International Journal of Research and Reviews in Artificial Intelligence
Vol. 1, No. 1, March 2011

www.sciacademypublisher.com

Adaptive Neuro-Controller for Three-Axes Attitude Control of Innovative Satellite

S. M. Sharun[1], M. Y. Mashor[1], M. N. Norhayati[1], W. N. Hadani[2], S. Yaacob[1]

[1]School of Mechatronic Engineering, Universiti Malaysia Perlis, Perlis,Malaysia .
[2]Institute of Engineering Mathematic, Universiti Malaysia Perlis, Perlis, Malaysia.

Correspondence should be addressed to siti_mrym@ymail.com, yusoff@unimap.edu.my, yatie_yasin@yahoo.com, hadani@unimap.edu.my, sazali22@yahoo.com

Abstract – There exists so many disturbance torques in space which may deviate the satellite from the desired attitude. To overcome the effects of the disturbance torques some stabilization has to be provided to the satellite. This paper describes the development of a nano-satellite Attitude Control System (ACS) which uses Adaptive Neuro-Controller (ANC) based on Hybrid Multi Layered Perceptron (HMLP) network. The objective of this paper is to analyze the time response of ANC in order to improve the efficiency of the three-axes attitude stabilization. The nano-satellite plant that was used in this simulation is called Innovative Satellite (InnoSAT). The performance of ANC controller was compared with Adaptive Parametric Black Box (APBB). Both controllers used Model Reference Adaptive Control (MRAC) as a control scheme and Weighted Recursive Least Square (WRLS) as an adjustment algorithm. The function of this algorithm is to adjust the controller parameters to minimize the error between the plant's output and the model reference's output. The simulation results indicated that ANC controller has significant improvement over APBB controller for varying operating conditions such as varying gain, noise and disturbance torques.

1. Introduction

Innovative Satellite (InnoSAT) is a nano class satellite, consists of the CubeSAT kit structure measuring 30cm x 10cm x 10cm, and a Texas Instrument MSP430 microcontroller with Salvo real-time operating system as the on board computer. The electrical power system of InnoSAT is capable of generating an average of 5W. InnoSAT uses UHF and VHF based communications system, and a three-axes based attitude determination and control system. Figure 1 shows the external view of InnoSAT. [1]

This paper describes the development of a nano-satellite Attitude Control System (ACS) for InnoSAT plant. ACS is the main sub-system in satellite development. The requirements of ACS are decided by the payload of the satellite as given in [2] [3]. The ACS controls the body orientation (attitude) of the satellite with respect to a reference frame. The ACS stabilizes the satellite after deployment and maintains a stabilized nominal attitude to conserve power. The ACS consists of attitude controllers that generate the control commands which drive the actuators to stabilize and / or change the satellite's attitude [4]. The attitude control algorithm resides in the ACS microprocessor and communicates to the on-board computer subsystem. The on-board computer processes the data through a control algorithm which is specially designed for the particular mission [5].

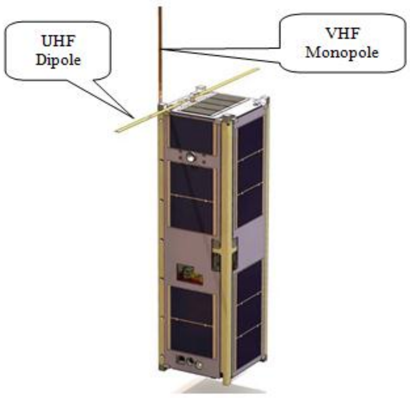

Figure 1. Standard CubeSAT Kit

The ACS operates exclusively as a three-axes attitude stabilized control system. Three-axes attitude stabilization is a type of stabilization in which a satellite maintains a fixed attitude relative to its orbital track. With a three-axes stabilization satellite, the solar panels can be kept facing the Sun and a directional antenna can be kept pointed at the Earth without having to be de-spun [6]. There are a few three-axes attitude controls using different method describes in [7] [8] [9].

A development of an intelligent real time control system based on neural network is possible for a satellite that is exposed to non-probabilistic uncertainties such as sun flare and noises [10]. For satellite attitude control system, a few approaches by using neural network have been developed [11] [12] [13].

A few performance comparisons have been done between adaptive neuro-controller based on HMLP network and other controllers. The result shows that ANC based on HMLP network gives significant improvement in the performance of controlling unstable system [14] [15]. The comparison is based on a double integrator and a nonlinear plant. In this research, the advantages of HMLP network combined with WRLS algorithm have been found to improve the efficiency of the three-axes attitude stabilization and time response.

2. Model of Satellite

Developing a mathematical model of the plant which adequately represents the real environment is very important and not an easy task. If the model is not adequate, the subsequent steps of analysis, prediction, controller, synthesis and so on, cannot be successful. Model should provide information at the most relevant level of precision, suppressing unnecessary details when appropriate. The model is neither too simple as it might gives an improper representation for the characteristics of the system nor too complex as it will be difficult to implement in real practical situation [16].

For InnoSAT model, there are a double integrator for Roll (X), Pitch (Y) and Yaw (Z) axes which having two poles at the origin of s-plane. This model is considered to present the tumbling behavior of a satellite in space after deployment and used to study the performance aspects of satellite behavior under various operating conditions. Since this model is dealing with second-order systems, some damping control must also be provided to improve stability. This means that the control torques will have to include a term that is dependent on the attitude rates to be measured or estimated.

The control torques to be activated is always a function of the attitude errors. The simplest torque control law is based on Euler angle errors. For a satellite with a diagonal inertia matrix and small Euler angle rotations, the attitude dynamic equations can be approximated as [2]:

$$\left.\begin{aligned} T_{dx} + T_{cx} &= I_x\ddot{\emptyset} \\ T_{dy} + T_{cy} &= I_y\ddot{\theta} \\ T_{dz} + T_{cz} &= I_z\ddot{\varphi} \end{aligned}\right\} \quad (1)$$

The Euler angles $\emptyset, \theta$ and φ are defined as the rotational angles about the satellite body axes: $\emptyset$, about the X axis; θ, about the Y axis; and φ, about the Z axis. The term ω_o represents the orbital angular velocity of the satellite. $T_c's$, are control moments to be used for controlling the attitude motion of the satellite; and $T_d's$, are those moments due to different disturbing environmental phenomena. These are second order linear differential equations of the Eulers angles. The Laplace Transform of the Roll, Pitch and Yaw axes from (1) are given by:

$$\left.\begin{aligned} s^2\emptyset_{(s)} - s\emptyset_{(0)} - \dot{\emptyset}_{(0)} &= \frac{T_{dx}}{I_x} + \frac{T_{cx}}{I_x} \\ s^2\theta_{(s)} - s\theta_{(0)} - \dot{\theta}_{(0)} &= \frac{T_{dy}}{I_y} + \frac{T_{cy}}{I_y} \\ s^2\varphi_{(s)} - s\varphi_{(0)} - \dot{\varphi}_{(0)} &= \frac{T_{dz}}{I_z} + \frac{T_{cz}}{I_z} \end{aligned}\right\} \quad (2)$$

The Euler angles and their derivatives with subscript 0 represent the initial conditions of the satellite attitude about its equilibrium position. For InnoSAT, the initial angles for all axes $(\emptyset_{(0)}, \theta_{(0)}, \varphi_{(0)})$ are assumed to be zero. Consequently, the transfer function of InnoSAT model for Roll, Pitch and Yaw axes equation are simplified as equation (3):

$$\left.\begin{aligned} \emptyset_{(s)} &= \left[\frac{T_{dx}}{I_x} + \frac{T_{cx}}{I_x} + \dot{\emptyset}_{(0)}\right]/s^2 \\ \theta_{(s)} &= \left[\frac{T_{dy}}{I_y} + \frac{T_{cy}}{I_y} + \dot{\theta}_{(0)}\right]/s^2 \\ \varphi_{(s)} &= \left[\frac{T_{dz}}{I_z} + \frac{T_{cz}}{I_z} + \dot{\varphi}_{(0)}\right]/s^2 \end{aligned}\right\} \quad (3)$$

3. Methodology

In this research, Model Reference Adaptive Control (MRAC) was chosen to be the controller scheme for ANC and APBB controllers. Hybrid Multi Layered Perceptron (HMLP) network has been selected as the basis for the ANC controller. Meanwhile, a Weighted Recursive Least Square (WRLS) algorithm is used as an adjustment mechanism to adjust the controller parameters.

3.1. Model Reference Adaptive Control

Mashor [17] proposed the MRAC scheme as shown in Figure 2. In this MRAC, a reference model is chosen to generate the desired output trajectory and to ensure the output of the controlled system tracking the desired reference output. In order to achieve the desired system performance in the sense of the closed-loop stability, adaptive laws were used to update the controller parameter.

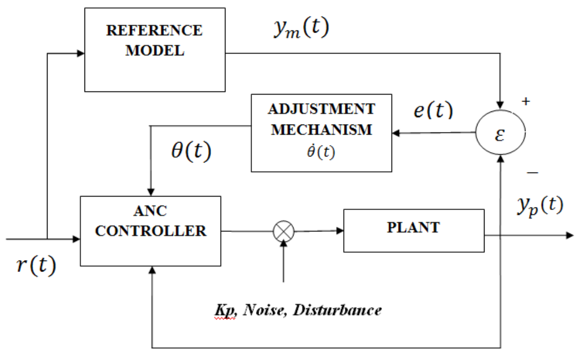

Figure 2. Block diagram of a model reference adaptive control

A stable linear continuous-time reference model is specified by the following differential equation:

$$y_m(t) = a_{m_1}y_m(t-1) - a_{m_2}y_m(t-2) + b_{m_0}r(t-1) + b_{m_1}r(t-2) \quad (4)$$

where $r(t)$ is the reference input and $y_m(t)$ is the reference model output; a and b are fixed model parameters and their values are chosen for any desired stable response. The model following error is defined by:

$$e(t) = y_m(t) - y_p(t) \quad (5)$$

where $y_p(t)$ is the output plant.

3.2. Hybrid Multi Layered Perceptron Network

Cybenko[18] and Funahashi [19] proved that the Multi Layered Perceptron (MLP) network with one hidden layer is sufficiently complete to approximate any continuous function with reasonable accuracy. However, the training process of MLP takes a large computation time and often leads to local minima problem. To solve this problem, MLP network with linear connection, called the Hybrid Multi Layered Perceptron (HMLP) network was introduced which was proved to have better performance than the conventional MLP network [20]. HMLP network with one hidden layer is shown in Figure 3 [21]. The network learns the relationship between pairs of inputs (factors) and output (responses) vectors by altering the weight and bias values. The HMLP network is built as an optimum network of modeling both linear and nonlinear systems. It can be seen that the HMLP network allows the network input to be connected directly to the output nodes with some weighted connections to form a linear system (dotted line connection). This additional linear system is parallel with the original nonlinear system from the standard MLP model (continuous line connection).

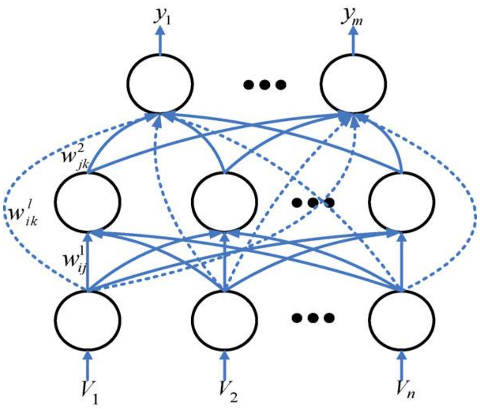

Figure 3. One_hidden_layer HMLP network

The output of the kth node in the output layer, $\hat{y}_k$ can be expressed as:

$$\hat{y}_k(t) = \sum_{j=1}^{n_h} w_{jk}^2 v_j^1(t) + \sum_{i=0}^{n_i} w_{ik}^l\, v_i^0(t); \qquad (6)$$

$$for\ 1 \le k \le m$$

where

$$v_j^1(t) = F\left(\sum_{i=1}^{n_i} w_{ij}^1 v_i^0(t) + b_j^1\right) \qquad (7)$$

where w_{ij}^1, w_{jk}^2 and w_{ik}^l denote the weights in the first layer, weights in the second layer and weights of extra linear connections between the input and output layer, respectively; b_j^1 and v_i^0 denote the thresholds in the hidden nodes and inputs that are supplied to the input layer respectively. The number of output nodes, inputs nodes and hidden nodes are represented by m, n_i and n_h respectively. $F(\cdot)$ is an activation function that is normally selected as a sigmoid function:

The weight w_{ij}^1, w_{jk}^2 and w_{ik}^l and threshold, b_j^1 are unknowns and should be selected to minimize the prediction error, define as:

$$\varepsilon_k(t) = y_k(t) - \hat{y}_k(t) \qquad (8)$$

where $y_k(t)$ and $\hat{y}_k(t)$ are the actual (or targeted) and the network (or predicted) output, respectively.

3.3. Adjustment Mechanism

The structure of controller shown in Figure 1 has linear parameters; hence any on-line estimation algorithm can be used to estimate the controller parameters. In this research, a Weighted Recursive Least Square (WRLS) have been used as a mechanism to adjust the parameters in a model reference adaptive control. WRLS algorithm is used as an estimation algorithm that will adjust the controller parameters to minimize the error between the plant output and the model reference output.

For all $t \ge t_0$, given $\hat{\theta}(t_0)$ and set $P(t) = \alpha[I]$, the WRLS estimate $\hat{\theta}(t_0)$ using the following recursive equations [17]:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + K(t)\left[y(t) - \varphi^T\hat{\theta}(t-1)\right] \qquad (9)$$

$$K(t) = P(t-1)\varphi(t)\,[\lambda I + \varphi^T P(t-1)\varphi(t)]^{-1} \qquad (10)$$

$$P(t) = [I - K(t)\varphi^T(t)]\,P(t-1)/\lambda \qquad (11)$$

Modified the equation (9) according to:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + K(t)e(t-1) \qquad (12)$$

where e is a difference between plant output and reference input and $\varphi(t)$ is the information vector that consists of the controller inputs. $\hat{\theta}(t)$ is the vector of controller parameters, $P(t)$ is covariant matrix and $\lambda(t)$ is forgetting factor. Other symbols are defined and assigned according to the standard WRLS algorithm [22].

3.4. Adaptive Parametric Black Box

Mashor [17] proposed a simple approach to parametric adaptive controller which is very similar to the control scheme of black box AI controller. The scheme offers a simple design approach of black box controller with simple structure of the parametric controller. The controller structure is an ARMAX model of a suitable order. However, a low order controller is preferable for fast updating of parameters. A second order controller structure is given below:

$$u(t) = c_0 + c_1 y(t-1) + c_2 y(t-2) + c_3 r(t) + c_4 r(t-1) + c_5 r(t-2) \qquad (13)$$

where c' s are the controller parameters that need to be adjusted to minimize the cost function.

4. Result and Discussions

In this section, simulation results of InnoSAT plant are presented. The simulation results were produced for the controllers based on some operating conditions such as varying gain, noise and disturbance torques. The InnoSAT characteristics and initial conditions are shown in Table 1.

Table 1. InnoSAT Characteristics and Initial Conditions

Moment of inertia I_x	0.0327 kg-m^2
Moment of inertia I_y	0.0498 kg-m^2
Moment of inertia I_z	0.0330 kg-m^2
Orbital rate ω_o	0.01095 rad/s
Initial angular velocity $\dot{\phi}_o$	5 deg
Initial angular velocity $\dot{\theta}_o$	5 deg
Initial angular velocity $\dot{\varphi}_o$	5 deg
Disturbance T_{dx}	5x10^{-6} N-m
Disturbance T_{dy}	5x10^{-6} N-m
Disturbance T_{dz}	5x10^{-6} N-m

After substituting the parameter value of InnoSAT, the transfer functions in (3) for Roll, Pitch and Yaw axes are become:

$$\left.\begin{aligned} \emptyset_{(s)} &= \frac{30.58T_{dx}+30.58T_{cx}+5}{s^2} \\ \theta_{(s)} &= \frac{20.08T_{dy}+20.08T_{cy}+5}{s^2} \\ \varphi_{(s)} &= \frac{30.21T_{dz}+30.21T_{cz}+5}{s^2} \end{aligned}\right\} \quad (14)$$

For the simulation, the InnoSAT plants can be described by a difference equation of the discrete form as:

$$x(t) = 2 * x(t-1) - x(t-2) + K_p(t) * 15.2 * \left(u_{sx}(t-1) + u_{sx}(t-2)\right) + 15.29 * \left(u_{dx}(t-1) + u_{dx}(t-2)\right) \quad (15)$$

$$y(t) = 2 * y(t-1) - y(t-2) + K_p(t) * 10.04 * \left(u_{sy}(t-1) + u_{sy}(t-2)\right) + 10.04 * \left(u_{dy}(t+1) + u_{dy}(t-2)\right) \quad (16)$$

$$z(t) = 2 * x(t-1) - x(t-2) + K_p(t) * 15.1 * \left(u_{sz}(t-1) + u_{sz}(t-2)\right) + 15.1 * \left(u_{dz}(t-1) + u_{dz}(t-2)\right) \quad (17)$$

where $K_p(t)$ is a varying gain, $u_s's(t)$ are the controller output and $u_d's(t)$ are the constant disturbance torque. Meanwhile $x(t), y(t)$ and $z(t)$ are the outputs from InnoSAT plant for Roll, Pitch and Yaw axes.

The input reference for this simulation is a square wave and step input. Model reference was selected as:

$$y_m(t) = y_m(t-1) - 0.15y_m(t-2) + 0.15r(t-1) \quad (18)$$

where *r(t)* is a square wave reference input signal. Parameter $a_{m1} = 1$, $a_{m2} = -0.15$ and $b_m = 0.15$ have been chosen such that a desired trajectory, $y_m(t)$ is obtained for the plant output, $y_p(t)$ to follow.

Table 2: Performance comparison between ANC and APBB controllers

	ANC			APBB		
System characteristic / Axis	X	Y	Z	X	Y	Z
Rise Time (s)	5.26	6.94	6.08	5.11	3.96	5.15
Settling Time (s)	33.01	37.48	41.63	146.65	Not settle	146.11
Percentage Overshoot (%)	8.37	12.03	5.26	129.83	164.44	129.34

The step response of the system between ANC and APBB controllers are shown in Figure 4. From the figure, the performance comparisons between the ANC and APBB controllers for all axes were computed and are as presented in Table 2. It can be observed that the performances of ANC for all axes are significantly better than the APBB controller in terms of settling time and percentage of overshoot. In terms of rise time, APBB controller shows good performance compared to ANC. However, output response of APBB controller has a long settling time and percentage of overshoot is more than 100%. For Pitch axis, output response of APBB controller is worst where it cannot converge at the end of time. Figure 5 shows the square wave output response of both controllers with unity gain. The figure illustrates that ANC controller produced better result than APBB controller for all axes.

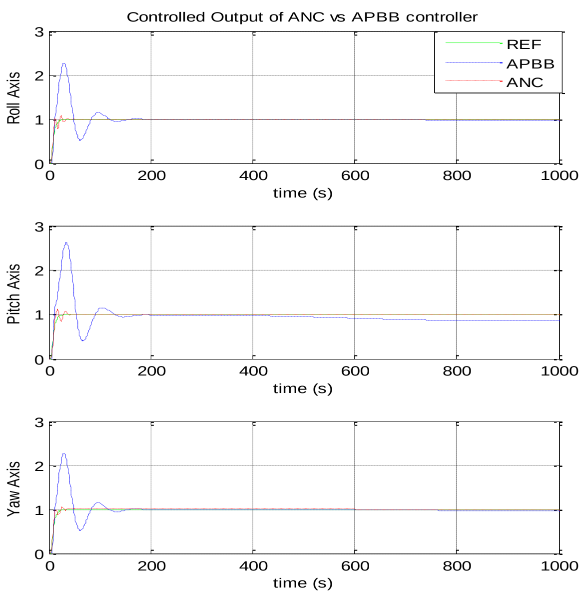

Figure 4. Step response of ANC and APBB controllers for unity gain

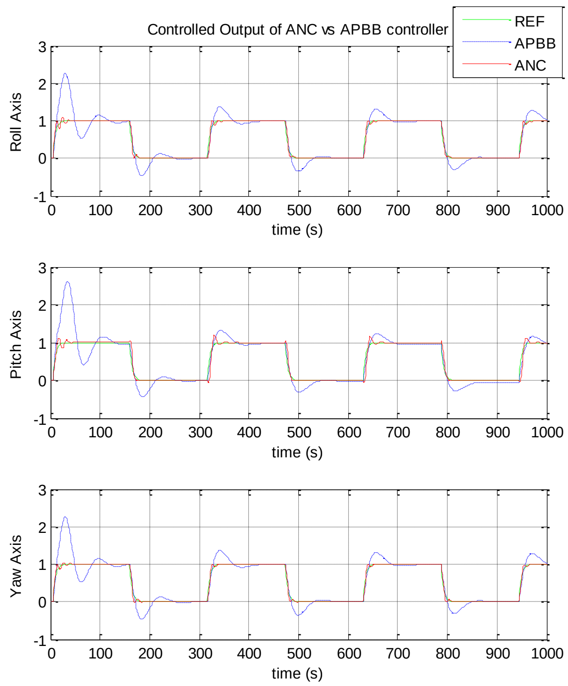

Figure 5. Comparison results with unity gain

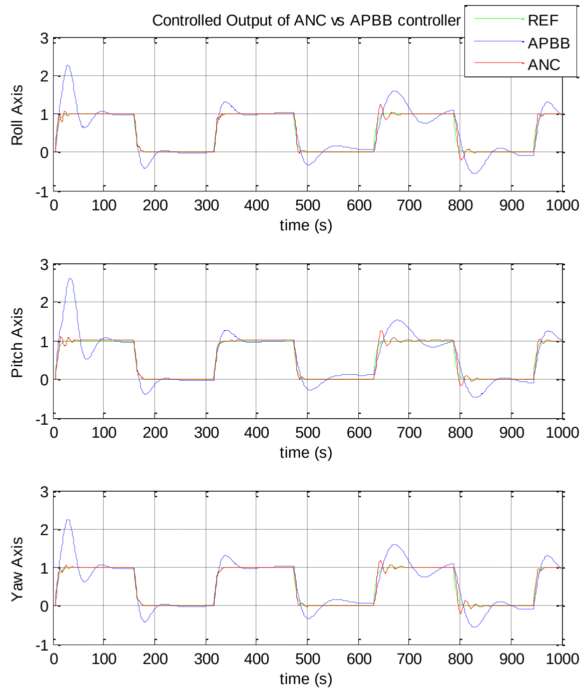

Figure 6. Comparison results with varying gain

As illustrate in Figure 6, the output response of ANC and APBB controllers with varying gain asymptotically follows the model reference output at the high gain. However, the output response of ANC slightly degrades with small oscillations at the low gain while output response for APBB controller is even worst for all axes.

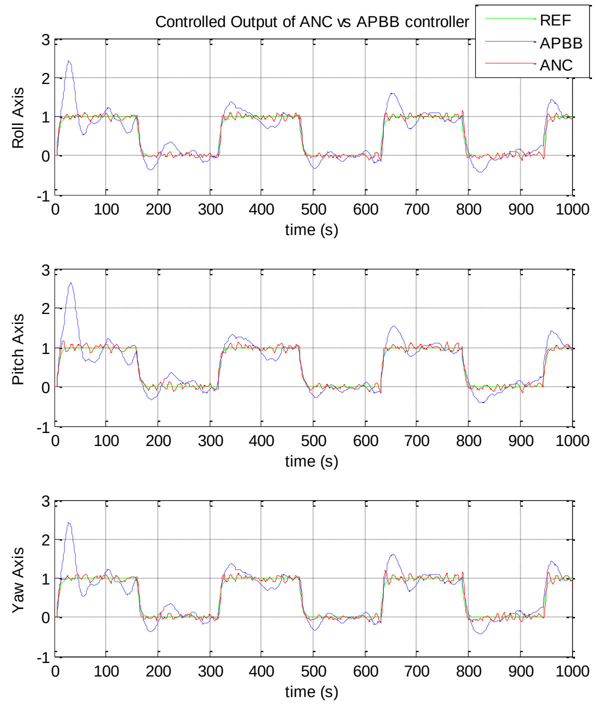

Figure 7. Comparison results with measurement noise

Figure 7 shows the system is subjected to measurement noise. The output response of ANC and APBB controllers can follow the reference model response very well despite of the significant noise but overshoot of APBB controllers for every cycle is quite high.

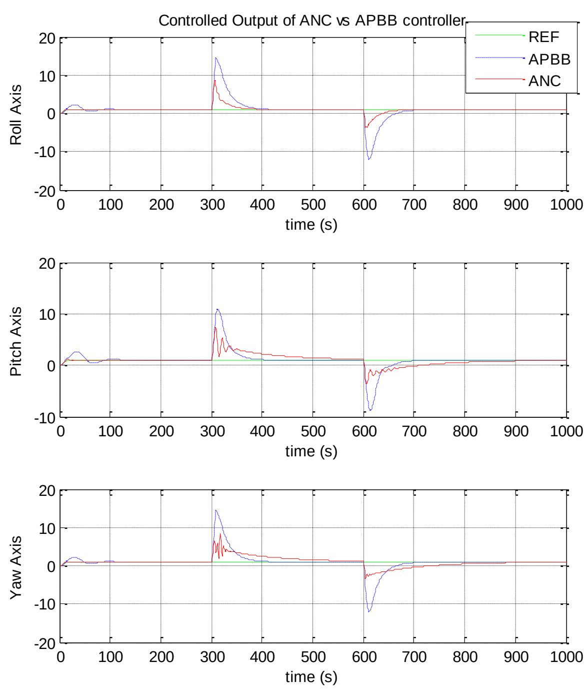

Figure 8. Comparison results with step disturbance

Figure 8 shows the output response for both controllers when the step disturbance with strength of 5% was introduced between 300s and 600s**.** From the figure, it can be observed that both controllers can handle the disturbance very well and can converge after certain time. However, the output response of APBB controller has high overshoot after the disturbance occur compared to ANC. From the output response, it is clear that performance of ANC is significantly better than APBB controller for all axes when dealing with disturbance.

5. Conclusions

An adaptive neuro-controller based on hybrid multi layered perceptron network for the Innovative Satellite plant has been presented. Its performance was compared to a adaptive parametric black box to control three-axes of InnoSAT attitude. The comparison is based on the time response performance and the capability of the controllers to track the model reference output. The results show that ANC provides significantly faster settling time with reduced overshoot and has improved the efficiency of the attitude stabilization. Based on the simulation results and performance analysis for both controllers, it can be concluded that the ANC based on HMLP network is sufficient to control the plants with unpredictable conditions such as varying gain, measurement noise and disturbance torque. It is also observed that ANC based on HMLP network is controllable and more stable than APBB controller.

Acknowledgment

The authors would like to thank Astronautic Technology (M) Sdn. Bhd., Malaysia who provides some information and advice for this work. We also gratefully acknowledge and thank the Ministry of Higher Education (MOHE) and Universiti Malaysia Perlis for providing the financial support under Fundamental Research Grant Scheme (FRGS) and Short-term Grant respectively**.**

References

[1] A. Yusoff, N. Hamzah and A. B. Arshad, “Announcement of Opportunity, Malaysia Universities Innovative Satellite,” Astronautic Technology (M) Sdn. Bhd., pp. 1-21, 2009.
[2] M. J. Sidi, Spacecraft Dynamics and Control, Cambridge University Press, 2001.
[3] J. R. Wertz, Spacecraft Attitude Determination and Control, Holland: Kluwer Academic Publishers, 1978.
[4] M. Yaakob, “Development of an Attitude Control System for InnoSAT Satellite,” M.S. Thesis, School of Mechatronic Engineering, University Malaysia Perlis, 2011.
[5] M. I. Martinelli and R. S. S. Pena, “Passive 3 axis attitude control of MSU-1 pico-satellite,” Acta Astronautica, vol.56, pp. 507–517, 2005.
[6] N. Sivaprakash and J. Shanmugam, “Neural Network Based Three Axis Satellite Attitudes Control Using Only Magnetic Torquers,” Proceeding of the 24th Digital Avionics Systems Conference, October 2005.
[7] M. L. Psiaki, “Magnetic torquer attitude control via asymptotic periodic linear quadratic regulation,” Journal of Guidance, Control, and Dynamics, vol. 24, pp. 386-393, Mar. 2001.
[8] K. L. Makovec, “A Nonlinear Magnetic Controller for Three-Axis Stability of Nanosatellites,” M.S. Thesis, Virginia Polytechnic Institute and State University, Blacksburg, Virginia, July 2001.
[9] F. Martel, P. K. Pal, and M. L. Psiaki, “Active magnetic control system for gravity gradient stabilized spacecraft,” Proceeding of the 2nd Annual AIAA/USU Conference on Small Satellites, Utah State University, USA, 1988.
[10] S. H. Zak, Systems and Control, Oxford University Press, 2003.
[11] K. KrishnaKumar, S. Rickard, and S. Bartholomew, “Adaptive neuro-control for spacecraft attitude control,” Journal Neuro-computing, pp. 131-148, 1995.
[12] A. R. Mehrabian and M. B. Menhaj, "A real-time neuro-adaptive controller with guaranteed stability," Applied Soft Computing, vol. 8, pp. 530-542, 2008.
[13] J. Rajasekaran, A. Chunodkar, and R. Padhi, "Structured model-following neuro-adaptive design for attitude maneuver of rigid bodies," Control Engineering Practice, vol. 17, pp. 676-689, 2009.
[14] S. M. Sharun, M. Y. Mashor, M. N. Norhayati, S. Yaacob, and W. N. W. Jaafar, “Adaptive neuro-controller for satellite attitude control,” Proceeding of the 4th International Conference of Postgraduate Education, Kuala Lumpur, Malaysia, November 2010.
[15] S. M. Sharun, M. Y. Mashor, M. N. Norhayati, S. Yaacob, and W. N. W. Jaafar, “Performance comparison between adaptive neuro-controller and adaptive parametric black box controller,” Proceeding of International Conference on Computer Applications & Industrial Electronics, Kuala Lumpur, Malaysia, December 2010.
[16] R.M. Mokthar and M.Y. Mashor, “An Approach By Fuzzy-Neural Network For Nonlinear System Identification,” Proceeding of the International Conference on Artificial Intelligence in Engineering & Technology, Sabah Malaysia, pp. 249-254, 2002
[17] M.Y. Mashor, “Indirect Model Reference Parametric Adaptive Controller”, Proceeding of the International Conference on Control, Instrumentation and Mechatronics Engineering, Johor Bahru, Malaysia, 2007.
[18] G. Cybenko, “Approximations by superposition of a sigmoidal function,” Mathematics of Control, Signals and Systems 2, pp. 303–314, 1989.
[19] K. Funashashi, “On the approximation realization on continuous mappings by neural networks,” Neural Network 2, pp. 182-192, 1989.
[20] M. Y. Mashor, “Hybrid Multilayered Perceptron Network,” International Journal of System Science, vol. 31, pp. 771-785, 2000.
[21] N. A. M. Isa and W. M. F. W. Mamat, “Clustered-Hybrid Multilayer Perceptron network for pattern recognition application,” Journal of Applied Soft Computing, vol. 11, pp. 1457-1466, 2010.
[22] K.J. Astrom and B. Witternmark, Adaptive Control, 2nd Ed. Lund Institute of Technology, Sweeden: Addison-Wesley Publishing Company, Inc.1995.

Siti Maryam Bt. Sharun
M. Edu (UTM, Malaysia) B. Eng. Computer Technology (UTM, Malaysia). Currently pursuing PhD in Mechatronic Engineering. Fields of interest are Artificial Intelligent and Control System.

Prof. Dr. Mohd. Yusoff Mashor
Ph.D (Sheffield, UK), M.Sc (Sheffield, UK). Fields of interest are Artificial Intelligence, System Identification, Control System, Image Processing, Bio-Medical. Currently he is a Professor at School of Mechatronic Engineering, University Malaysia Perlis.

Prof. Dr. Sazali Yaacob
Ph.D (Control Engineering) (Sheffield, UK), M.Sc. (System Engineering) (Surrey, UK), B.Eng. (Hons) (Electrical Engineering) (UM, Malaysia), C.Eng.MIEEE. Field of interest are AI Applications, Control Theory, Acoustic.