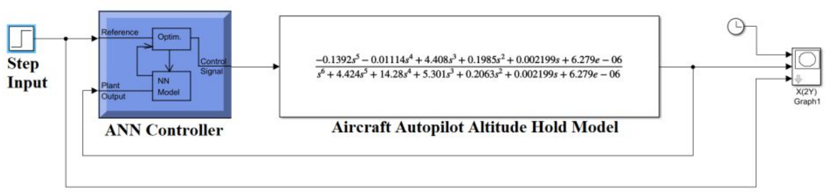

FIG. 10. FEEDBACK CONTROL SYSTEM FOR THE AIRCRAFT MODEL USING ANN CONTROLLER

V. RESULTS AND DISCUSSION

This section presents the results and discussion to evaluate that how by using the proposed methodology this study has achieved the objectives extracted from the literature review. After the validation of the mathematical model of the aircraft for the autopilot altitude-hold in Fig. 3, it became feasible to use the same model for the generation of data for ANN. MATLAB and SIMULINK have been used for the simulation of the entire model. For the transfer function of the aircraft model MATLAB has been used whereas SIMULINK has been used for the ANN Controller as shown in Fig. 10. The final simulations are executed in the SIMULINK model which is an integrated part of MATLAB.

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The ANN controller has been trained for desired altitude ranging from 0-1000 feet in this study. The aircraft model is then simulated for the step input commands of 500 feet (Fig. 11) and 1000 feet (Fig. 12) with the simulation time of 30 sec to analyze the autopilot altitude-hold response of the aircraft. The aircraft model is also simulated for a pulse input command ranging from 0-1000 feet and back to 0 feet (Fig. 13) with the simulation time of 100 sec to investigate the transient as well as steady-state response of the aircraft during the sharp maneuvers. It can be observed from Figs. 11-12 that the proposed ANN controller is smoothly achieving the desired objectives and activating the autopilot altitude-hold mode within a suitable time without any overshoot and steady-state error.

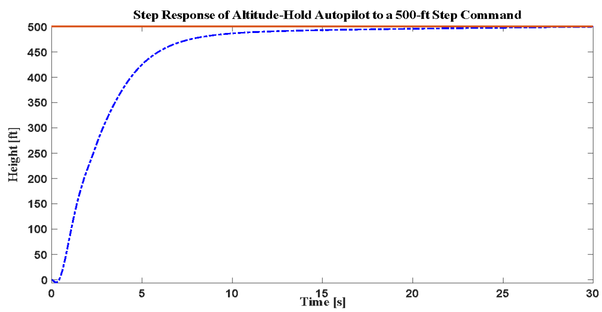

FIG. 11. STEP RESPONSE OF ALTITUDE-HOLD AUTOPILOT TO A 500-FT STEP COMMAND

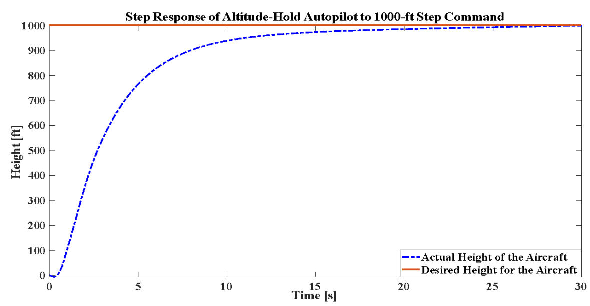

FIG. 12. STEP RESPONSE OF ALTITUDE-HOLD AUTOPILOT TO A 500-FT STEP COMMAND

For further testing the performance of the proposed ANN control algorithm, the Boeing 747 model is further investigated under transient maneuvers as shown in Fig. 13. The result shows that the aircraft model is responding very well to the desired signal and achieving the expected results during transient input. These simulation results ensure that the proposed model is capable of maintaining any altitude within the given training data.

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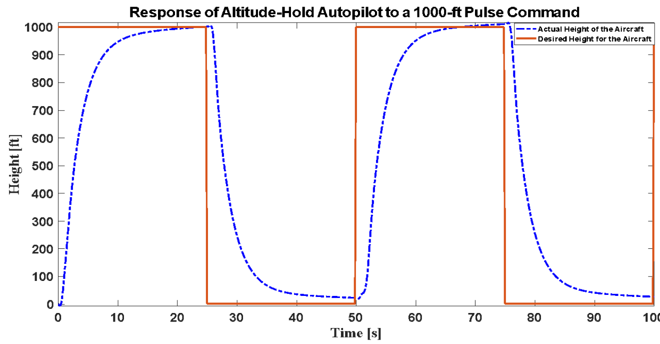

FIG. 13. STEP RESPONSE OF ALTITUDE-HOLD AUTOPILOT TO A 500-FT STEP COMMAND

VI. CONCLUSION

This study presents altitude-hold autopilot system for the Boeing 747 aircraft based on the ANN. The adopted mathematical model was suitable to capture the aircraft longitudinal dynamics in continuous-time domain. The results of the aircraft model were validated with the previous studies and this ensured that this model can be used for the generation of data for ANN. For the control design generic architecture of NN with sigmoid activation function and back-propagation technique is discussed. Finally, three different control approaches; model predictive control, model reference adaptive control, and feedback linearization control were reviewed to be used with the neural network plant model for the training of the aircraft model. Using the neural network model predictive architecture, the aircraft model was analyzed for 500 and 1000 feet step inputs and a pulse input ranging from 0-1000 feet. It was observed that the plant is following the given desired input and achieving all the objectives of this study with promising performance.

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