NANO-SATELLITE ATTITUDE CONTROL SYSTEM BASED ON ADAPTIVE NEURO-CONTROLLER

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

[1]*School of Mechatronic Engineering, Universiti Malaysia Perlis, Malaysia,* siti_mrym@ymail.com
[2]*Institute of Engineering Mathematics, Universiti, Malaysia Perlis, Malaysia,* hadani@unimap.edu.my

ABSTRACT. The current research focuses on designing of an intelligent controller for attitude control system (ACS) of nano-satellite. The nano-satellite namely Innovative Satellite (InnoSAT) was organized by Agensi Angkasa Negara (ANGKASA) to attract the interest of Malaysian universities in satellite development. In this study, an intelligent controller based on Hybrid Multi Layered Perceptron (HMLP) network was developed. The network used model reference adaptive control (MRAC) system as a control scheme to control a time varying systems where the performance specifications are given in terms of a reference model. The Weighted Recursive Least Square (WRLS) algorithm will adjust the controller parameters to minimize error between the plant output and the model reference output. The objective of this paper is to analyze the tracking performance of ANC based on HMLP network and ANC based on standard MLP network for controlling a satellite attitude. The simulation results indicate that ANC based on HMLP network gave better performance than ANC based on standard MLP network.

Keywords: Intelligent controller, Hybrid Multi Layered Perceptron, nano-satellite

INTRODUCTION

Small satellites become more popular in the last few decades due to their relative simplicity resulting in an attractive short period of design and in low cost (Bushenkov, 2002 & Martinelli & Pena, 2005). Beginning in 1999, California Polytechnic State University and Stanford University developed the CubeSat specifications to help universities worldwide to perform space science and exploration. A CubeSat is a type of miniaturized satellite for space research that usually has the size of 10cm x10cm x10cm, volume of exactly 1 liter, weighs no more than 1 kilogram, and typically uses commercial, off-the-shelf electronics components (Gregory, 2004). InnoSAT consists of a few CubeSats stacked together, which carries a few payloads designed by Astronautic Technology Sdn. Bhd. (ATSB) and Malaysian Universities. Attitude Control System (ACS) is part of the attitude determination and control system payload. The ACS fully operates as a three-axis attitude stabilization control system. Attitude refers to the coordinate for satellite movement in space where the coordinate are the data for x, y and z axes. The data are the main information to evaluate the movement of the satellite (Yaakop *et al*., 2009). The usual ACS used in small or large satellites includes several kinds of sensors, actuators and an on-board computer that processes the data through a control algorithm (Martinelli & Pena, 2005).

In satellite attitude control system, a few approaches have been developed by using neural network (Krishnakumar *et al*., 1995; Hao *et al*., 2004; Talebi & Patel, 2005; & Sivaprakash & Shanmugam, 2005). A development of an intelligent real time control system based on neural network is possible for the satellite in space that is exposed to non-probabilistic uncertainties such as sun flare and time dependant noises in measurement (Zak, 2003).A few comparisons performance have been done between adaptive neuro-controller based on HMLP network and other controllers. The results show that ANC based on HMLP network give significant improvement in the performance of controlling unstable system (Sharun *et al*., 2010a; Sharun *et al*., 2010b & Sharun *et al*., 2010c). In this current study, the advantages of HMLP network and the WRLS algorithm are combined to improve the performance of tracking control technique in varying operating conditions such as noise, varying gain and disturbance torques.

MODEL OF SATELLITE

Since InnoSAT model is dealing with second-order systems, some damping control must also be provided to improve stability. Thus 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 (Sidi, 2001):

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

The Euler angles $\emptyset$, θ 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. I_x, I_y and I_z are the moments of inertia for satellite body. These are second order linear differential equations of the Eulers angles. The Laplace Transform of the Roll, Pitch and Yaw axes from Eq. 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 Eq. 3:

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

DESIGN SCHEME OF ADAPTIVE NEURO-CONTROLLER

Model Reference Adaptive Control System

Mashor (2007) proposed the model reference adaptive control (MRAC) system as shown in Figure 1. 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 desired system performance in the sense of the closed-loop stability, adaptive laws are used to update the controller parameter.A stable linear continuous-time reference model is specified by the following differential equation (Mashor, 2007):

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

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, which is the controlled system is expected to acquire. The model following error is defined by:

$$e(t) = y_m(t) - y_p(t) \tag{5}$$

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

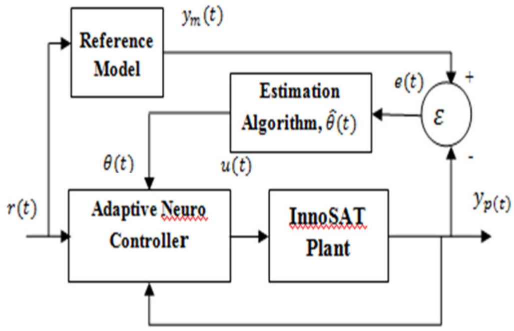


Figure 1. Block diagram of a model reference adaptive control (MRAC) system.

Figure 2. One_hidden_layer HMLP network

Hybrid Multi Layered Perceptron Network

Hybrid Multi Layered Perceptron (HMLP) network has been proposed by Mashor (2000). It has been selected as the basis for the ANC in this current study. A HMLP network with one hidden layer is shown in Figure 2.The network allows the network inputs to be connected directly to the output nodes with some weighted connections to form a linear system (dotted line connections) in parallel with the original nonlinear system from the standard MLP model (continuous line connection). These additional linear input connections do not significantly increase the complexity of the MLP network since the connections are linear. Simple RLS algorithm will be used to train the network since the parameters of the network appeared linearly within the network model. In this paper, both controllers used weighted recursive least square (WRLS) algorithm as a mechanism to adjust the controller parameters. Detail explanations about WRLS algorithm could be found in (Astrom, 1995).

The HMLP network with one hidden layer can be expressed by the following equation:

$$\hat{y}_k(t) = \sum_{j=1}^{n_h} w_{jk}^2\, F\left(\sum_{i=1}^{n_i} w_{ij}^1 x_i^0(t) + b_j^1\right) + \sum_{i=0}^{n_i} w_{ik}^l\, x_i^0(t); \tag{6}$$

$$for\ 1 \le j \le n_h\ and\ 1 \le k \le m$$

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 x_i^0 denote the thresholds in the hidden nodes and inputs that are supplied to the input layer respectively. The number of output node, 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:

$$F\big(v(t)\big) = \frac{1}{1+e^{-v(t)}} \tag{7}$$

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:

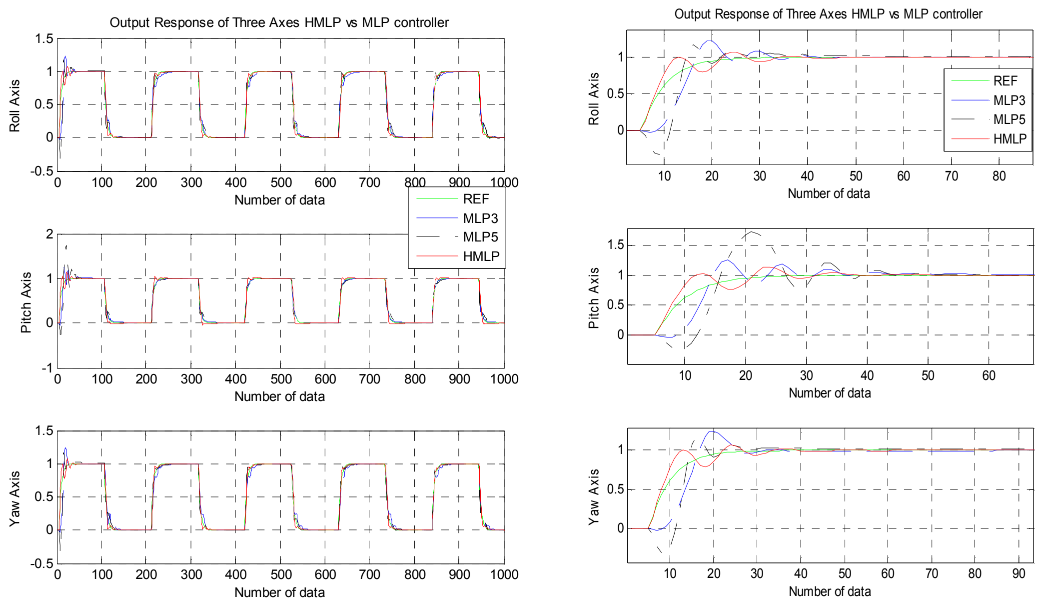
$$\varepsilon_k(t) = y_k(t) - \hat{y}_k(t) \tag{8}$$

where $y_k(t)$ and $\hat{y}_k(t)$ are the actual and the network output.

RESULTS AND DISCUSSIONS

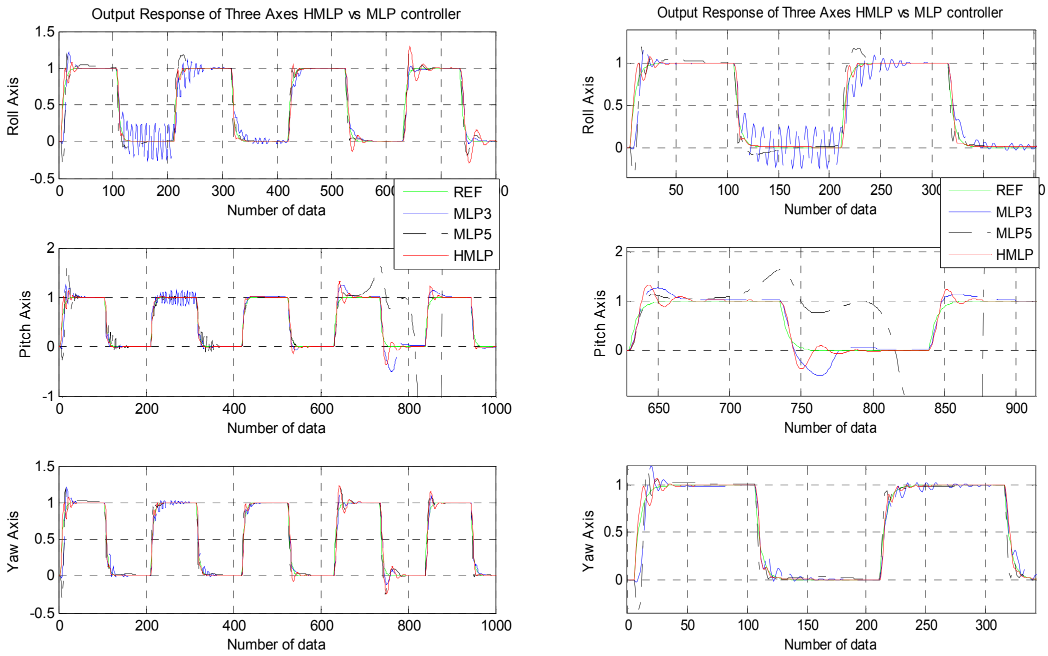
With the same number of input, hidden and output nodes, the HMLP network will have extra weights that are equal to the number of input nodes. Equation for calculating number of weight can be referred to Mashor (2000). To be fair for this ANCs comparison, the MLP network with extra hidden node is also considered. Therefore, HMLP network will be assigned to have 3 hidden nodes whereas MLP network with 5 hidden nodes is also considered for comparison. So that, HMLP network with 3 hidden nodes (HMLP) will have 35 weights, MLP network with 3 hidden nodes (MLP3) will have 27 weights and MLP with 5 hidden nodes (MLP5) will have 45 weights. Thus, in this ANCs comparison the MLP network with 5 hidden nodes will have extra weight over the HMLP network with 3 hidden nodes.

By referring to Figure 3(a), the output response at unity gain for all axes shows that the ANC controllers can track smoothly the model reference. However, MLP controllers possess delay time and undershoot which make it taking longer time to converge as shown in Figure 3(b). Figure 4(a) and (b) shows the output response of ANC controllers at varying gain where HMLP controller asymptotically follows the desired response at the high gain but degrades with small oscillations at the low gain. Meanwhile, output response of MLP controllers is even worst especially for Pitch axis where it has divergence output response. Figure 5 shows the response of the system when a step disturbance was introduced between 300s and 600s. Output response from HMLP controller for all axes is better than output response from the MLP controllers because it able to converge in a shorter time after disturbance. Meanwhile, MLP controllers have divergence output response for Roll and Yaw axes.



(a) **(b)**

Figure 3. (a) Output response of ANC's controller with unity gain. (b) After they have been zoomed.



(a) **(b)**

Figure 4. (a) Output response of ANC's controller with varying gain. (b) After they have been zoomed.

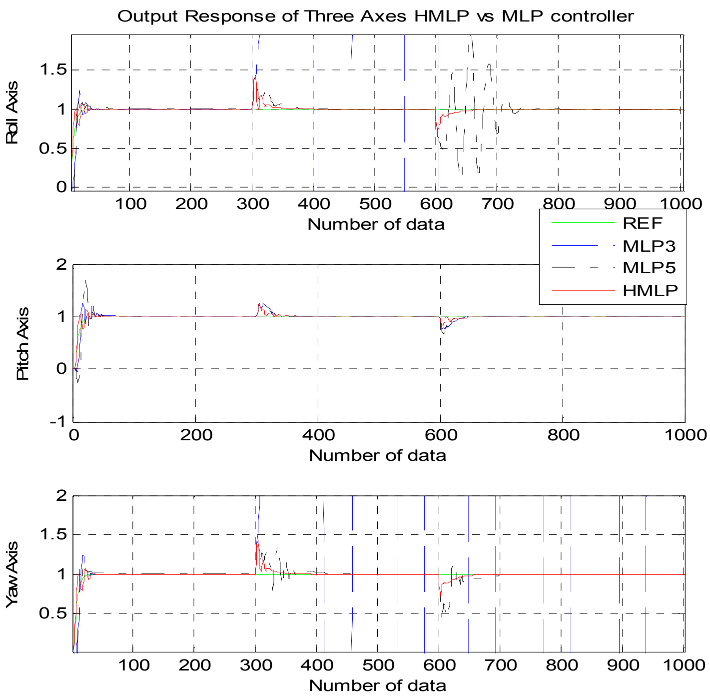


Figure 5. Output response of ANC's controller with step disturbance

CONCLUSIONS

On the above analyzing, simulation results of ANC based on HMLP network and ANC based on standard MLP network are compared for satellite attitude control of InnoSAT plant. The comparison is based on the capability of the controlled output tracking the model reference. The simulated data were used for the comparison. From Figure 3 to 5, it is observed that performance of the HMLP controller was improved from both MLP controllers in terms of tracking the model reference output. The simulation results signify that the ANC based on HMLP network is sufficient to control the plants with unpredictable conditions and disturbances. It was observed that ANC based on HMLP network is controllable and more stable than standard MLP network with more hidden nodes.

REFERENCES

Astrom, K. J., & Witternmark B. (1995). *Adaptive Control, 2nd Ed*. Lund Institute of Technology, Sweeden: Addison-Wesley Publishing Company, Inc.

Bushenkov, V. A. (2002). Attitude stabilization of a satellite by magnetic coils. *Journal of Acta Astronautica*, vol. 50, no. 12, pp. 721–728.

Gregory, B. S. (2004). *Attitude control system for ION, The Illinois Observing Nanosatellite*. M. S. Thesis, Faculty of Electrical Engineering, University of Illinois.

Hao, H., Sun, Z., & Zhang, Y. (2004). Fault diagnosis on satellite attitude control with dynamic neural network. *State Key Lab of Intelligent Technology and Systems*, Dept. of Computer Science & Technology, Tsinghua University.

Krishnakumar, K., Rickard, S., & Bartholomew, S. (1995). Adaptive neuro-control for spacecraft attitude control. *Journal Neuro-computing*, pp. 131-148.

Martinelli, M. I., & Pena, R. S. S. (2005). Passive 3 axis attitude control of MSU-1 pico-satellite. *Journal of Acta Astronautica*, vol.56, pp. 507 – 517.

Mashor, M. Y. (2007). Indirect Model Reference Parametric Adaptive Controller. *International Conference on Control, Instrumentation and Mechatronics Engineering,* Johor Bahru, Malaysia.

Mashor, M. Y. (2000). Hybrid Multilayered Perceptron Network. *International Journal of System Science*, vol. 31, pp. 771-785.

Sharun, S. M., Mashor, M. Y., Jaafar, W. N. W., Norhayati, M. N., Yaacob, S., & Yaakob, M. (2010a) Performance comparison between HMLP and MLP network using RLS algorithm. *International Postgraduate Conference on Engineering*, Perlis, Malaysia.

Sharun, S. M., Mashor, M. Y., Jaafar, W. N. W., Yaacob, S., & Norhayati, M. N. (2010b). Performance comparison between adaptive neuro-controller and adaptive parametric black box controller. *International Conference on Computer Applications & Industrial Electronics*, Kuala Lumpur, Malaysia.

Sharun, S. M., Mashor, M. Y., Jaafar, W. N. W., Yaacob, S., & Norhayati, M. N. (2010c). Adaptive neuro-controller for satellite attitude control. *4th International Conference of Postgraduate Education*, Kuala Lumpur, Malaysia.

Sidi, M. J. (2001). *Spacecraft Dynamics and Control*. Cambridge University Press.

Sivaprakash, N., and Shanmugam, J. (2005). Neural network based three axis satellite attitude control using only magnetic torques. *24th Digital Avionics Systems Conference*.

Talebi, H. A., & Patel, R. V. (2005). Neural network-based fault detection scheme for satellite attitude control systems. *IEEE Conference on Control Applications*, Toronto, Canada.

Yaakop, M., Yaacob, S., Saad, A. R. M., & Harihran, M. (2009). Development of attitude control system on RCM3400 microcontroller. *Conference on Innovative Technologies in Intelligent Systems and Industrial Applications*, Kuala Lumpur, Malaysia.

Zak, S. H. (2003). *Systems and Control*. Oxford University Press.