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Artificial Neural Networks based Attitude Controlling of Longitudinal Autopilot for General Aviation Aircraft

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Abstract: Generally, Aircraft fly in three axes plane by controlling aileron, rudder and elevator. They are designed to change and control the moments about the roll, pitch and yaw axes. The control system of the aircraft is divided into two portions, longitudinal and lateral control. In longitudinal control, the elevator controls pitch or the longitudinal motion of aircraft system. The pitch of aircraft is control by elevator which usually situated at the rear of the airplane running parallel to the wing that houses the ailerons. PID controllers are commonly used in many control systems because of their simple structures and intuitionally comprehensible control algorithms. But these methods are poor at disturbance rejection. In this paper ANN-PID (Artificial Neural Networks-Proportional Integral Derivative) controller is introduced, taking the advantages of PID controller. The performance of control schemes, PID and ANN-PID controllers with respect to the pitch angle of aircraft longitudinal dynamics are investigated by applying different disturbances like step, sinusoidal, band limited white noise, Repeating Sequence, Chirp signal. Simulation is developed within Simulink and MATLAB (Matrix laboratory) for evaluation of the control strategies.

Keywords: Artificial neural networks; Dynamic performance analysis; Flight control systems; Longitudinal autopilot; Matrix laboratory; Proportional integral derivative controller

I. INTRODUCTION

An autopilot is a mechanical, electrical, or hydraulic system used in an aircraft to diminish the human pilot [1,2]. The actual use of an autopilot was to provide, pilot relief during cruise modes. Autopilots perform operations more swiftly, accurately than the human pilot.

The main aim of an autopilot is to track the desired input command. Autopilot can be displacement type or pitch type (Figure 1). A well-known autopilot which is used for aircraft control which controls angular orientation of the aircraft is Displacement autopilot. The pitch displacement autopilot concept for a General Aviation Aircraft is examined.

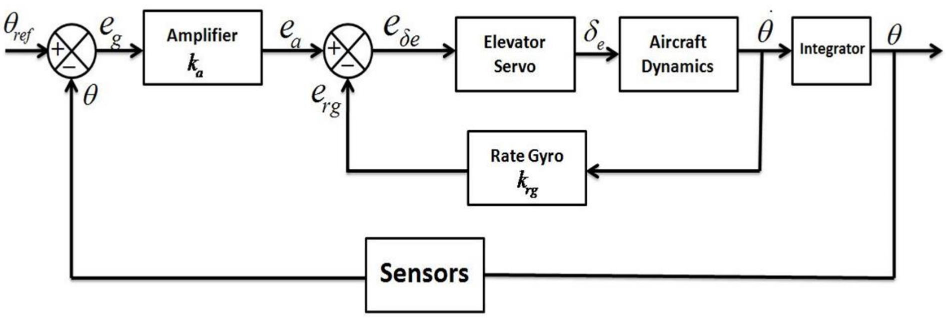

Figure 1: Block diagram for a pitch attitude control system employing pitch rate feedback.

1.1. Aircraft Dynamics

The equations 1, 2 and 3 are the longitudinal equations of motion for an aircraft. The following assumptions should be made for these equations: the longitudinal(X) and lateral (Z) axes are lies in the plane of symmetry, aircraft to be rigid body, constant mass and quasi steady flow, the center of gravity of the aircraft is at the origin of the system, Also assuming the aircraft body to be rigid, steady flow should be quasi and mass to be constant [3,4].

$$\left(\frac{mV_T}{Sq}\dot{u} - C_{xu}\right)u + \left(-\frac{c}{2V_T}C_{x\ddot{\alpha}}\dot{\alpha} - C_{x\alpha}\alpha\right) + \left(\frac{-c}{2V_T}C_{xq}\dot{\theta} - C_w(cos\theta)\theta\right) = C_{Fx_a} \quad (1)$$

$$(C_{zu}u) + \left(\frac{mV_T}{Sq} - \frac{c}{2V_T}C_{z\ddot{\alpha}}\right)\dot{\alpha} - C_{z\alpha}\alpha + \left(-\frac{mV_T}{Sq} - \frac{c}{2V_T}C_{zq}\right)\dot{\theta} + C_w(sin\theta)\theta = C_{Fz_a} \quad (2)$$

$$-(C_{mu}u) + \left(\frac{c}{2V_T}C_{m\ddot{\alpha}}\dot{\alpha} - C_{m\alpha}\alpha\right) + \left(\frac{I_y}{sqc}\ddot{\theta} - \frac{c}{2V_T}C_{mq}\dot{\theta}\right) = C_{Fm_a} \quad (3)$$

1.2. Short Period Approximation

The short period oscillations are occurred at constant forward speed, hence substituting u=0 in equation of motion. In the X direction, the forces contribute to the forward speed, therefore, the equation contribute to the short period oscillation in the X axis direction. Neglecting $C_{z\ddot{\alpha}}$ from these assumptions the equations turn out to be

$$\left(\frac{mV_T}{Sq}s - C_{x\alpha}\right)\alpha + [\left(-\frac{mV_T}{Sq} - \frac{c}{2V_T}C_{zq}\right)s + C_w(sin\theta)]\theta = C_{z\delta_e}\delta_e \quad (4)$$

$$\left(\frac{c}{2V_T}C_{m\ddot{\alpha}}s - C_{m\alpha}\right)\alpha + \left(\frac{I_y}{sqc}s^2 - \frac{c}{2V_T}C_{mq}s\right) = C_{z\delta_e}\delta_e \quad (5)$$

Where δ_e is the elevator deflection, here elevator command is given $C_{z\delta_e} = \frac{c}{l_t}C_{m\delta_e}\delta_e$. The value of $\frac{c}{l_t}$ is 4.89 calculated from the geometrical figures of the general aviation aircraft [5]. The transfer function is obtained for the longitudinal autopilot to control the general aviation aircraft by solving the equations 4 and 5.

The transfer function of the General Aviation Aircraft is given in equation 6 from the short period approximation.

$$\frac{\theta(s)}{\delta_e(s)} = \frac{-11.8(s + 1.97)}{(s^2 + 5s + 12.96)} \quad (6)$$

The Elevator servo or Servo actuator is considered as an electric motor to deflect the aerodynamic control surfaces here. Hence it can be represented as a first order system as shown in equation 7.

$$\frac{\delta_e}{e_g} = \frac{k_a}{\tau_s s + 1} \quad (7)$$

Where δ_e is elevator deflection angle, k_a is elevator servo gain, e_g is input error voltage, τ_s is servo motor time constant. τ_s fall in the range 0.05-0.25s for a typical servo motor. The equation 8 represents the represents the transfer function for servo elevator.

$$\frac{\delta_e(s)}{e_g(s)} = \frac{-1}{s + 12.5} \quad (8)$$

II. CONVENTIONAL OFFLINE PID CONTROLLER TECHNIQUES

2.1. Ultimate Gain/Ultimate Cycle Methods

The closed loop methods are also called as Ultimate cycle/Ultimate Gain methods.

- Ziegler–Nichols Closed-Loop (Figure 2)

- Pessen's overshoot
- Tyreus-Luyben

2.2 The Ziegler-Nichols PID Tuning Procedure

The procedural steps to apply these methods are as follows

Step 1: Design the system with only proportional (P) controller with unity feedback.

Step 2: Adjust the proportional gain value until the system exhibits the sustained oscillations (Figure 3).

Step 3: This gain value represents critical gain (K_C) of the system. Note the time period of oscillations. This time represents the critical time period (T_C).

Step 4: From these K_C and T_C values, calculate PID parameter gains based on the above methods. The PID gain parameters are calculated for different methods are as given as follows [6-8].

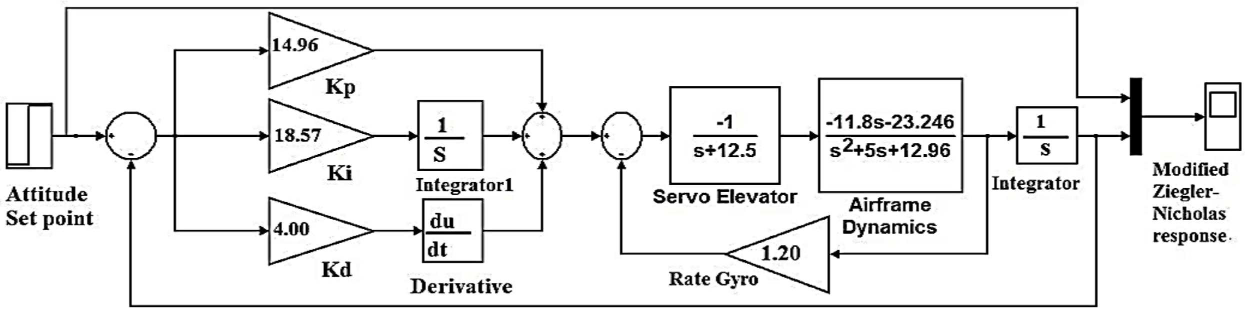

Figure 2: MATLAB/SIMULINK model for system designed with Ziegler Nicholas PID controller.

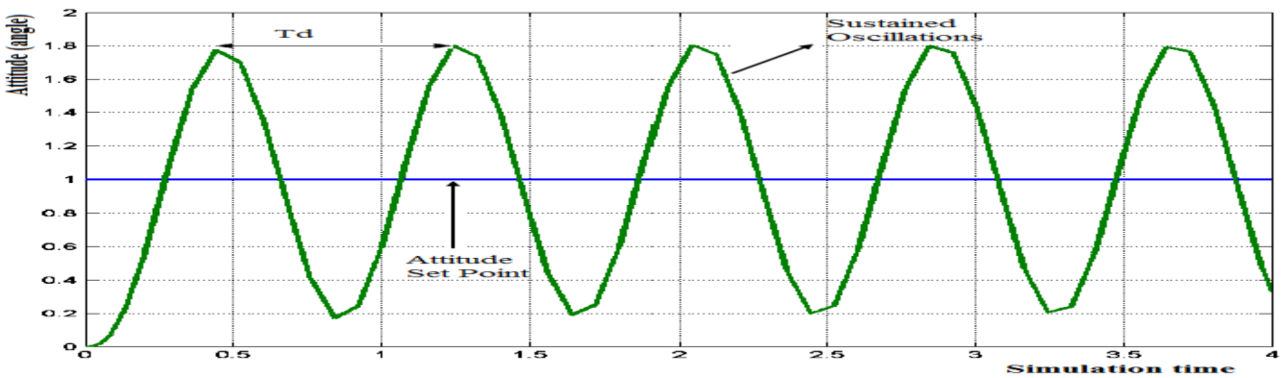

Figure 3: Closed loop ultimate cycles.

2.3. Tyreus-Luyben PID controller

Luyben and Luyben proposed the Tyreus and Luyben's tuning method is based on oscillations as in the Ziegler-Nichols' method, but with modified formulas for the controller parameters to obtain better stability in the control loop compared with the Ziegler-Nichols' method. PI and PID controllers are most available to the closed loop response for Tyreus-Luyben (considered to be the Ziegler-Nichols value). The response of the system is less oscillatory and less sensitive to uncertainty when tuning with Tyreus-Luyben parameters. Parameters (k_p, k_i and k_d) for various methods are tabulated below (Table 1).

Parameter	Ziegler-Nicholas	Modified Ziegler-Nicholas	Tyreus-Luyben	Pessen's Method-1
k_p	14.96	14.96	33.66	14.96
k_i	18.57	18.57	19.01	55.73
k_d	4	4	9.03	6.03

Table 1: Parameters (k_p, k_i and k_d) for various methods.

Combined MATLAB/SIMULINK model of the aircraft attitude control system designed with TLPID and ANN-PID for comparison are shown in Figure 4.

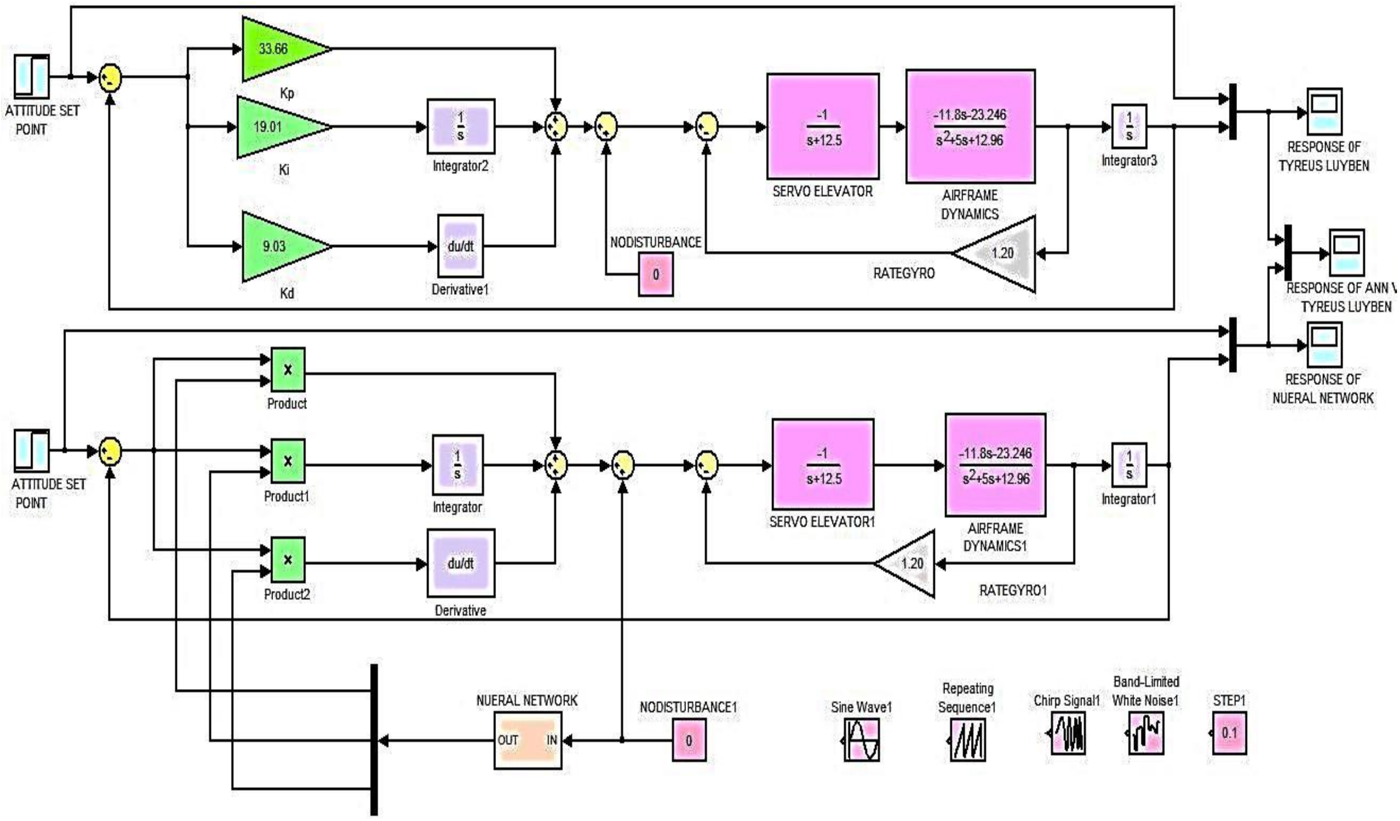

Figure 4: Combined MATLAB/SIMULINK model of the aircraft attitude control system designed with TLPID and ANN-PID for comparison.

III. ARTIFICIAL NEURAL NETWORKS

An artificial neural network is a network which is consisting of number of highly interconnected information processing elements. The revolutionary work of McCulloch and Pitts (1943) was the foundation for the growth of different architectures of neural networks.

3.1. Design of an Artificial Neural Network

Procedural steps:

The flow for design of a neural network is as follows:

Step 1: Finalize the input and target parameters for the problem and prepare the data sheet with input data and their corresponding target.

Step 2: Normalize the given data using the equation 9 and prepare the normalized data sheet [9,10].

$$x_{norm} = \frac{x_k - x_{min}}{x_{max} - x_{min}} \quad (9)$$

$$x_k = actual\ value\ of\ the\ parameter$$
$$x_{min} = minimum\ value\ of\ the\ parameter$$
$$x_{max} = minimum\ value\ of\ the\ parameter$$

Step 3: Initialize the synaptic weights and consider some value for learning rate (η) and momentum factor (α) in their ranges. Generally, learning rate is considered in the range of 0.1 to 0.3 and momentum factor is considered in the range of 0.5 to 0.9

Step 4: Consider some architecture for the neural network which includes the type of the network, activation function of the neurons, number of hidden layers and number of hidden neurons etc. [11-16].

According to K Sinha, by trial and error method it can be choose by starting with some number of neurons which is an integer value, near to the geometric mean (GM) of number of inputs and outputs, and is shown in below equation:

$$p = \sqrt{q * n}$$

Where, p = Integer near to GM of q and n
q = Number of inputs
n = Number of outputs

Step 5: Train the network with the training data considered in step-2 using some training algorithm based on the considered architecture of the network.

Step 6: Test the network with test data set and note the correlation coefficient.

Step 7: Consider other architecture for the network and note the correlation coefficients corresponding to the architecture by testing it with the test data set.

Step 8: Consider the best architecture and retrain the network and test it.

Step 9: Check whether the results are satisfying. If satisfied go to step-15 otherwise step-10.

Step 10: Train the network by varying one of the parameters like learning rate, momentum factor, and number of hidden neurons. If results are still not satisfying, then vary two at time.

Step 11: Test the network with test data set and note the correlation coefficient.

Step 12: Check whether results are satisfying. If satisfied, go to step-15 Otherwise go to step-13.

Step 13: Check any other parameters to vary. If no other parameters to vary then go to step-14 otherwise go to step-10.

Step 14: The problem can’t be handled satisfactorily.

Step 15: Stop and use the network in the application.

IV. RESULTS

Figure 5 shows the comparison of responses of the system designed with different closed loop tuning methods.

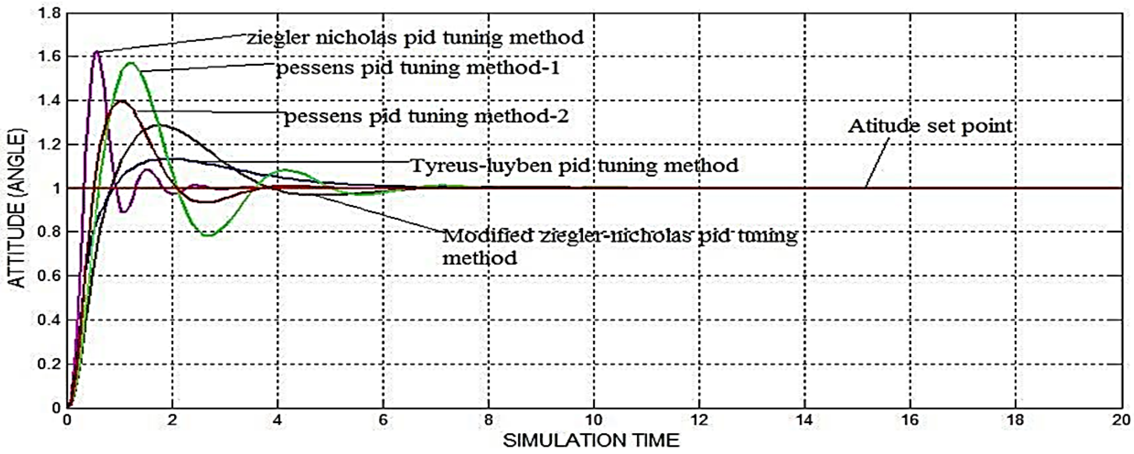

Figure 5: Comparison of responses of the system designed with different closed loop tuning methods.

Table 2 shows time domain performance parameters.

S. No	Controller Used	Time Domain Performance Parameters					
		Delay Time	Rise Time	Settling Time (T_s)	Peak Overshoot (M_P) in %	Transient Behavior	% Steady state Error (E_{SS})
1	**Ziegler Nicholas PID**	0.2323	0.3376	2.2637	62.7	Oscillatory	0
2	**Modified ZN PID**	0.4319	0.8508	6	28.56	Oscillatory	0
3	**Tyreus-Luben PID**	0.3138	0.902	5.2	13.27	Smooth	0
4	**Pessen's Method-1 PID Controller**	0.386	0.6219	6.5	56.93	Oscillatory	0
5	**Pessen's Method-2 PID Controller**	0.3192	0.526	3.69	39.5	Oscillatory	0

Table 2: Time domain performance parameters.

TLPID vs. ANN-PID responses for various models given, are shown in the following graphs (Figures 6-10).

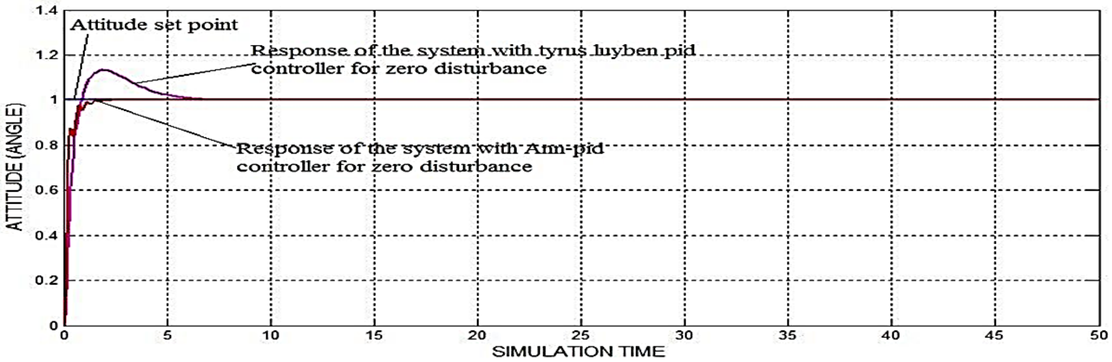

Figure 6: TLPID vs. ANN-PID responses without any disturbances applied.

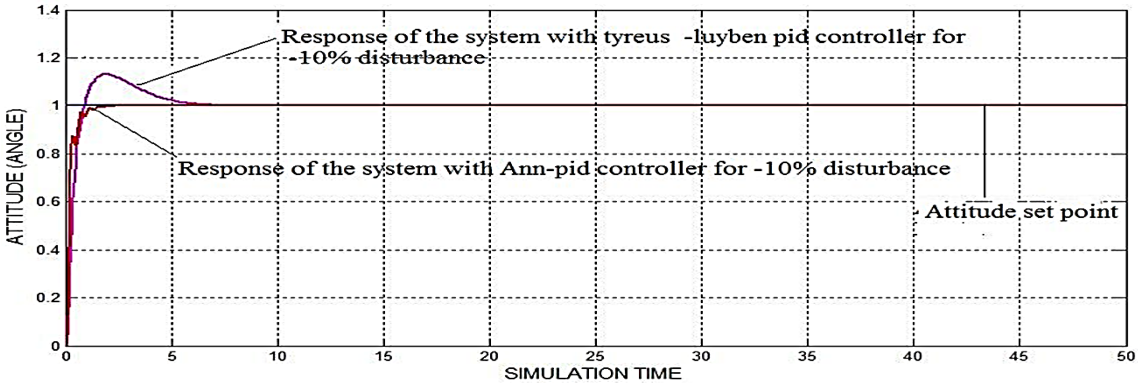

Figure 7: TLPID vs. ANN-PID responses for a disturbance of -10%.

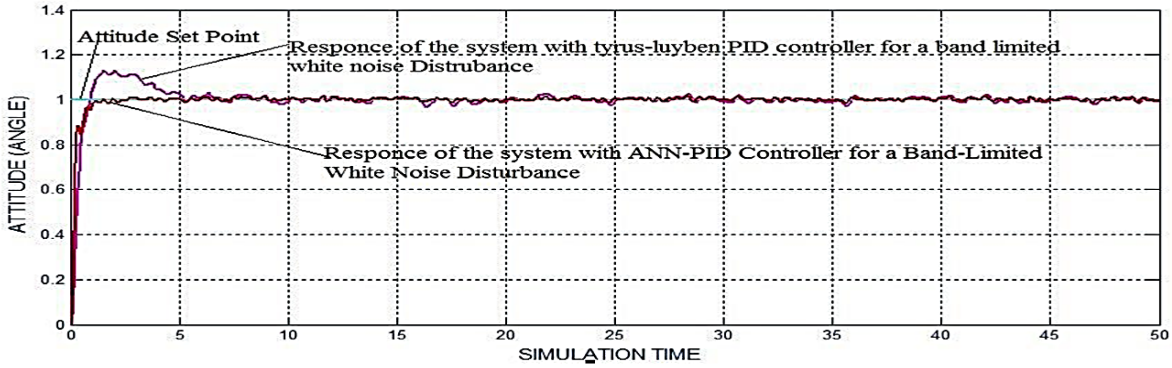

Figure 8: TLPID vs. ANN-PID responses for a band limited white noise disturbance.

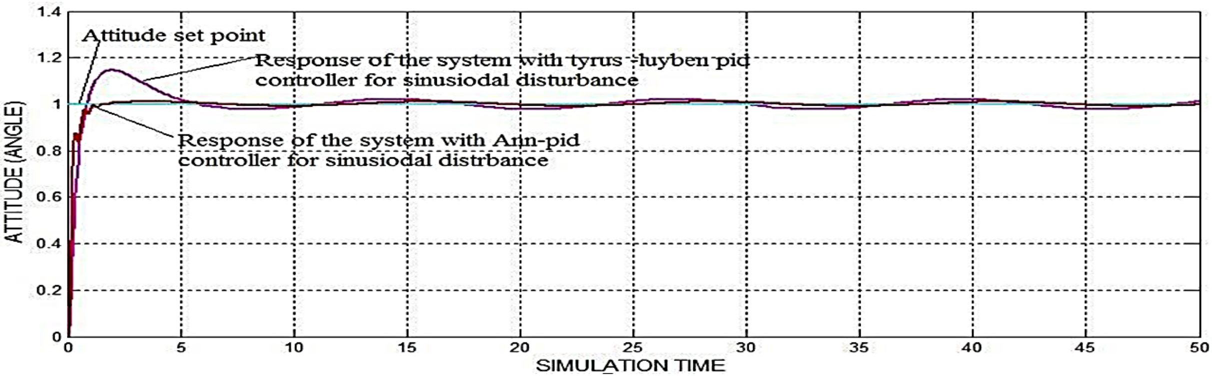

Figure 9: TLPID vs. ANN-PID responses for a sinusoidal disturbance.

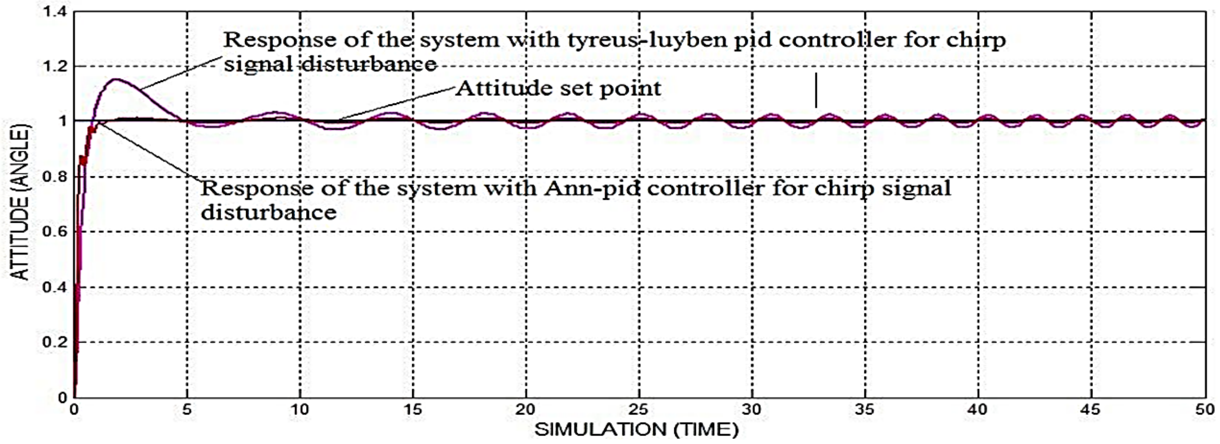

Figure 10: TLPID vs. ANN-PID responses for a chirp signal disturbance.

Types of disturbance with dynamic performance specifications for the conventional TL- PID and for the proposed ANN-PID with improvement are shown in Table 3.

S. No	**Type Of Disturbance**	**Dynamic Performance Specification**	**For the Conventional TL- PID Control System**	**For The Proposed ANN-PID Control System**	**Improvement**
1	No Disturbance	Delay Time (T_D) in Sec	0.314	0.1885	0.1225
		Rise Time (T_R) in Sec	0.896	0.664	0.232
		Settling Time (T_S) in Sec	5.16	2.258	2.902
		Peak Overshoot (M_P) in %	13.3	0	13.3
		% Steady State Error (E_{SS})	0	0	0
2	A Step Disturbance	Delay Time (T_D) in Sec	0.3377	0.1885	0.1492
	Of	Rise Time (T_R) in Sec	0.9022	0.666	0.2362
	'-10%'	Settling Time (T_S) in Sec	5.1515	2.6525	2.499
		Peak Overshoot (M_P) in %	13.15	0	13.15
		% Steady State Error (E_{SS})	0	0	0
3	A Sinusoidal Disturbance	Delay Time (T_D) in Sec	0.318	0.1885	0.1295
		Rise Time (T_R) in Sec	0.8791	0.66	0.2191
		Settling Time (T_S) in Sec	5.02	1.492	3.528
		Peak Overshoot (M_P) in %	14.76	0	14.76
		% Steady State Error (E_{SS})	0	0	0
4	Band limited white noise disturbance	Delay Time (T_D) in Sec	0.3078	0.1876	0.1202
		Rise Time (T_R) in Sec	0.9046	0.672	0.2326
		Settling Time (T_S) in Sec	5.08	1.88	3.2
		Peak Overshoot (M_P) in %	12.83	0	12.83
		% Steady State Error (E_{SS})	0	0	0
5	Chirp signal Disturbance	Delay Time (T_D) in Sec	0.3139	0.1885	39.94
		Rise Time (T_R) in Sec	0.8747	0.6578	24.79
		Settling Time (T_S) in Sec	4.95	1.4739	70.27
		Peak Overshoot (M_P) in %	14.86	0	100
		% Steady State Error (E_{SS})	0	0	0

Table 3: Types of disturbance with dynamic performance specifications for the conventional TL- PID and for the proposed ANN-PID with improvement.

VI. CONCLUSION

From the simulations done it can be observed that the dynamic performance specifications are getting effected severely even with the better conventional PID controller loop when an online disturbance occurs in the loop, which is the primary cause for this innovation. The dynamic performance specifications could be controlled and maintained at optimum values with respect to the conventional controller. The proposed ANN based PID controller for Aircraft's attitude control system can tune the PID parameters automatically with respect to the disturbances or error variations and so, effectively provide disturbance rejection. Hence, the proposal increases stability.

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