

Neuro-fuzzy system based proportional derivative gain optimized attitude control of CubeSat under LEO perturbations

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ABSTRACT

Prompt attitude stabilization is more challenging in Nano CubeSat due to its minimal capacity, weight, energy, and volume-constrained architecture. Fixed gain non-adaptive classical proportional integral derivative control methodology is ineffective to provide optimal attitude stability in low earth orbit under significant environmental disturbances. Therefore, an artificial neural network with fuzzy inference design is developed in a simulation environment to control the angular velocity and quaternions of a CubeSat by autonomous gain tuning of the proportional-derivative controller according to space perturbations. It elucidates the dynamics and kinematics of the CubeSat attitude model with reaction wheels and low earth orbit disruptions, i.e., gravity gradient torque, atmospheric torque, solar radiation torque, and residual magnetic torque. The effectiveness of the proposed ANFIS-PD control scheme shows that the CubeSat retained the three-axis attitude controllability based on initial quaternions, the moment of inertia, Euler angle error, attitude angular rate, angular velocity rate as compared to PID, ANN, and RNN methodologies. Outcomes from the simulation indicated that the proposed controller scheme achieved minimum root mean square errors that lead towards rapid stability in roll, pitch, and yaw axis respectively within 20 s of simulation time.

1. Introduction

Over the previous decade, spacecraft has played a vital role in the research and economic growth of the worldwide nation and has implementations in remote sensing, communication, networking, metrology, horticulture, etc. [1]. Knowing the attitude-behavior of a spacecraft before it is manufactured and placed in operation orbit enables the designer to select the optimal control system to ensure that the mission is accomplished as intended [2]. Small satellites came to the space research network as an alternative to high-cost satellites having long production periods when Jordi Puig-Suari and Bob Twiggs invented a modular design called the CubeSat in Nano (1 kg–10 kg) and micro (10 kg–100 kg) size models [3,4]. These CubeSats can be as beneficial as the larger satellites when an accurate and reliable 3-axis-stabilized CubeSat is established and verified [5]. Various feasible linear and nonlinear control approaches are becoming prominent for resolving attitude control issues by developing miniature reaction wheels/magnetic torques (MTs) as an

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actuator [6]. Though, CubeSat's inherent limitations i.e. size, density, and energy make it hard to accomplish high-performance missions. Moreover, the majority of the CubeSat's altitude is in low Earth orbit, where external disturbances are significant, affecting attitude stability significantly [7]. As, a result, many approaches have been implemented, with promising outcomes mentioned in the literature on the attitude control subsystem (see Tables 4 and 5).

Hence, Calvo et al. [8] proposed the arbitrary arithmetical analysis for the evaluation of conventional proportional-integral-derivative (PID) and a Fuzzy control algorithm for attitude control of onboard Nano satellite called QBITO in QB50 mission, in terms of exactness, efficiency, and robustness. Castañedo et al. [9] modified the fuzzy rules by genetic algorithm and obtained a stable attitude feedback controller response from the satellite. Walker et al. [10] addressed the effectiveness and performance parameters of the Nano satellite's attitude control subsystem through the distinct design of fuzzy logic relying on genetic algorithm-based mono-objective and multi-objective optimization methods during the whole mission of the satellite. Also, the adaptive neuro-fuzzy inference system (ANFIS) resolved time-draining issues related to the state-dependent Riccati equation (SDRE) in Ref. [11] by utilization of neural network and first-order Takagi–Sugeno (TS) fuzzy model for Nanosatellites. Furthermore, Kosari et al. [12] developed a versatile attitude controller system for the Geo-Sat by designing the fuzzy-based proportional integral derivative (FPID) controller using (single input fuzzy inference engine) SIFIE and (preferential fuzzy inference engine) PFIE with a sliding mode control mechanism. While to counter external disturbance, an H_∞ controller scheme was proposed by Ref. [13] to create a state feedback attitude controller for magnetically actuated Nano-satellites. Hence, Fazlyabet al. [14] developed a modified Rodrigues parameters feedback law based on a three-layered neural system for the estimation of obscure unsettling external disturbances and uncertainty in a dynamic model to handle the attitude control problem of the satellite.

An asymptotic three-axis attitude stabilization for the LEO satellite was developed by considering the synchronous utilization of three reaction wheels (RW) and three magnetic torques (MTs) for the concurrent operation of angular momentum regulation [15]. Moreover, small satellites with neural network-based attitude control structures using 4 variable speed control moment gyros (VSCMG) in pyramid shape achieved larger torque with less energy consumption as compared to reaction wheels [16]. An optimal adaptive fuzzy proportional-integral-derivative type slide mode controller (AFPID-SMC) for the re-entry vehicle's attitude control subsystem was developed by online adjustment of the proportional-integral-derivative type sliding mode mechanism and estimation of disturbance by radial basis function neural network (RBFNN) subject to model uncertainty and turbulence [17]. The robust adaptive type-2 fuzzy neural network controller was introduced for attitude control of magnetic rigid satellites by using ellipse type-2 membership functions (MF) and slide mode control (SMC) adjustment rules [18]. Kim et al. [19] addressed the 3-axis attitude regulation problem by linear time-varying model predictive control (MPC) approach, which was formulated by the Laguerre function to minimize MPC's online computational burden under gravity gradient disturbance torque for inertial pointing problems. Space turbulence and actuator uncertainties are handled by a neural network-based adaptive back-stepping attitude control algorithm [20] to ensure the asymptotic stability of the nonlinear satellite model. Colagrossi et al. [21] addressed the 3-axis orientation control problem of an entirely magnetic actuated pico satellite by integration of a B-dot control algorithm and proportional-derivative controller.

In [22], adaptive second-order fast terminal slide mode control with neural network-based architecture was designed for the Lorentz-based satellite's attitude control system subject to model uncertainties and environmental turbulence in space. Such obscure disturbances and uncertainties are approximated by radial basis function neural network (RBFNN) and Lyapunov stability analysis ensured the overall stability of the system. Zhong et al. [23] examined the flexible satellite's three-axis orientation control issues and proposed an innovative Lyapunov stability analysis with a compensator to account for uncertainties in the robust and effective performance of system. A self-tuning control strategy was developed for fractional order proportional-integral-derivative (FPID) controller by an adaptive network-based fuzzy inference system [24]. Liu et al. [25] presented a robust attitude control system design for spacecraft during the space debris removal process using an adaptive fuzzy sliding mode controller scheme and performance was evaluated with slide mode controller methodology. An intelligent fuzzy PD + I controller was presented by Ref. [26] to control the Nano attitude control system of Innovative Satellite InnoSAT. However, as per the literature survey, significant work has not been observed on the gain scheduling scheme of quaternion-angular velocity feedback PD controller by soft computing techniques for attitude control of CubeSat along with LEO perturbations. So, designing and implementing an ANFIS-based PD attitude control scheme in a more advanced simulation environment is of utmost importance for CubeSat under nonlinear reaction wheels' phenomena and varying perturbations. The present paper suggests the preceding contributions:

- Designing, testing, and validation of ANFIS structure for attitude dynamics, kinematics, and environmental disturbance model of CubeSat along with reaction wheels actuating mechanism.
- Quaternions angular velocity feedback PD gains (K_p , K_d) scheduled by a trained ANFIS-based system according to external disturbances.

This paper consists of the following parts. Section 2 presents the attitude model of CubeSat and reaction wheels with their external perturbations. In section 3, optimized gain tuning of quaternions angular velocity feedback PD controller by trained ANFIS-based system is presented. Section 4 demonstrates the simulation results of the proposed methodology along with other techniques and section 5 comprises of conclusion and future work.

2. CubeSat attitude model with external perturbations

System modeling is obtained from numerous standard equations to analyze the response of the CubeSat to external perturbation forces and control torques, which determines the satellite's orientation stability for optimum antenna pointing towards the earth

station.

2.1. Satellite attitude dynamics

Satellite dynamics uses the condition of movement to stimulate the body frame angular velocity compared with the inertial frame by utilizing external torque. Inertial frame F_i , orbit frame F_o , and body reference frame F_b are three major frames of interest for the attitude control of satellites [27]. Meanwhile, satellite kinematics is responsible for ascertaining the satellite attitude by handling the angular velocity data, which is the output of dynamics equations [28–31]. The underlying equation defines the basic rotational motion of a satellite [32].

$$I\dot{\omega} + \omega^{\otimes}H = u \quad (1)$$

$I = I^T \in R^{3 \times 3}$ represents the moment of inertia (kgm^2) with its diagonal elements being 0.0067, 0.0419 & 0.0419 in x, y, and z directions respectively, $\omega = [\omega_x \ \omega_y \ \omega_z]^T \in R^3$ signifies the angular velocity vector of satellite concerning the body frame of reference, $\omega^{\otimes}$ denotes skew-symmetric matrix, $H = I\omega$ is the angular momentum and $u \in R^3$ shows input control torque of satellite defined by $u = \tau_c + \tau_d$ where τ_c is control input torque provided by three reaction wheels called τ_{rw} and τ_d is the total low earth orbital disturbances that cover gravity gradient torque (τ_g), atmospheric drag torque (τ_a), solar radiation torque (τ_s), and residual magnetic dipole torque (τ_m). Within the sight of external disturbance torques, Eq. (1) can be modified as:

$$I\dot{\omega} + \omega^{\otimes}I\omega = \tau_{rw} + \tau_g + \tau_a + \tau_s + \tau_m \quad (2)$$

Within the sight of RWs, the dynamic condition ought to be modified to catch the angular momentum of the wheels given as $h = I_w\Omega_w$, where I_w and Ω_w signifies the moment of inertia and angular velocity of the wheels. Hence, the total angular momentum of CubeSat becomes $I\omega + h = I\omega + I_w\Omega_w$. By incorporating the angular momentum of RWs,

$$I\dot{\omega} + \omega^{\otimes}[I\omega + I_w\Omega_w] = \tau_{rw} + \tau_g + \tau_a + \tau_s + \tau_m \quad (3)$$

Hence, the dynamic equation of CubeSat becomes [33],

$$\begin{bmatrix} I_{xx} & 0 & 0 \\ 0 & I_{yy} & 0 \\ 0 & 0 & I_{zz} \end{bmatrix} \begin{bmatrix} \dot{\omega}_x \\ \dot{\omega}_y \\ \dot{\omega}_z \end{bmatrix} + \begin{bmatrix} 0 & -\omega_z & \omega_y \\ \omega_z & 0 & -\omega_x \\ -\omega_y & \omega_x & 0 \end{bmatrix} \left(\begin{bmatrix} I_{xx} & 0 & 0 \\ 0 & I_{yy} & 0 \\ 0 & 0 & I_{zz} \end{bmatrix} \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} + I_w \begin{bmatrix} \Omega_{wx} \\ \Omega_{wy} \\ \Omega_{wz} \end{bmatrix} \right) = \tau_{rw} + \tau_g + \tau_a + \tau_s + \tau_m \quad (4)$$

Input control torque (τ_{rw}) comes from the reaction wheel which is the main actuator utilized for attitude control of CubeSat. These RWs are microdevices that create control torque by accelerating a flywheel mass with a DC motor. The streamlined model of RW torque obtained by $(n^* - n)k - T_f$, Where n^* denotes the required speed produced by the DC motor and n is the real speed of rotor shaft obtained by $\int(\tau_{rw}/J)$ and k represents winding coefficient and T_f is torque friction. The connection between rotor shaft speed and applied armature voltage is signified in the following Eq. (5) [34,35].

$$n^*(s) = (K_T / (L_a J_m s^2 + (R_a J_m + L_a B_m) s + (R_a B_m + K_b K_T))) v(s) \quad (5)$$

In Eq. (5), $n^*(s)$ represents angular speed (rad/s), K_T is torque constant (Nm/A), L_a is armature inductance (H), J_m is rotor inertia (kgm^2), R_a is armature resistance (Ω), B_m is viscous friction coefficient (Nms/rad), K_b is back-emf constant (Vs/rad), and $v(s)$ is applied voltage (V).

2.2. External perturbations

Numerous unsettling nonlinear external disturbance torques influences Nano cube satellite attitude angles. In LEO orbits [36], the large disturbance torques are gravity gradient torque, atmospheric drag torque, solar radiation torque, and residual magnetic dipole torque [37,38]. In which, gravity gradient torque represents a function that describes each irregular body inside the scope of the gravitational field of the earth, interpreted as;

$$\tau_g = (3\mu / r_o^3) \mathbf{u}_e \times I \mathbf{u}_e \quad (6)$$

Earth's gravitational coefficient is represented as $\mu = 3.986 \times 10^{14} \text{m}^3/\text{s}^2$, the distance from earth's center dignified as r_o , inertia matrix and unit vector towards nadir are represented as I and $\mathbf{u}_e$ respectively. In the body frame of reference, Eq. (6) can be modified as;

$$\tau_g = (3\mu / r_o^3) \mathbf{c}_3 \times I \mathbf{c}_3 = 3\omega_o^2 \mathbf{c}_3 \times I \mathbf{c}_3 = 3 \left(\begin{bmatrix} 0 & -\sqrt{\mu/R^3} & 0 \end{bmatrix}^T \right)^2 \mathbf{c}_3 \times I \mathbf{c}_3 \quad (7)$$

$\mathbf{c}_3$ is the third column of the revolution matrix from the body frame to an orbital frame and ω_o is orbital angular velocity and R is the radius of the orbit. Similarly, atmospheric drag torque or aerodynamic torque is generated by the cross result of the aerodynamic force vector F_{aero} and displacement vector between the Center of Mass (CoM) and Geometric Center (GC), r_{COM-GC} of a cube satellite [39].

$$\tau_a = r_{COM-GC} \times F_{aero} \quad (8)$$

The aerodynamic drag disturbance force F_{aero} acquired by $0.5\rho_a C_d A v^2 u_{aero}$, where ρ_a is the density of the atmosphere and C_d is the coefficient of aerodynamic drag. The satellite orbital velocity is shown as v and the direction of the force on the satellite is represented by u_{aero} that can be specified as $[-1 \ 0 \ 0]^T$ shows satellite's subsequent drag force acting in the negative orbital speed direction taking down the altitude and elevation. The cross-sectional area of the satellite is denoted by A . With aerodynamic drag, sunlight radiates huge amounts of electromagnetic waves that also exert physical pressure torque on the satellite's body. Such disturbance torque is applied on the axis opposite to the waves directed towards the sun which is the cross result of the displacement vector r_{COM-GC} and radiation intensity vector F_{rad} .

$$\tau_s = r_{COM-GC} \times F_{rad} \quad (9)$$

the pressure of radiation intensity vector F_{rad} defined by $P_{rad} A C_p u_{rad}$, where P_{rad} is mean force flux of radiation pressure which is equal to $(F_e / c) = 4.5 \times 10^{-6} \text{kgm}^{-1}\text{s}^{-2}$, in which F_e is mean combined energy flux, c is the speed of light, A is satellite's cross-sectional area, C_p is satellite's surface absorption resides between 1 & 2 and u_{rad} is the vector describing the possessing capacity of force on satellite [40]. Another major disturbance is residual magnetic dipole torque created by electronic modules in satellites and incorporating a leftover magnetic dipole field in the structure. Residual magnetic dipole torque is calculated by cross product between the earth's magnetic field B and residual moment m_r in the satellite's body frame [41].

$$\tau_m = m_r \times B \quad (10)$$

where m_r is considered as a residual moment in $A - m^2$ equal to $[0.001 - 0.001 \ 0.005]^T$ and B is vector type of magnetic dipole of earth's magnetic field that is modeled as a basic dipole L-Shell Model represented as $\frac{\mu_0}{4\pi r^3} (3(m \cdot \vec{r})\vec{r} - m) + \frac{2\mu_0}{3} m \delta^3(r)$, in which r is the satellite position unit vector and m is the earth's vector dipole moment.

2.3. Satellite attitude kinematics

The dynamic equation of a cube satellite with reaction wheel torques and external disturbance torques is modified by integrating the angular velocity in each axis. Then, obtained angular rates are incorporated into the kinematics section to decide the satellites orientation movement, which is described by quaternions (q) to represent rotation as $[q_1 \ q_2 \ q_3 \ q_4]^T$. The satellite's orientation is acquired by rotation from the orbital frame to the body frame with the help of Directional Cosine Matrix (DCM) and then this matrix is parameterized by the quaternions $R_{b/o} \Leftrightarrow q_{b/o}$, so the satellite kinematics are described by following Eq. (11) [30].

$$\dot{q} = \frac{1}{2} \Psi(\omega) q = \frac{1}{2} \Xi(q) \omega \quad (11)$$

$\Psi(\omega)$ is 4×4 satellite's angular velocity matrix and $\Xi(q)$ is 4×4 quaternion matrix, by substitution in Eq. (11) we obtained following Eq. (12).

$$\begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \\ \dot{q}_4 \end{bmatrix} = \frac{1}{2} \begin{bmatrix} 0 & \omega_z & -\omega_y & \omega_x \\ -\omega_z & 0 & \omega_x & \omega_y \\ \omega_y & -\omega_x & 0 & \omega_z \\ -\omega_x & -\omega_y & -\omega_z & 0 \end{bmatrix} \begin{bmatrix} q_1 \\ q_2 \\ q_3 \\ q_4 \end{bmatrix} = \frac{1}{2} \begin{bmatrix} q_4 & -q_3 & q_2 & q_1 \\ q_3 & q_4 & -q_1 & q_2 \\ -q_2 & q_1 & q_4 & q_3 \\ -q_1 & -q_2 & -q_3 & q_4 \end{bmatrix} \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \\ 0 \end{bmatrix} \quad (12)$$

In this paper, Directional Cosine Matrix (DCM), quaternions (q), and roll (φ), pitch (θ), and yaw (ψ) angles have been used for attitude representation. With the numerically tackled quaternions, DCM can be formulated as in Eq. (13) and it can be denoted as continuous three foremost axis revolutions. The association between Euler angles and DCM can be characterized as in Eq. (14). Where $s(\cdot)$ and $c(\cdot)$ signify $\sin(\cdot)$ and $\cos(\cdot)$ respectively for roll, pitch, and yaw angles in 321 rotational arrangements [42].

$$DCM = \begin{bmatrix} 1 - 2(q_2^2 + q_3^2) & 2(q_1 q_2 + q_3 q_4) & 2(q_1 q_3 - q_2 q_4) \\ 2(q_2 q_1 - q_3 q_4) & 1 - 2(q_1^2 + q_3^2) & 2(q_3 q_2 + q_1 q_4) \\ 2(q_1 q_3 + q_2 q_4) & 2(q_2 q_3 - q_1 q_4) & 1 - 2(q_1^2 + q_2^2) \end{bmatrix} \quad (13)$$

$$DCM = \begin{bmatrix} c(\theta)c(\psi) & c(\theta)s(\psi) & -s(\theta) \\ s(\varphi)s(\theta)c(\psi) - c(\varphi)s(\psi) & s(\varphi)s(\theta)s(\psi) + c(\varphi)s(\psi) & s(\varphi)c(\theta) \\ c(\varphi)s(\theta)c(\psi) + s(\varphi)s(\psi) & c(\varphi)s(\theta)s(\psi) - s(\varphi)s(\psi) & c(\varphi)c(\theta) \end{bmatrix} \quad (14)$$

3. Control methodology

In the controller section, a closed-loop hybrid ANFIS-PD control methodology is implemented to achieve the three-axis attitude control stability of CubeSat against continuous external disturbances.

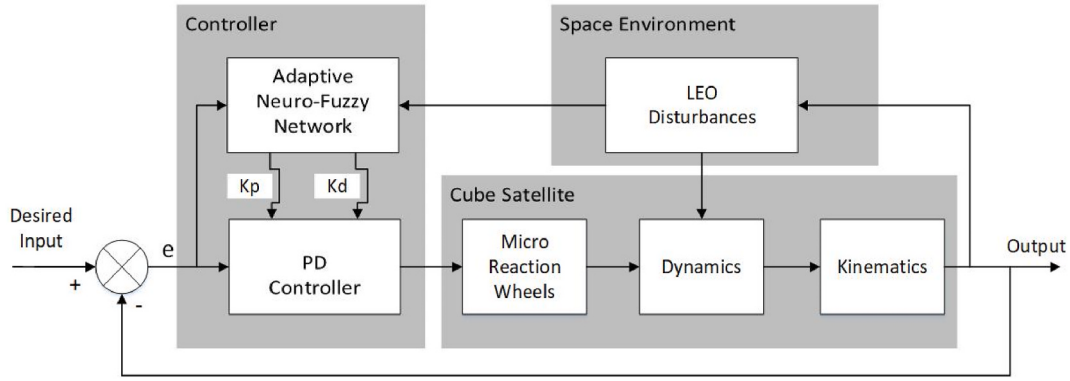


Fig. 1. Proposed attitude control structure.

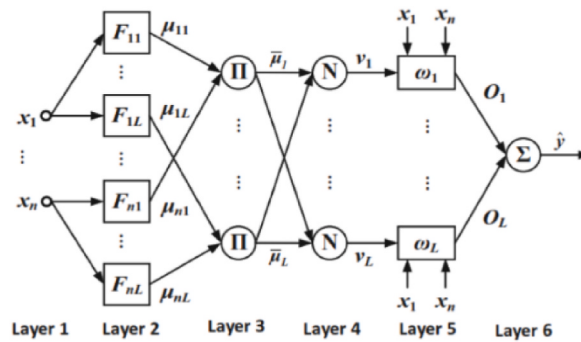


Fig. 2. General architecture of MISO ANFIS [29].

3.1. ANFIS-based PD control

In the ANFIS controller, the neural network trains the fuzzy membership functions (MFs) with the least square and gradient descent method to control the angular velocity and quaternions by tuning the proportional-derivative gains according to external disturbances. The block diagram of the suggested control methodology for CubeSat is shown in Fig. 1.

In this scheme, the error signal is simultaneously supplied to both controllers (ANFIS & PD) for the minimization of error and to get the desired value at the input of reaction wheels to maintain reference attitude. Whereas PD is a relatively simple law of control. Several various PD controllers exist, but they are essentially the same. If errors in attitude and angular velocity are used in feedback, then PD-control can be written as, [43].

$$\tau = -[K_p \ K_d][q_e \ \omega_e]^T \quad (15)$$

where $\omega_e = \omega_s - \omega_d = [\omega_{e,1} \ \omega_{e,2} \ \omega_{e,3}]^T$ is the angular velocity error vector, $q_e = [q_{e,1} \ q_{e,2} \ q_{e,3}]^T$ is the quaternion attitude error vector and K_p and K_d are both controller gains that are regarded as scalar. Relation between q_e , q_d and q_s is exemplified in Eq. (16) [30,44].

$$q_e = \begin{bmatrix} q_{d4} & q_{d3} & -q_{d2} & -q_{d1} \\ -q_{d3} & q_{d4} & -q_1 & q_2 \\ q_{d2} & -q_{d1} & q_4 & q_3 \\ q_{d1} & q_{d2} & -q_3 & q_4 \end{bmatrix} \begin{bmatrix} q_{s1} \\ q_{s2} \\ q_{s3} \\ q_{s4} \end{bmatrix} \quad (16)$$

Eq. (16), q_d and q_s represents the desired and current attitude of the quaternions of q_{R_b/R_o} and ω_d & ω_s are the desired and current angular rates of $\omega_{F_b/F_o}^{R_b/R_o}$. Hence, the following equations are obtained as a control command input for each axis;

$$\tau_x = -K_{xp}q_{e,1} - K_{xd}\omega_{e,1} \quad (17a)$$

$$\tau_y = -K_{yp}q_{e,2} - K_{yd}\omega_{e,2} \quad (17b)$$

$$\tau_z = -K_{zp}q_{e,3} - K_{zd}\omega_{e,3} \quad (17c)$$

Furthermore, typical PD control on cube satellites does not yield good outcomes because of nonlinear and time-varying dynamics.

Table 1
Statistical properties of data for the design of ANFIS.

Parameters	Max. Value	Min. Value	Average Value
$\omega_{e,1}$	83.21886	− 1.04301	0.25874
$\omega_{e,2}$	88.22795	− 1.14770	0.27450
$\omega_{e,3}$	105.1456	− 1.35801	0.32670
$q_{e,1}$	0.517849	− 0.51605	5.2×10^{-4}
$q_{e,2}$	0.555144	− 0.54726	4.8×10^{-4}
$q_{e,3}$	0.656363	− 0.65221	7.4×10^{-4}
τ_{dx}	1.49×10^{-5}	− 1.43×10^{-5}	7.75×10^{-8}
τ_{dy}	2.98×10^{-5}	− 4.68×10^{-5}	− 3.41×10^{-7}
τ_{dz}	2.49×10^{-5}	− 2.39×10^{-5}	− 1.38×10^{-7}
K_p	134.9873	4.534783	69.7523
K_d	59.99427	2.813947	31.2143

The initial stable gains are computed by empirical method but these gains are constant and need to be varied according to orbital disturbances. Thus, the gain scheduling mechanism is achieved in this paper by an adaptive neuro-fuzzy inference system (ANFIS). Hence, Multi-input and multi-output (MIMO) framework is considered with various ANFIS multi-input and single-output (MISO) structures for attitude control of cube satellites through combined Takagi-Sugeno fuzzy inference (T-SFIS) method and neural network scheme. A general MISO framework of ANFIS for disturbance torques estimation and PD gain scheduling is demonstrated in Fig. 2.

The designed MISO ANFIS arrangement elucidates fuzzy inference R^l : IF x_1 is F_{1l} , ..., x_n is F_{nl} , then $\hat{y}$ is ω_l where $x_i(k)$ is the linguistic variable for i th input, F_{il} is the fuzzy set related to x_i in the l th fuzzy implication, $\hat{y}$ is the output variable of the network and ω_l is the l th of the weight linked to i th input. However, the i th entry of $x_i(k)$ is extracted from the system and sent to the feed-forward neural network (FNN). In addition, l is the index of rules, where $l = 1 \dots L$, and L is the number of existing rules [45]. In FNN, the first layer transmits the input signal to the fuzzification layer in which each node is identified as F_{il} which defines various types of MFs such as triangular, trapezoidal, Gaussian, and bell-shaped. Triangular and Gaussian MFs delivered optimum disturbance approximation and PD gain scheduling schemes respectively. The triangular MF is given as,

$$\mu_{il} = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{c-x}{c-a}, & b \leq x \leq c \\ 0, & c \leq x \end{cases} \quad (18)$$

in Eq. (18), a and c describes the *feet* of the membership function, and b defines its *peak*. However, Gaussian MF is shown as;

$$\mu_{il} = e^{-\frac{(x-c)^2}{2\sigma^2}} \quad (19)$$

where c and σ denote the mean and standard deviation of the Gaussian function of the l th term for i th variable of input. The third layer is regarded as the participation layer marked with (II), whose output is the product of all signals entering this node.

$$\bar{\mu}_l = \prod_{i=1}^n \mu_{il} \quad (20)$$

Each node is marked with N in the fourth layer, and those nodes determine the ratio of each rule's firing power to the total sum of all those rules. The normalized firing strengths are considered as an outcome of this layer;

$$v_l = \bar{\mu}_l / \sum_{l=1}^L \bar{\mu}_l \quad (21)$$

where $0 < v_l \leq 1$ and $\sum_{l=1}^L v_l = 1$ the fifth layer is the defuzzification layer which produces crisp output. Each node is labeled with ω_l and has the following node function;

$$\omega_l = \left(\sum_{i=1}^n \varphi_{il} \right) w_l \quad (22)$$

in which, φ_{il} conducts first order polynomial of MFs, w_l is the variable of this node and each node output O_l is equal to $\omega_l v_l$. Where, v_l is the normalized firing strength from the prior layer. The final layer of FNN, adds up all input signals given as,

$$\hat{y} = \sum_{l=1}^L O_l = \sum_{l=1}^L \omega_l v_l \quad (23)$$

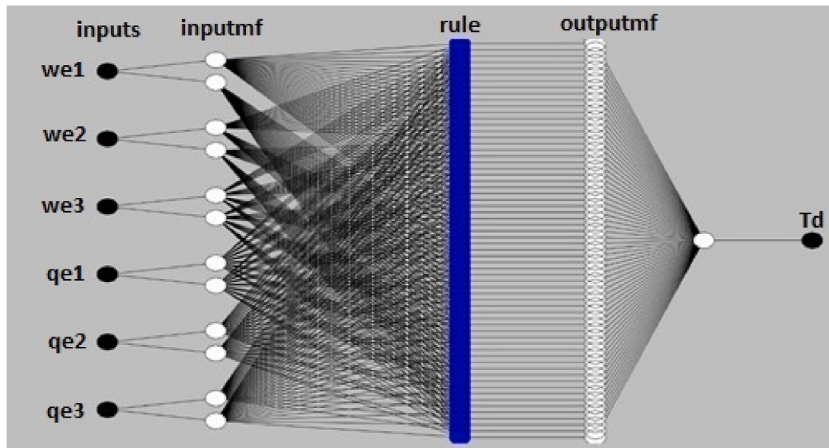


Fig. 3. ANFIS structure for disturbance torque estimation.

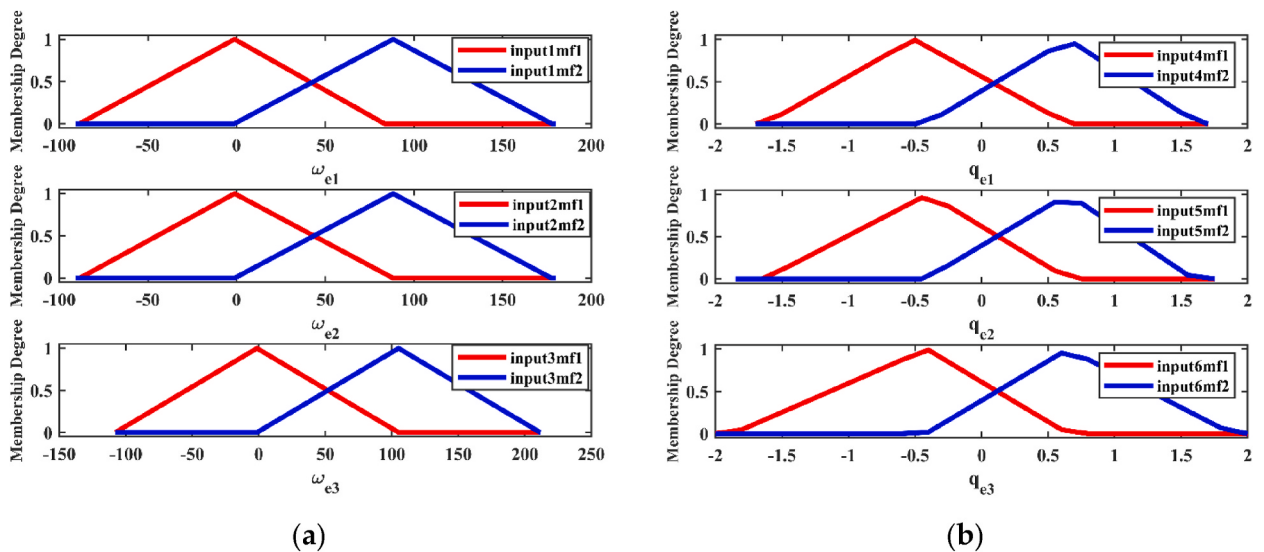


Fig. 4. Trained input MFs of six inputs comprises of angular velocity error vector and quaternions error vector: (a) Trained MFs of ω_e for linear output triangular type MFs; (b) Trained MFs of q_e for linear output triangular type MFs.

in this study, data required for designing of attitude controller is collected by the attitude model of CubeSat with LEO disturbances. Hence, Table 1 provides min, max, and average values of input and output parameters of the dataset that comprises 10,000 values, in which 70% of the total data is used for training while 30% is used for testing. The performance validation of the model is evaluated based on testing data for certain input values that are not trained. The training process of ANFIS starts by defining fuzzy sets for each input variable along with their MFs in two sets of configurations, one for disturbance torques and the other for the PD gain scheduling scheme.

3.2. ANFIS configuration for disturbance torques

In this experiment, the dataset is congregated for quaternion error vector, angular velocity error vector as six inputs, and estimated disturbance torque is taken as an output from attitude model of CubeSat as shown in Fig. 3. For this purpose, three individual MISO ANFIS are designed for x, y and z axis of disturbance torques.

Testing and training errors were detected with 64 fuzzy rules designed by the Sugeno inference system for analyzing the performance from triangular to trapezoidal, bell-shaped, Sigmoid, and Gaussian MFs through the grid portioning method. From the experiment results, it is examined that ANFIS configuration with triangular-shaped MFs gives minimal root mean square error for T_d in each axis, and produces output MFs that can be either linear or constant. It is observed that, as we have 2 input MFs for each type of MFs, so, increasing the amount of input membership functions from 2 to 3 causes a delay in the learning process. Hence, triangular

Table 2Experimental results for τ_{dx} in terms of linear output MFs.

Input Mfs	Number of input MFs	Number of epochs	RMSE	Avg. testing error for training data	Avg. testing error for testing data
Triangular	2	500	0.22×10^{-4}	0.22023×10^{-4}	0.16703×10^{-2}
Trapezoidal	2	500	0.23×10^{-4}	0.23458×10^{-4}	0.11982×10^{-1}
Bell-shaped	2	500	0.24×10^{-4}	0.24336×10^{-4}	0.14097×10^{-2}
Gaussian	2	500	0.26×10^{-4}	0.25642×10^{-4}	0.76975×10^{-2}
Sigmoidal	2	500	0.28×10^{-4}	0.27785×10^{-4}	0.13038×10^{-1}

Table 3Experimental results for τ_{dx} in terms of constant output MFs.

Input Mfs	Number of input MFs	Number of epochs	RMSE	Avg. testing error for training data	Avg. testing error for testing data
Triangular	2	500	0.44×10^{-3}	0.44288×10^{-3}	0.19592×10^{-2}
Sigmoidal	2	500	0.20×10^{-1}	0.2045×10^{-1}	0.291
Bell-shaped	2	500	0.13	0.13345	0.34373
Gaussian	2	500	0.39	0.39001	1.1606
Trapezoidal	2	500	0.57	0.57562	5.5449

Table 4Experimental results for τ_{dy} in terms of linear output MFs.

Input Mfs	Number of input MFs	Number of epochs	RMSE	Avg. testing error for training data	Avg. testing error for testing data
Triangular	2	500	0.14×10^{-4}	0.13948×10^{-4}	0.95837×10^{-3}
Gaussian	2	500	0.25×10^{-4}	0.24587×10^{-4}	0.452×10^{-2}
Trapezoidal	2	500	0.26×10^{-4}	0.25724×10^{-4}	0.17498×10^{-1}
Bell-shaped	2	500	0.32×10^{-4}	0.32269×10^{-4}	0.66675×10^{-3}
Sigmoidal	2	500	0.49×10^{-4}	0.48959×10^{-4}	0.34962×10^{-2}

Table 5Experimental results for τ_{dy} in terms of constant output MFs.

Input Mfs	Number of input MFs	Number of epochs	RMSE	Avg. testing error for training data	Avg. testing error for testing data
Triangular	2	500	0.536×10^{-3}	0.53617×10^{-3}	0.14624×10^{-2}
Sigmoidal	2	500	0.2821×10^{-1}	0.28213×10^{-1}	0.57526×10^{-1}
Bell-shaped	2	500	0.174405	0.1744	0.22805
Gaussian	2	500	0.586456	0.58646	0.85453
Trapezoidal	2	500	0.89291	0.892913	2.3357

Table 6Experimental results for τ_{dz} in terms of linear output MFs.

Input Mfs	Number of input MFs	Number of epochs	RMSE	Avg. testing error for training data	Avg. testing error for testing data
Trapezoidal	2	500	0.29×10^{-4}	0.28801×10^{-4}	0.4813×10^{-2}
Triangular	2	500	0.30×10^{-4}	0.30022×10^{-4}	0.35224×10^{-3}
Bell-shaped	2	500	0.35×10^{-4}	0.34856×10^{-4}	0.74521×10^{-3}
Gaussian	2	500	0.43×10^{-4}	0.42817×10^{-4}	0.79433×10^{-2}
Sigmoidal	2	500	0.44×10^{-4}	0.44399×10^{-4}	0.30934×10^{-2}

Table 7Experimental results for τ_{dz} in terms of constant output MFs.

Input Mfs	Number of input MFs	Number of epochs	RMSE	Avg. testing error for training data	Avg. testing error for testing data
Triangular	2	500	0.339×10^{-3}	0.33866×10^{-3}	0.63501×10^{-2}
Bell-shaped	2	500	0.833×10^{-2}	0.83351×10^{-2}	0.19532
Sigmoidal	2	500	0.231×10^{-1}	0.2311×10^{-1}	0.31647
Gaussian	2	500	0.455887	0.45589	1.4811
Trapezoidal	2	500	0.672681	0.67268	2.1143

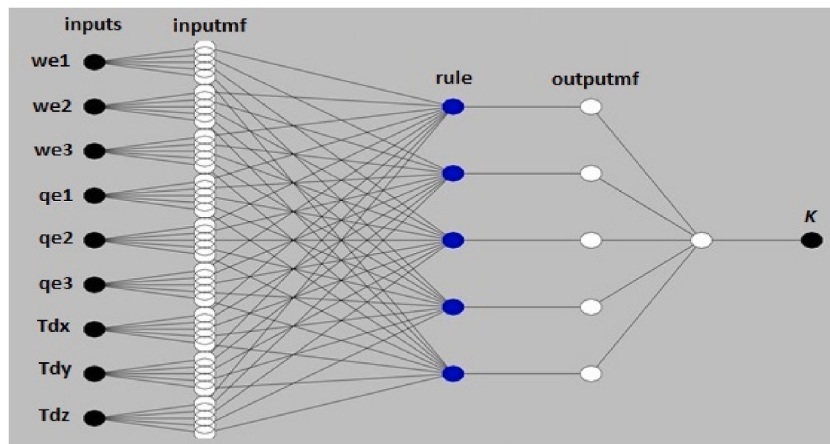


Fig. 5. ANFIS structure for gain scheduling.

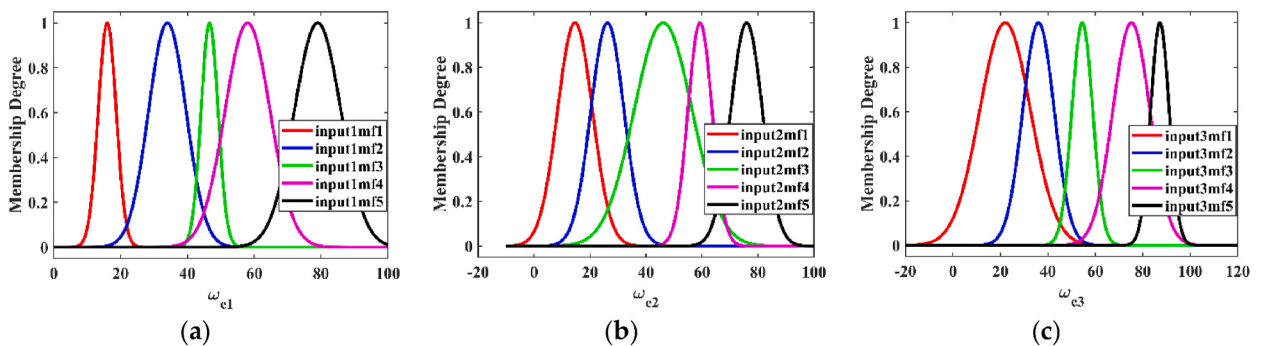


Fig. 6. Trained MFs of input angular velocity error vector element: (a) Trained MFs of ω_{e1} for linear output Gaussian type MFs; (b) Trained MFs of ω_{e2} for linear output Gaussian type MFs; (c) Trained MFs of ω_{e3} for linear output Gaussian type MFs.

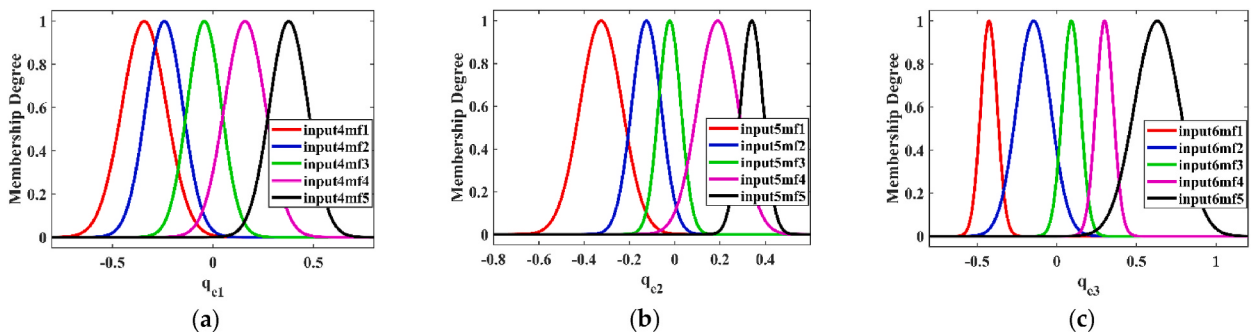


Fig. 7. Trained MFs of input quaternions error vector element: (a) Trained MFs of q_{e1} for linear output Gaussian type MFs; (b) Trained MFs of q_{e2} for linear output Gaussian type MFs; (c) Trained MFs of q_{e3} for linear output Gaussian type MFs.

MFs-based fuzzy rules were used for disturbance torques estimation due to the least error, which is shown in below Fig. 4.

Comparison analysis of various types of input MFs for linear and constant type output MFs are given in the following Tables 2–7 which gives us the RMSE for different types of input MFs in the Sugeno fuzzy inference system (see Table 6). As per the experiment, only triangular input MF achieved the least RMSE and least average testing error for training data in x & y axis of disturbance torques, meanwhile, trapezoidal MF attained the least RMSE in only the z-axis. Furthermore, the least average testing error was obtained with Bell-shaped MF for untrained testing data in x & y axis of disturbance torques in linear output MF type. Also, triangular MF achieved better response in terms of least error in testing data x, y, and z axis in constant and linear types of MF respectively (see Table 3).

It is pragmatic that the ANFIS model for disturbance torques having two triangular-shaped MFs gives minimum root mean square error as shown in Fig. 9 for 500 epochs.

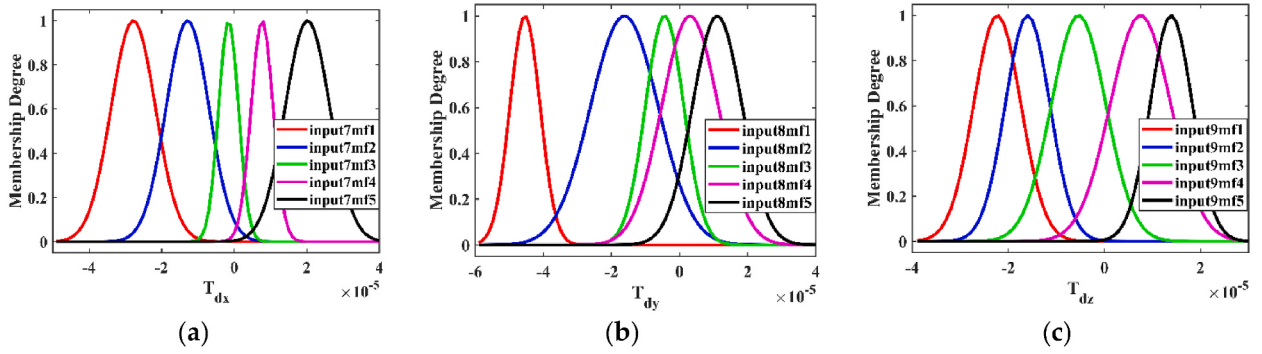


Fig. 8. Trained MFs of input external disturbance torques: (a) Trained MFs of τ_{dx} for linear output Gaussian type MFs; (b) Trained MFs of τ_{dy} for linear output Gaussian type MFs; (c) Trained MFs of τ_{dz} for linear output Gaussian type MFs.

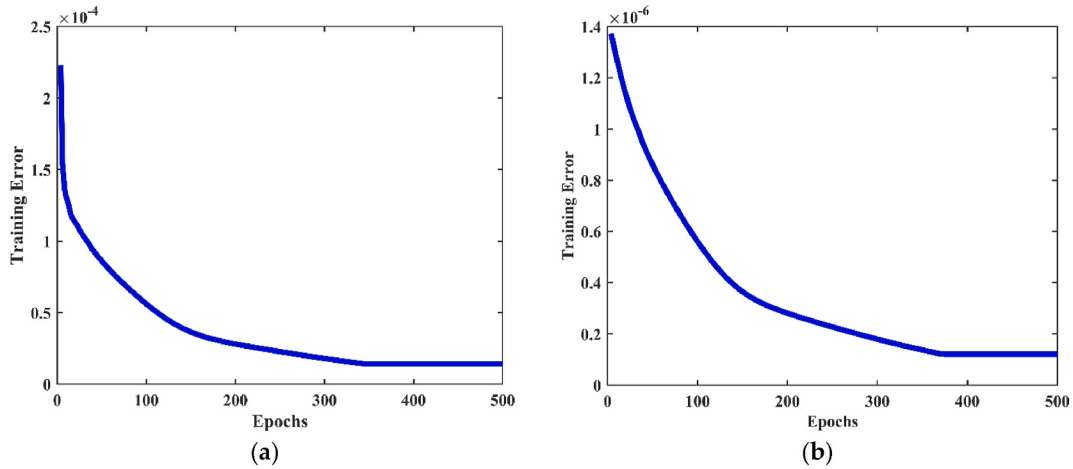


Fig. 9. Training error of ANFIS: (a) For disturbance torques (b) For gain scheduling.

Table 8

Experimental results for K_p and K_d in terms of linear output MFs.

Variables	Input Mfs	Number of input MFs	Number of epochs	RMSE	Avg. testing error for training data	Avg. testing error for testing data
K_p	Gaussian	5	500	0.12×10^{-6}	0.12115×10^{-6}	0.31618×10^{-6}
K_d	Gaussian	5	500	0.33×10^{-6}	0.33367×10^{-6}	0.94825×10^{-6}

3.3. ANFIS configuration for PD gain scheduling

In this investigation, quaternion error, angular velocity error, and estimated disturbance torque are taken as inputs and K_p & K_d gains are used as outputs. The ANFIS arrangement shown in Fig. 5, comprises nine input elements and scalar gain K for PD gain scheduling, so, for this purpose, two individual MISO ANFIS structures are designed for K_p and K_d (see Fig. 6).

The neuro-fuzzy systems automatically generate FIS by using the sub-clustering method due to nine input elements that are only supported by Gaussian MFs. The trained rules enable the system to effectively generate the output by producing 5 MFs for the given input values. In Figs. 7–9, the trained input membership functions for ω_e , q_e , and T_d are shown in terms of the linear form of output MF. Comparison analysis of RMSE, testing error for training, and testing data of Gaussian type cluster input MFs for linear type output MFs are given in the following Table 8. It is found that training and testing of ANFIS give out FIS of Sugeno type inference engine with five MFs having Gaussian shape yields minimal RMSE as shown in Fig. 9 for 500 iterations.

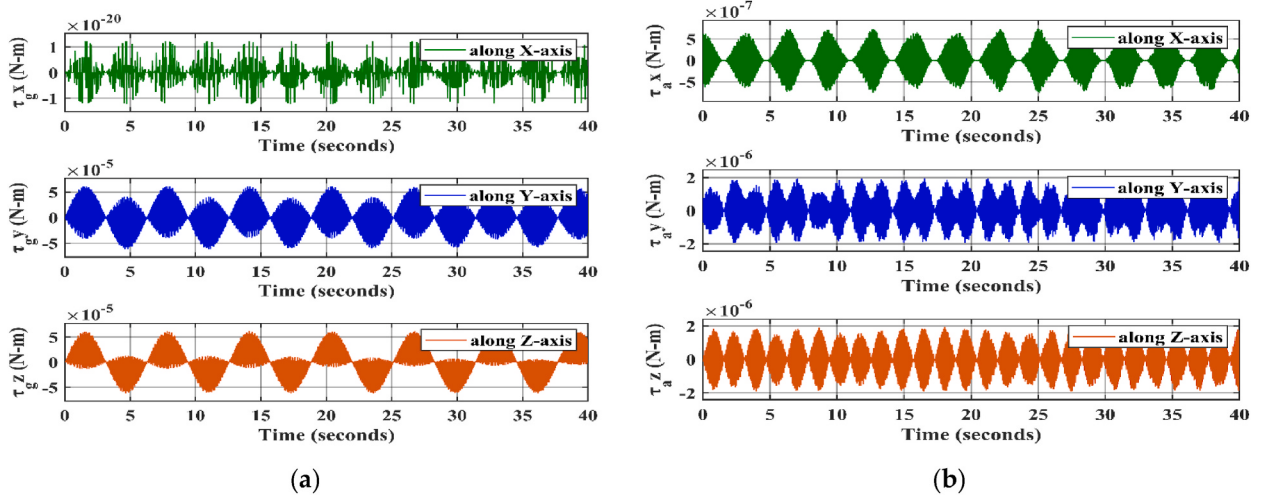
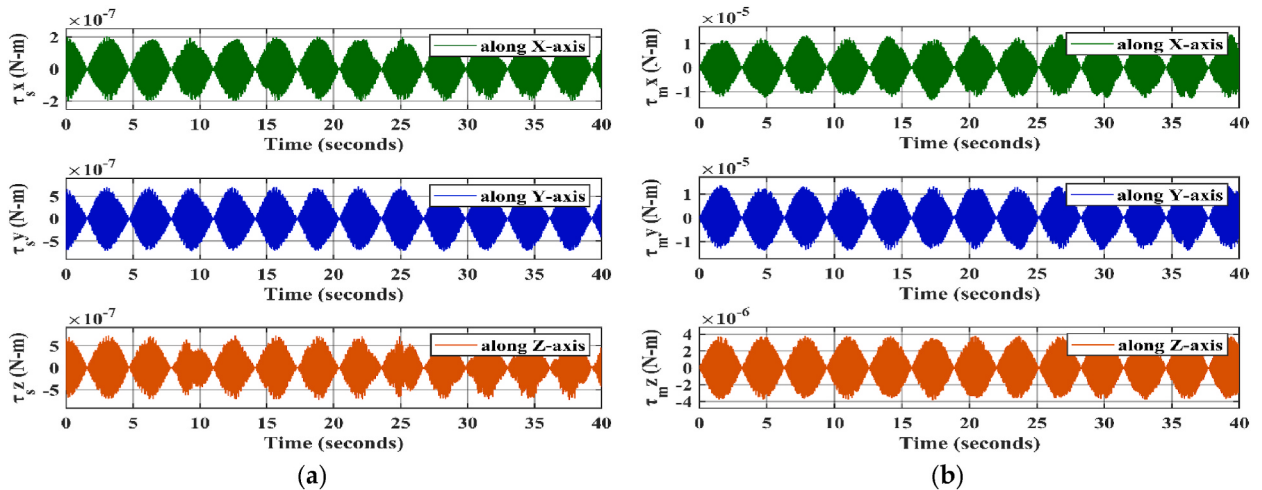
4. Simulation results

The performance of the proposed quaternions angular velocity feedback PD control system based on ANFIS is analyzed with PID, ANN, and RNN schemes. Controllers are designed and implemented in MATLAB software. The preliminary conditions were selected for

Table 9

Initial requirements for simulating attitude control scheme.

Parameters	Notations	Values
Initial Euler angles (deg)	$\varphi_0, \theta_0, \psi_0$	$[16.34^\circ \ 11.36^\circ \ 12.95^\circ]$
Initial quaternions	$\mathbf{q}_0 = [q_1 \ q_2 \ q_3 \ q_4]^T$	$[0.9803 \ 0.0971 \ 0.1133 \ 0.1295]^T$
Initial angular velocity (deg/sec)	$\boldsymbol{\omega}_0 = [\omega_x \ \omega_y \ \omega_z]^T$	$[83.22 \ 88.23 \ 105.1]^T$
Desired Euler angles (deg)	$[\varphi \ \theta \ \psi]$	$[10^\circ \ 20^\circ \ 30^\circ]$
Desired quaternions	$\mathbf{q}_d = [q_1 \ q_2 \ q_3 \ q_4]^T$	$[0.9515 \ 0.2393 \ 0.1893 \ 0.0381]^T$
Desired angular velocity (deg/sec)	$\boldsymbol{\omega}_d = [\omega_x \ \omega_y \ \omega_z]^T$	$[0.023 \ 0.0038 \ -0.0037]^T$
Simulation time (sec)	T	40

**Fig. 10.** Low earth orbital environmental perturbations acted on each axis of CubeSat: (a) Gravity gradient torque; (b) Aerodynamic drag torque.**Fig. 11.** Low earth orbital environmental perturbations acted on each axis of CubeSat: (a) Solar radiation torque; (b) Residual magnetic dipole torque.

simulation as shown in Table 9.

The proposed methodology gives equilibrium of three-axis attitude under the influence of cyclic external disturbances as shown in Fig. 10, in which (a) represents major gravity gradient disturbance torque that is continuously varying concerning the gravitational field of earth and aerodynamic drag is shown in (b) which is the leading disturbance torque at a lower altitude around 500 km, unsettles the angles of attitude from the target value.

The residual magnetic dipole torque represents the cross product of the residual field of electronic components and the

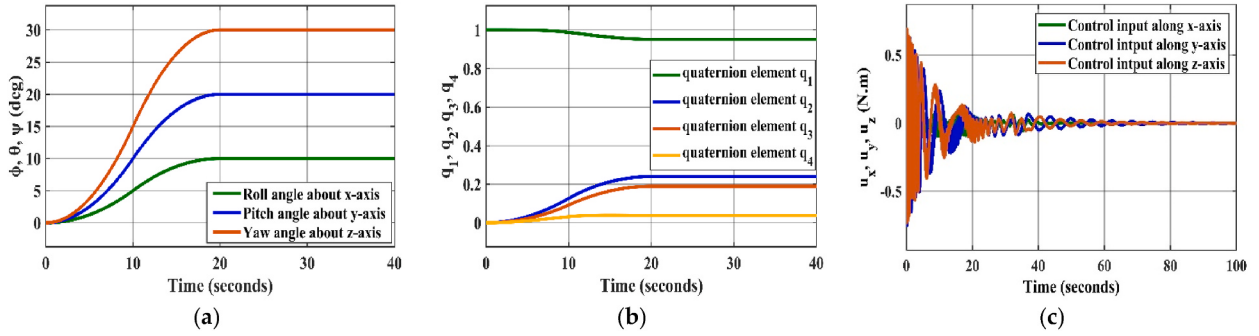


Fig. 12. Fixed gain PID controller response: (a) Targeted Euler angles; (b) Targeted Quaternions; (c) PID controller effort.

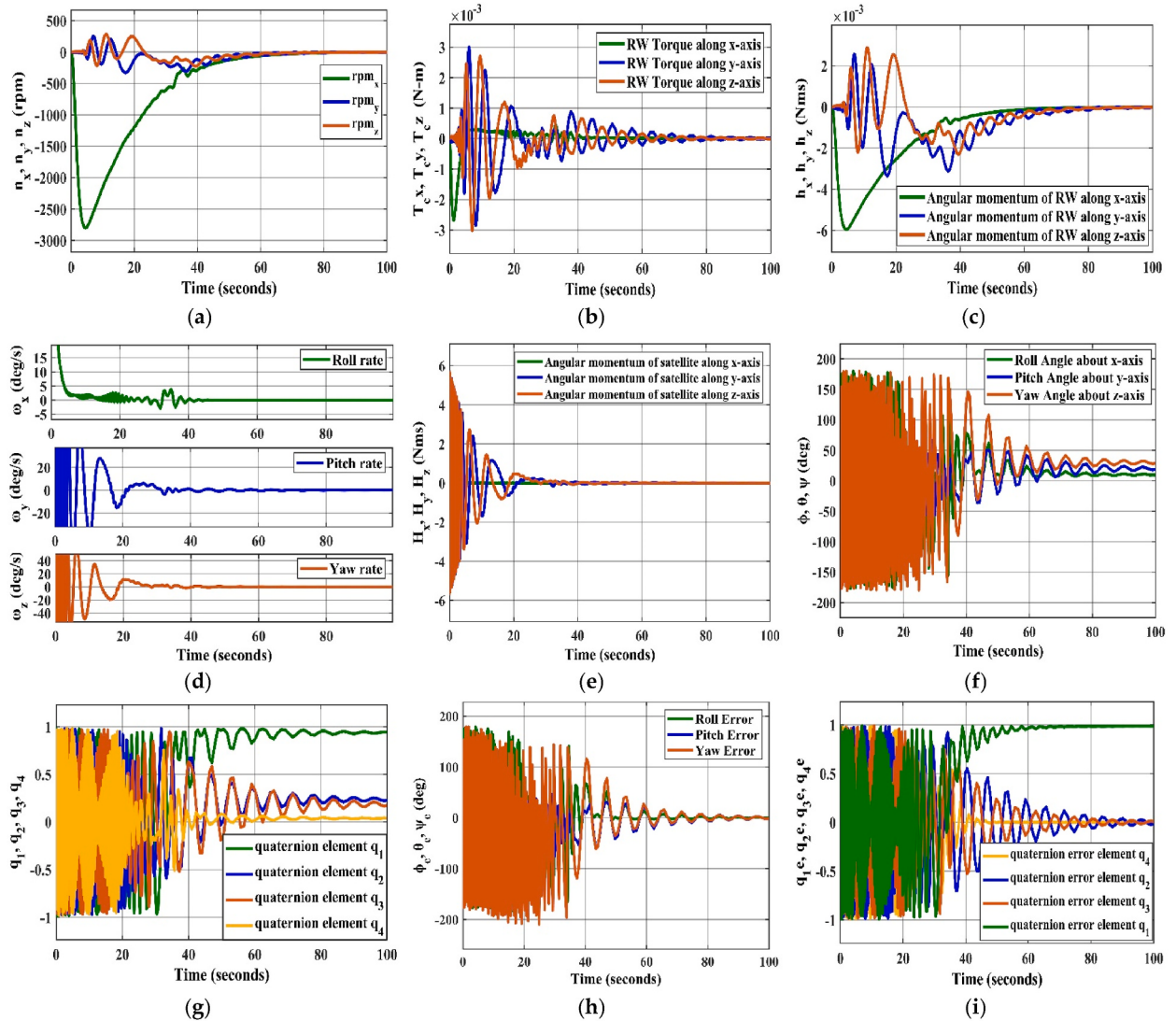


Fig. 13. Fixed gain PID controller response: (d) Angular speed of RWs; (e) Control torque of RWs; (f) Angular momentum of RWs; (g) Angular velocity of CubeSat; (h) Angular momentum of CubeSat; (i) Output Euler angles; (j) Output Quaternions; (k) Euler angle error; (l) Quaternions error.

Table 10
Learning parameters of ANN for the attitude control system of Cube Satellite.

Parameters	For Disturbance Torques and Gain Scheduling
Maximum No of epochs to train	1000
Performance Goal	0.00
Maximum Validation failures	6
Least performance gradient	$1e^{-7}$
Training rate	0.001
Transfer Functions	logsig, tansig, purelin
Proportion of increasing training rate	10
Proportion of decreasing training rate	0.1
Epochs between displays	20
Maximum time taken for learning process (min)	18

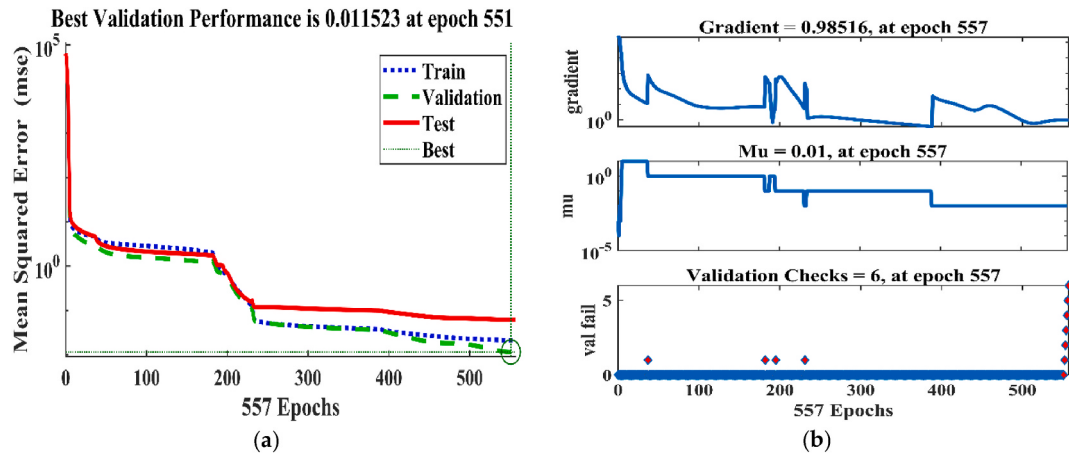


Fig. 14. Artificial neural network training for disturbance torques: (a) Training error (b) Training state.

geomagnetic field of Earth in Fig. 11 in (a). The sun's radiation can also generate a slight torque on the satellite's surface which is less as compared to other disturbances as shown in (b).

4.1. Conventional PID controller

This scheme provides fixed gain to obtain desired angles, as in Fig. 12, (a) and (b) show targeted Euler angles and quaternion vector elements for CubeSat that must rotate from the initial attitude to the desired level at 20sec and after that, it must reach to steady-state response with the help of the controller. The classical PID controller gives commanded control input to reaction wheels in (c), which is disturbed, gradually decreasing and non-convergence behavior at the start but later on it meets nearly to zero as simple control law cannot handle nonlinearities and disturbances in the system promptly.

Three RWs are modeled, and the angular speed of RWs is increasing due to the lack of its attitude handling capability shown in Fig. 13 in (a), thus the drive control torque from RWs attempted to tackle satellite attitude in (b) with oscillating behavior. This torque tries to control the dynamics of the satellite with non-convergent torque amplitude. The moment of inertia and angular speed of wheels determined the angular momentum of RWs in (c) and surges in angular momentum encountered due to the high angular speed of the wheels. Furthermore, after separation from the launcher, higher angular velocities of the satellite need to be controlled in minimum time but angular velocity keeps on getting fluctuations due to the non-adaptive nature of simple control in (d) and reduced to zero after 80 s. The angular momentum of the satellite depends on the angular velocity which is high even after its control, so momentum on each axis has unstable nonlinear behavior as shown in (e) till 80 s. As a result, the output attitude Euler angles and quaternions are diverted from desired attitude angles due to the high angular momentum of the satellite as shown in (f), (g), and attained target values at 100 s. Consequently, the PID controller is not able to handle this nonlinear behavior quickly. Hence, Euler angle error and quaternion error decrease by taking extra time which leads to poor attitude stability performance of CubeSat, which can be seen in (h) and (i).

4.2. ANN-based controller

The artificial neural network-based controller uses a multilayer feedforward backpropagation network with a Levenberg-Marquardt training function and Gradient descent with momentum weight and bias learning function. ANN model is designed for disturbance torques estimation and gains scheduling having learning parameters like epochs, performance goal, gradient, and neuron

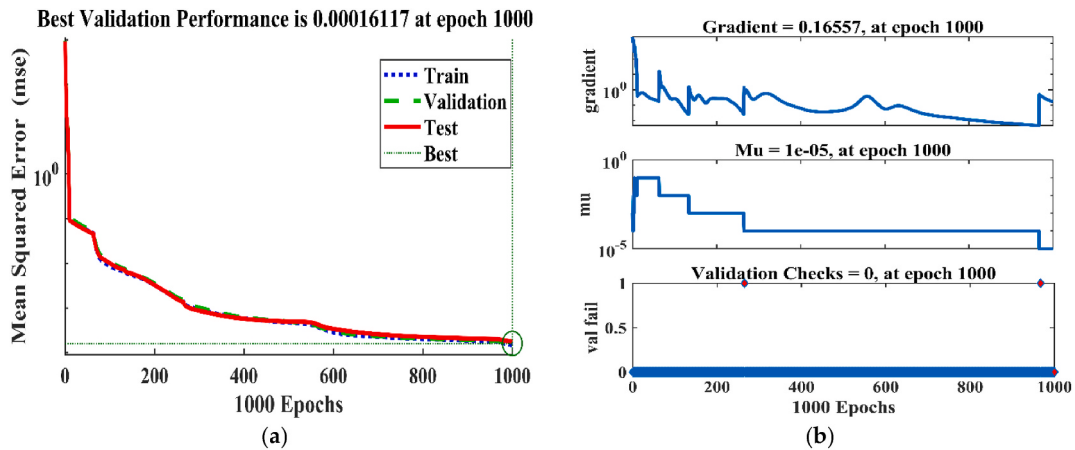


Fig. 15. Artificial neural network training for gain scheduling: (a) Training error (b) Training state.

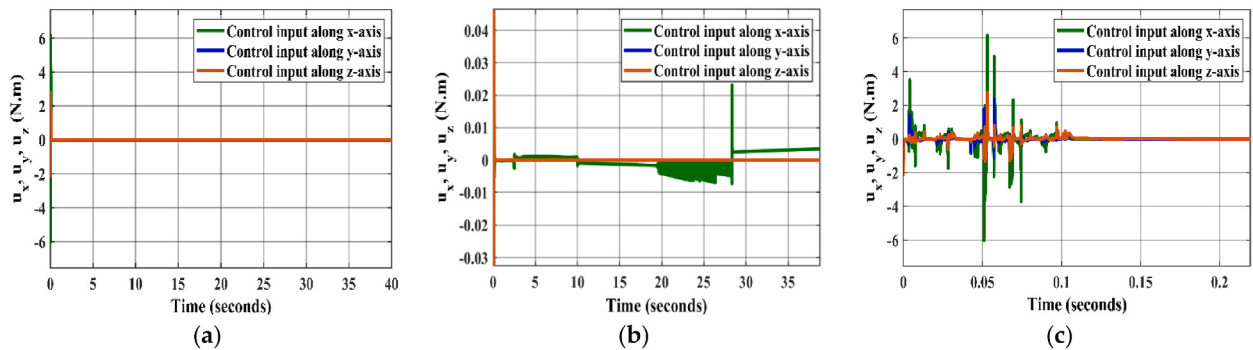


Fig. 16. Proposed controller effort: (a) Adaptive gain ANN-PD controller response; (b) Zoom-in x-axis of ANN-PD control response; (c) Zoom-in y-axis of ANN-PD control response.

model (logsig, tansig, purelin) that are given in Table 10.

Best validation performance is obtained with minimum MSE as shown in Figs. 14 and 15 with training gain, gradient, and validation checks at different epochs. The trained network provided good results as compared to the previous fixed gain PID control methodology. As a result, adaptive commanded control input oscillates at the start of the graph due to the high momentum of the satellite, observed in Fig. 16, panel (a). In (b), the attitude stabilization of CubeSat is achieved by controlling the attitude angle of the single roll axis and controller input converged to zero before 0.15sec, observed in (c).

The maximum angular speed of RWs reached at 6000 rpm in below Fig. 17, panel (a), then gradually decreases and converges to constant speed which reveals that the attitude rate is now in the normal desired range. Henceforth, the drive control torque reaches 0.015 mN m and then decreases smoothly as shown in (b). The reaction torque approaches zero as the wheel's speed decreases. The angular momentum of RWs presented in (c), converges near to constant value due to the controlled angular speed of the wheels. Finally, the tumbling effect in the angular velocity of the satellite was reduced and stable within less than 10sec as compared to the previous PID control simulation. The regulated angular momentum and torque of RWs tackled high angular velocity in (d). The attitude stabilization of CubeSat is achieved by the controlled angular velocity that is shown in (e), indicating higher negative velocity spikes in the x and z axis and then gradually reaching near zero before 30sec. As presented in (f), the proposed control law obtained adaptive gain on all axis before 0.2sec. The angular momentum of the satellite also decreases as velocity decreases as shown in (g). The estimated disturbance torques in x, y, and z axis are projected by the adaptive feedforward back propagation neural network which is identified in (h).

Hence, the ANN attitude controller efficiently regulates the roll, pitch, and yaw angles in minimal time as compared to PID. The steady-state response is achieved after 23sec of simulations, presented in Fig. 17 in (i), and the same behavior is also shown in (j) for four-vector elements of quaternions. The Euler angle error decreases and approaches zero as time increases and hence, attitude stabilization is achieved after 23sec, which is shown in (k). Similar to the Euler angle error results, the q1, q2, and q3 quaternion error vector element has the same converging behavior near zero, and q4 sets itself at the maximum level of value 1 as shown in (l). The designed ANN controller tuned the PD gains with respect to estimated external disturbance torques to get optimal stable desired Euler angles.

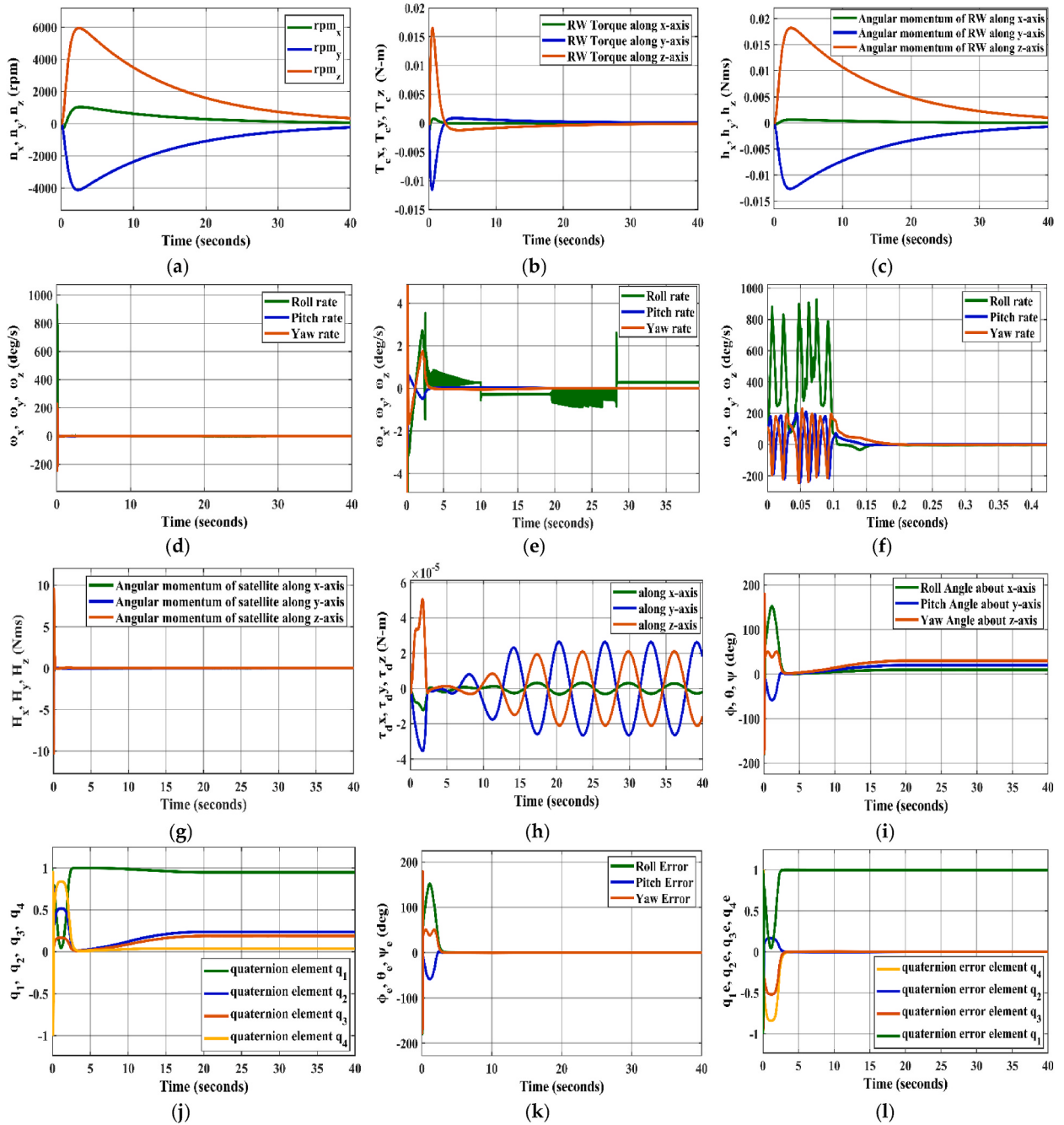


Fig. 17. ANN-PD methodology outcomes: (a) Angular speed of RWs; (b) Control torque of RWs; (c) Angular momentum of RWs; (d) Angular velocity of CubeSat; (e) Zoom-in x-axis of satellite's angular velocity; (f) Zoom-in y-axis of satellite's angular velocity; (g) Angular momentum of CubeSat; (h) Estimated disturbance torques by ANN network; (i) Output Euler angles; (j) Output Quaternions; (k) Euler angle error; (l) Quaternions error.

4.3. RNN-based controller

The recurrent neural network-based controller used a multilayer Elman back propagation network with a Levenberg-Marquardt training function and Gradient descent weight and bias learning function. RNN model is also designed for disturbance torques estimation and gain scheduling having learning parameters like epochs, performance goal, gradient, and neuron model (logsig, tansig, purelin) that are given in below Table 11.

Best validation performance is obtained with minimum MSE as shown in Figs. 18 and 19 with training gain, gradient, and

Table 11
Learning parameters of RNN for the attitude control system of Cube Satellite.

Parameters	For Disturbance Torques and Gain Scheduling
Maximum No of epochs to train	1000
Performance Goal	0.00
Maximum Validation failures	6
Least performance gradient	$1e^{-7}$
Training rate	0.001
Transfer Functions	logsig, tansig
Proportion of increasing training rate	10
Proportion of decreasing training rate	0.1
Epochs between displays	20
Maximum time taken for learning process (min)	22

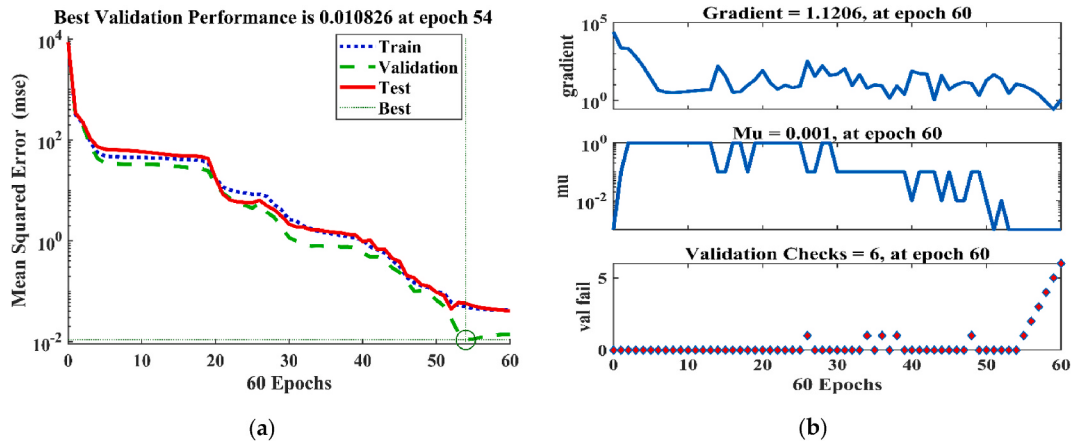


Fig. 18. Recurrent neural network training for disturbance torques: (a) Training error (b) Training state.

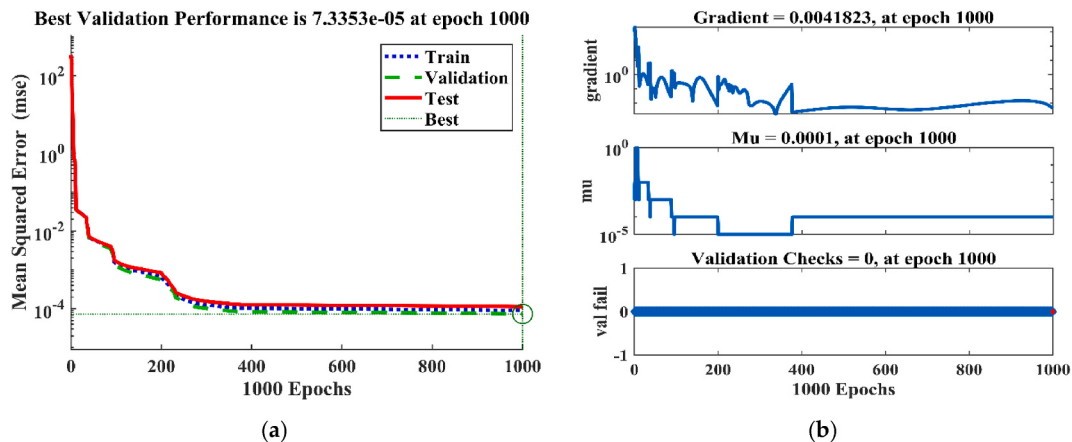


Fig. 19. Recurrent neural network training for gain scheduling: (a) Training error (b) Training state.

validation checks at different epochs. The trained network provided good results as compared to previous PID and ANN control methodologies. As a result, adaptive control input jump high at the start of the graph due to the high momentum of the satellite, observed in Fig. 20, panel (a). In (b), the attitude stabilization of CubeSat is achieved by controlling the attitude angle of the single roll axis and controller input converges to zero before 0.12sec, observed in (c).

The maximum angular speed of RWs reached at 5350 rpm in below Fig. 21, panel (a), then gradually decreases and converges to constant speed which reveals that the attitude rate is now in the normal desired range. Henceforth, the drive control torque reaches 5mNm and then decreases smoothly as shown in (b). The reaction torque approaches zero as the wheel's speed decreases. The angular momentum of RWs presented in (c), converges near to constant value due to the controlled angular speed of the wheels. Finally, the tumbling effect in the angular velocity of the satellite is reduced and stable within less than 4sec as compared to ANN and PID

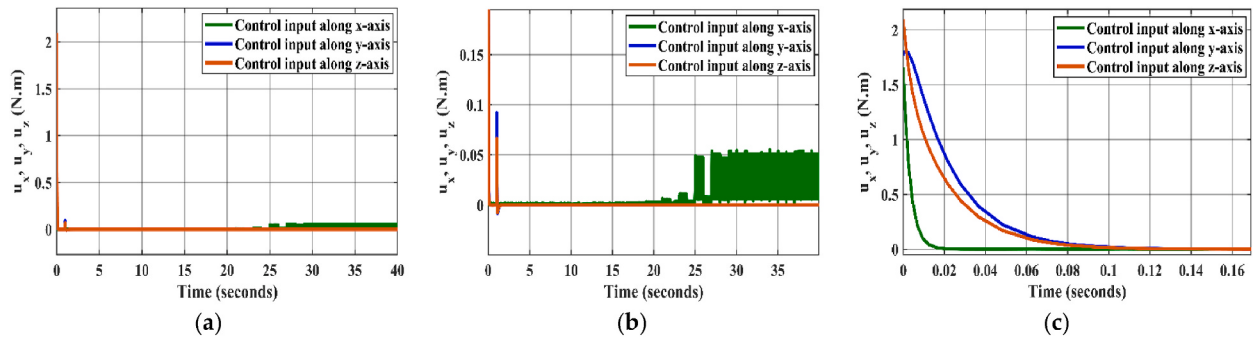


Fig. 20. Proposed controller effort: (a) Adaptive gain RNN-PD controller response; (b) Zoom-in x-axis of RNN-PD control response; (c) Zoom-in y-axis of RNN-PD control response.

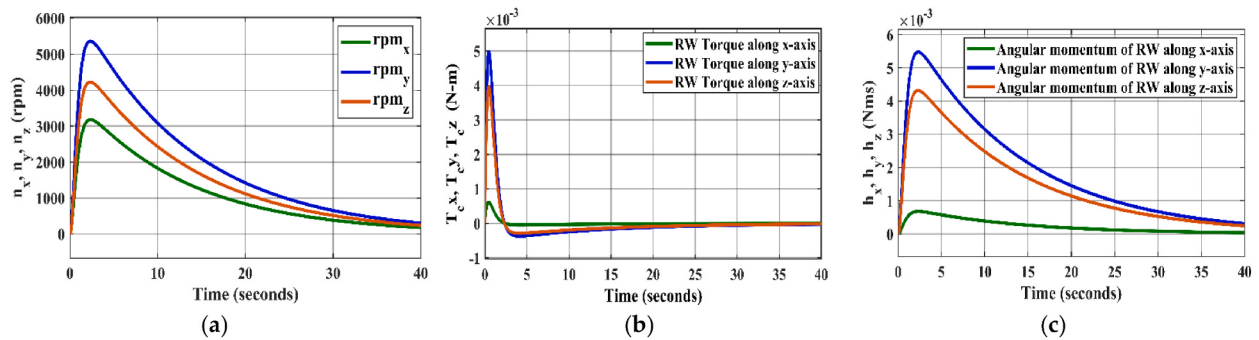


Fig. 21. RNN-PD methodology outcomes: (a) Angular speed of RWs; (b) Control torque of RWs; (c) Angular momentum of RWs.

techniques. The regulated angular momentum and torque of RWs tackled high angular velocity in Fig. 22, panel (a). The attitude stabilization of CubeSat is achieved by the controlled angular velocity that is shown in (b), indicating higher negative velocity spikes in the y-axis and then gradually reaching near zero before 5sec. As presented in (c), the proposed control law obtained adaptive gain on all axis. The angular momentum of the satellite also decreases as velocity decreases as shown in (d). The estimated disturbance torques in the x, y, and z axis are projected by a recurrent neural network which is identified in (e). Hence, the proposed attitude controller efficiently regulates the roll, pitch, and yaw angles in minimal time but with a large negative spike in z-axis at the start of the graph. The steady-state response is achieved after 20sec of simulation, presented in (f) and the same behavior have also been shown in (g) for the four-vector element of quaternions. The Euler angle error decreases and approaches zero as time increases and hence, attitude stabilization is achieved after 20sec, which is shown in (h). Similar to the Euler angle error results, the q1, q2, q3 quaternion error vector element has the same converging behavior near zero and q4 sets itself at the maximum level of value 1 as shown in (i). Therefore, RNN controller is slightly better than ANN in term of output Euler angles.

4.4. ANFIS-PD controller

The ANFIS-based PD controller gives adaptive commanded control input that reached high at the start of the graph due to the high momentum of the satellite, observed in Fig. 23, panel (a). In (b), the attitude stabilization of CubeSat is achieved by controlling the attitude angle of the single roll axis and controller input converges to zero before 0.005sec, observed in (c).

The maximum angular speed of RWs reached at 5156 rpm in below Fig. 24, panel (a), then gradually decreases and converges to constant speed which reveals that the attitude rate is now in the normal desired range. Henceforth, the drive control torque reaches 4.67mNm and then decreases smoothly as shown in (b). The reaction torque approaches zero as the wheel's speed decreases.

The angular momentum of RWs presented in Fig. 24 in (c), converges near to constant value due to the controlled angular speed of the wheels. Finally, the tumbling effect in the angular velocity of the satellite has reduced and stable within less than 3sec as compared to PID, ANN, and RNN control simulation. The regulated angular momentum and torque of RWs tackled high angular velocity in Fig. 25, panel (a). The attitude stabilization of CubeSat is achieved by the controlled angular velocity that is shown in (b), indicating higher negative velocity spikes in the y-axis and then gradually reaching near zero before 22sec. As presented in (c), the proposed control law obtained adaptive gain on all axis. The angular momentum of the satellite also decreases as velocity decreases as shown in (d). The estimated disturbance torques in the x, y, and z axis are projected by the adaptive Neuro-fuzzy inference system which is identified in (e). Hence, the proposed attitude controller efficiently regulates the roll, pitch, and yaw angles in minimal time. The steady-state response is achieved after 20sec of simulation, presented in (f) and the same behavior have also shown in (g) for the four-

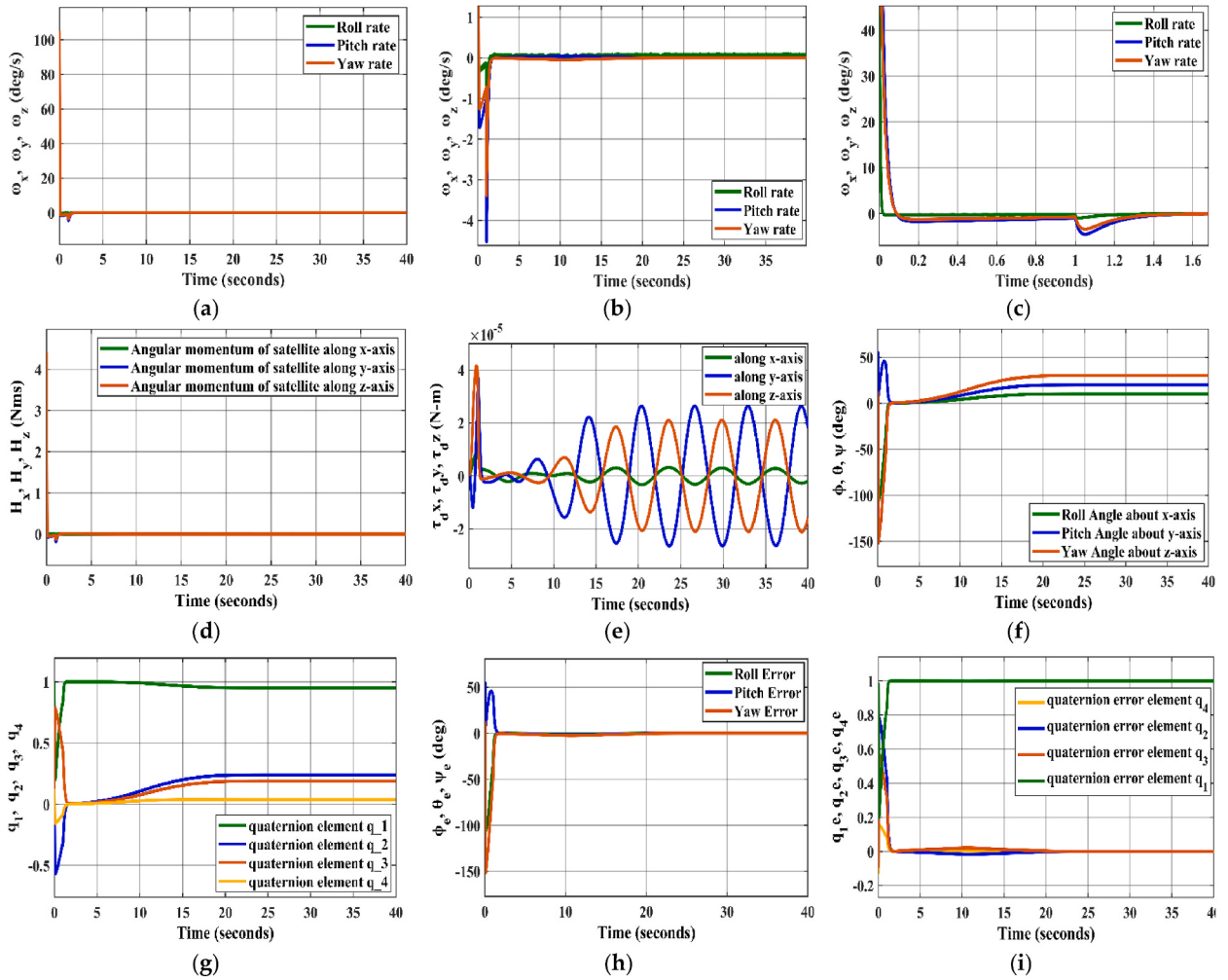


Fig. 22. RNN-PD methodology outcomes: (a) Angular velocity of CubeSat; (b) Zoom-in x-axis of satellite's angular velocity; (c) Zoom-in y-axis of satellite's angular velocity; (d) Angular momentum of CubeSat; (e) Estimated disturbance torques by RNN network; (f) Output Euler angles; (g) Output Quaternions; (h) Euler angle error; (i) Quaternions error.

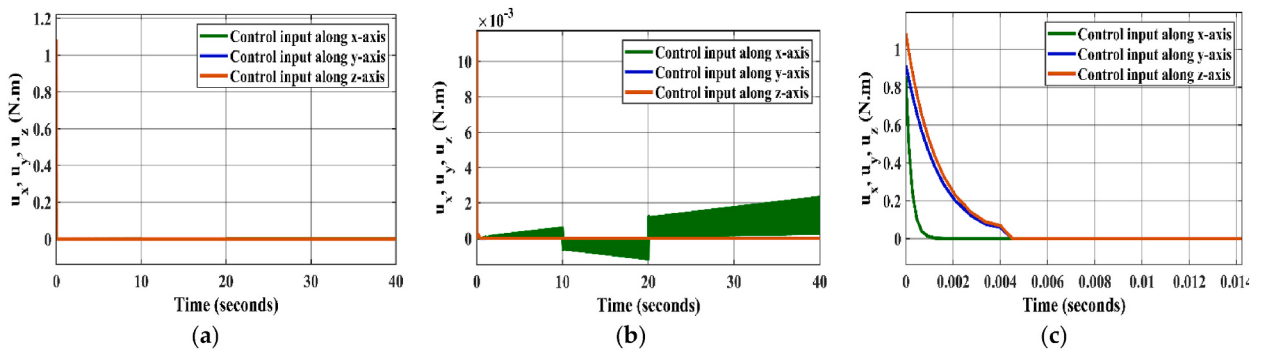


Fig. 23. Proposed controller effort: (a) Adaptive gain ANFIS-PD controller response; (b) Zoom-in x-axis of ANFIS-PD control response; (c) Zoom-in y-axis of ANFIS-PD control response.

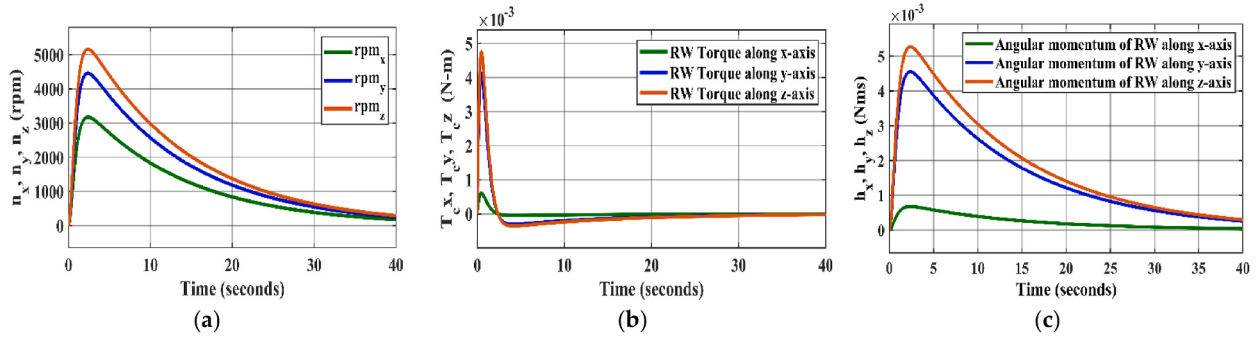


Fig. 24. ANFIS-PD methodology outcomes: (a) Angular speed of RWs; (b) Control torque of RWs; (c) Angular momentum of RWs.

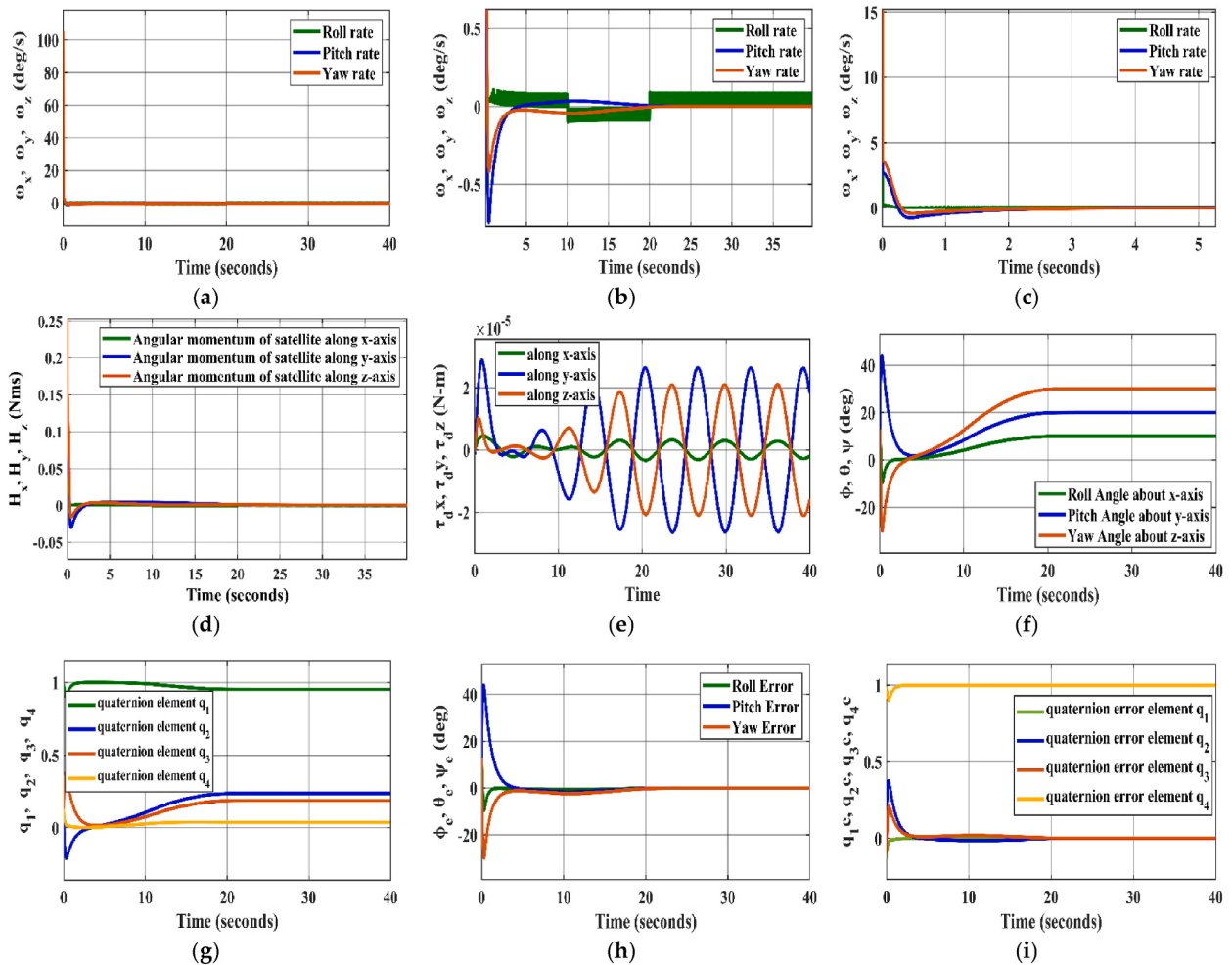


Fig. 25. ANFIS-PD methodology outcomes: (a) Angular velocity of CubeSat; (b) Zoom-in x-axis of satellite's angular velocity; (c) Zoom-in y-axis of satellite's angular velocity; (d) Angular momentum of CubeSat; (e) Estimated disturbance torques by ANFIS network; (f) Output Euler angles; (g) Output Quaternions; (h) Euler angle error; (i) Quaternions error.

vector element of quaternions. The Euler angle error decreases and approaches zero as time increases and hence, attitude stabilization is achieved after 20sec, which is shown in (h). Similar to the Euler angle error results, the q_1 , q_2 , and q_3 quaternion error vector element has the same converging behavior near zero, and q_4 sets itself at the maximum level of value 1 as shown in (i). Therefore, the ANFIS-PD controller is capable of reducing the initial body speeds on a single axis to about 0.0037 deg/sec to reach optimal Euler angles during simulation time. The designed controller tuned the PD gains with respect to estimated external disturbance torques.

Table 12
Performance comparison of the proposed approach.

Controllers	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)
PID	2.59	1.60
ANN	1.61×10^{-4}	1.27×10^{-2}
RNN	7.33×10^{-5}	8.56×10^{-3}
ANFIS	1.44×10^{-14}	1.20×10^{-7}

4.5. Result analysis

The suggested approach controls the CubeSat under external disruptions, and performance comparison has also been accomplished within the specifications defined. It can be seen from the simulations and statistical result in the following Table 12, that ANFIS is capable to achieve stable attitude angles with minimum MSE and RMSE within 20 s of simulation time as compared to other techniques under environmental disturbances.

5. Conclusions

In this study, the proposed ANFIS methodology is very effective to analyze its performance with respect to the stability of CubeSat under LEO disturbances to regulate the Euler angles. To accomplish this task, the adaptive neuro-fuzzy inference system is designed along with the four-layered neural network. The appropriate PD attitude controller strategy based on ANFIS interacts with various aspects, like persistent variations in space environmental fluctuations, higher satellite angular velocity, distorted angular momentum, and nonlinear behavior of the reaction wheel. Eventually, the attitude control methodology achieved a minimum RMSE error and attained an Euler angle error near zero as related to fixed gain PID, adaptive ANN, and RNN controller. Performance evaluation and MATLAB graphs indicated that the ANFIS controller is more efficient for our proposed system. This work can be further extended in the future by the experimental testing of CubeSat attitude control with various techniques such as Granular extension of the Sugeno type fuzzy model (G-FIS) and Granular neural networks (GNN) and integral sliding mode control (ISMC).

Author contribution statement

Zsolt Conka: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Muhammad Faisal Shehzad: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Aamer Bilal Asghar; Mujtaba Hussain Jaffery: Performed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Data availability statement

Data will be made available on request.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Zsolt Conka reports financial support was provided by Slovak Research and Development Agency. Zsolt Conka reports a relationship with Ministry of Education Science Research and Sport of the Slovak Republic that includes: funding grants.

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