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PERFORMANCE COMPARISON BETWEEN ADAPTIVE NEURO-CONTROLLER AND PID CONTROLLER FOR SATELLITE ATTITUDE CONTROL

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Abstract—In this paper, an intelligence controller namely Adaptive Neuro-controller (ANC) based on Hybrid Multilayered Perceptron (HMLP) network is developed for the attitude control of a nano-satellite. The neural network is using Model Reference Adaptive Control (MRAC) as a control scheme. The control scheme was used to control a time varying systems where the performance specifications are given in terms of a reference model. Weighted Recursive Least Square (WRLS) algorithm has been used to adjust the controller parameters to minimize the error between the actual output and the model reference output. The convergence rate of the ANC is further improved by using WRLS as the adjustment parameter. The objective of this paper is to compare the time response and tracking performance between artificial intelligence controller and conventional Proportional-Integral-Derivative (PID) controller in orientation control system of a satellite attitude. These controllers have been tested using a nano-satellite plant with some variations in operating conditions such as varying gain, noise and disturbance torques. The simulation results indicated that ANC based on HMLP network gave significant improvement over PID controller.

Keywords: Adaptive Neuro-controller, Hybrid Multilayered Perceptron, Model Reference Adaptive Control, Weighted Recursive Least Square, Proportional-Integral-Derivative

1. INTRODUCTION

Generally, most of the smallest satellites are less expensive to develop and build than the dedicated missions required by conventional satellites. Development of conventional satellite needs capital and expertise intensive and requiring multi-year development. Thus, severely limiting participation by science and engineering students. The reasonably low cost of space research projects and engineering development of satellites less than 10 kg has attracted some 80 educational institutions around the world to this field [1, 2].

The attitude control system (ACS) is the main sub-system in satellite development. The requirements of ACS are decided by the payload of the satellite as given in [3, 4]. The usual ACS used in small or large satellites includes several kinds of sensors, actuators and an onboard computer. On board computer processes the data through a control algorithm which is specially designed for the particular mission [5]. In order to allow precise pointing of an antenna toward the Earth and to allow direct solar panels toward the Sun, a satellite must maintain a certain attitude while in orbit. The satellite receives interference from phenomena such as the Earth's gravitation, airflow, magnetic fields, and the solar wind. This makes it necessary to control attitude to maintain the satellite's stability [6]. There are three basic types of satellite control systems. The first one is a spin control where the entire satellite is spun. The next one is a dual-spin control where the major portion spun while only the payload despun. Finally, the last basic type of satellite control system is a three-axis active control where the major part of satellite despun [7].

One of the most important issues in satellite control design is the attitude stabilization and control, which is the combination of mathematics, dynamics, and control theories. Intelligent controllers could be utilized for this problem. Intelligent controllers do not base on models, whereas traditional controllers are based on the precondition that the whole dynamics can be accurately modelled. As a result, numerous intelligent controllers such as adaptive neuro- controller have been proposed to replace the traditional ones [8]. Developing intelligent controller for satellites attitude control aims at dealing with the large variation of system parameters and relevant uncertainties in the environment [9]. The ability to adapt to variations in plant dynamics and environment automatically has made such adaptive controllers increasingly important for various applications.

Neural networks have been proven to be capable of approximating any real continuous functions on a compact set to arbitrary accuracy. It is very powerful techniques in the discipline of systems control, especially when the controlled systems have large uncertainties and strong non- linearities. Therefore, neural network have been extensively employed in the attitude control [10]. The advantages of neural network controllers are they can provide a 'black box' controller which can be re-trained for other applications. It is also can adapt to change in the uncertainty conditions; and provide 'soft' failure characteristics and nonlinear control laws [11].

For satellite attitude control system, a few approaches by using neural network have been developed [12–15]. Mehrabian [16] proposed a model reference adaptive neuro-controller using feed-forward neural networks with momentum back-propagation (MBP) learning algorithm. This controller was utilized to control a nonlinear system. However, it needs some tuning of parameters requiring a few trails and error to be properly selected. Rajasekaran [17] developed a structured model-following Neuro Adaptive control. From simulation studies, this adaptive controller is found to be very effective in executing precise large attitude maneuvers in the presence of uncertainties and constant disturbances. However, some of the other practical issues such as sensitivity to noise, actuator time delays, time varying disturbance torques and robustness to un-modelled dynamics have not being addressed in the paper.

In this current study, the advantages of HMLP network and the WRLS algorithm are combined to improve the performance of time response and tracking control technique in varying operating conditions such as noise, varying gain and disturbance torques. The performance of the ANC was compared to conventional PID controller.

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 accurate enough, the subsequent steps of analysis, prediction, control, synthesis and so on, cannot successful be carried out. Model should provide information at the most relevant level of precision and, 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 [18].

In this paper, the mathematical model of the plant is an Innovative Satellite (InnoSAT). InnoSAT is based on the basic unit known as CubeSat. A CubeSat is a type of miniaturized satellite for space research that usually has the size of 10cm x 10cm x 10cm, volume of exactly 1 liter, weighs no more than 1 kilogram, and typically uses commercial, off-the-shelf electronics components. Beginning in 1999, California Polytechnic State University and Stanford University developed the CubeSat specifications to help universities worldwide to perform space science and exploration [19]. InnoSAT is a nano class satellite and consists of three CubeSats stacked together, which carries a few payloads designed by a few Malaysian Universities. InnoSAT education package consists of the CubeSAT kit structure measuring 30cm x 10cm x 10cm.

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 behaviour of a satellite in space after deployment and used to study the performance aspects of satellite behaviour 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 [3]

$$\begin{aligned} T_{dx} + T_{cx} &= I_x\ddot{\phi} \\ T_{dy} + T_{cy} &= I_y\ddot{\theta} \\ T_{dz} + T_{cz} &= I_z\ddot{\psi} \end{aligned} \quad (1)$$

These are second order linear differential equations of the Eulers angles. The Euler angles ϕ, θ and ψ are defined as the rotational angles about the satellite body axes: ϕ, about the X axis; θ, about the Y axis; and ψ, about the Z axis. $T_c^{'}s$, 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. From Eq.(1) it easily follows that

$$\begin{aligned} \ddot{\phi} &= \frac{T_{dx}}{I_x} + \frac{T_{cx}}{I_x} \\ \ddot{\theta} &= \frac{T_{dy}}{I_y} + \frac{T_{cy}}{I_y} \\ \ddot{\psi} &= \frac{T_{dz}}{I_z} + \frac{T_{cz}}{I_z} \end{aligned} \quad (2)$$

By Laplace-transforming the Eq.(2), the characteristic equation for the motion about the Roll, Pitch and Yaw axes are become

$$\begin{aligned} s^2\phi_{(s)} - s\phi_{(0)} - \dot{\phi}_{(0)} &= \frac{T_{dx}}{I_x} + \frac{T_{cx}}{I_x} \\ s^2\theta_{(s)} - s\theta_{(0)} - \dot{\theta}_{(0)} &= \frac{T_{dy}}{I_y} + \frac{T_{cy}}{I_y} \\ s^2\psi_{(s)} - s\psi_{(0)} - \dot{\psi}_{(0)} &= \frac{T_{dz}}{I_z} + \frac{T_{cz}}{I_z} \end{aligned} \quad (3)$$

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 ($\phi_{(0)}, \theta_{(0)}, \psi_{(0)}$) are assumed to be zero. Consequently, the transfer function of InnoSAT model for Roll, Pitch and Yaw axes equation are simplified as Eq.(4)

$$\begin{aligned}
\phi_{(s)} &= \left[\frac{T_{dx}}{I_x} + \frac{T_{cx}}{I_x} + \dot{\phi}_{(0)}\right] / s^2 \\
\theta_{(s)} &= \left[\frac{T_{dy}}{I_y} + \frac{T_{cy}}{I_y} + \dot{\theta}_{(0)}\right] / s^2 \\
\psi_{(s)} &= \left[\frac{T_{dz}}{I_z} + \frac{T_{cz}}{I_z} + \dot{\psi}_{(0)}\right] / s^2 \qquad (4)
\end{aligned}$$

3. DESIGN SCHEME OF ADAPTIVE NEURO CONTROLLER

3.1. Model Reference Adaptive Control

In model reference adaptive control (MRAC), a reference model is chosen to generate the desired output trajectory, and the main task of MRAC is to ensure the output of the controlled system to follow the output of the reference model, in addition to closed-loop stability. Adaptive laws are used to update the controller parameters to achieve desired system performance in the sense of closed-loop stability and output tracking of a desired reference output [20, 21]. Unlike the conventional adaptive control schemes, the control scheme in Figure 1 does not estimate the plant parameters but directly estimate the controller parameters [22].

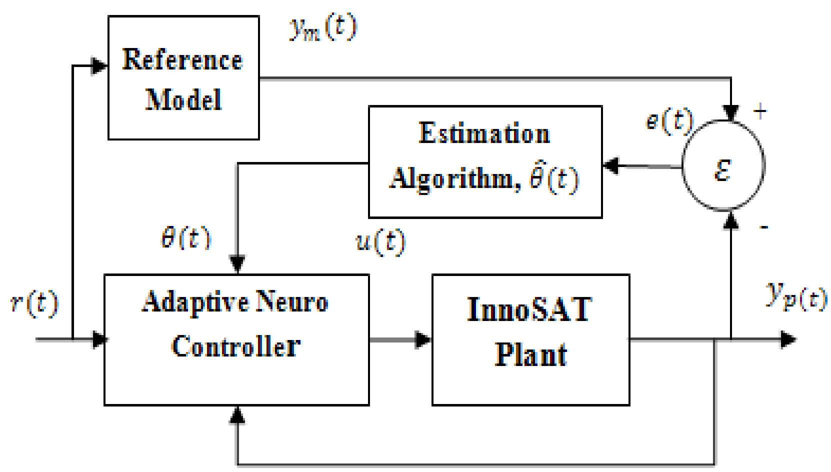


Figure 1: Block diagram of a model reference adaptive control scheme (MRAC)

The MRAC objective is met if $u(t)$ is chosen so that the close loop transfer function from $r(t)$ to $y_p(t)$ have stable poles and is equal to $y_m(t)$, the transfer function of the reference model. A stable linear continuous-time reference model is specified by the following differential equation [22]

$$y_m(t) = a_{m_1} y_m(t-1) - a_{m_2} y_m(t-2) + b_{m_0} r(t-1) + b_{m_1} r(t-2) \qquad (5)$$

where $r(t)$ is bounded reference input and $y_m(t)$ is reference model output; a_m and b_m are fixed model parameters and their values are chosen for any desired stable response, which the process system is expected to acquire. Thus, the MRAC desired to design a controller that computes a control action signal, such that the overall control system responds dynamically as the specified reference model. The model following error is defined by

$$e(t) = y_m(t) - y_p(t) \tag{6}$$

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

3.2. Hybrid Multi Layered Perceptron (HMLP) Network

Artificial neural networks (ANN) model was inspired from the morphology of biological neural system and organization of brain structures; attempt to emulate human-like performance. Among the many ANN models, the multilayer perceptron (MLP) is the most widely used. The MLP network is a variant of multilayer feedforward neural network. It can be trained to form arbitrary decision surfaces in the input space. However, the training process of multilayer perceptron takes a large computation time and often leads to local minima problem [11, 23].

To solve this problem, MLP network with linear connection, called the Hybrid Multilayer Perceptron (HMLP) network was introduced which was proved to have better performance than the conventional MLP network [24]. It has been selected as the basis for the ANC in the current study. The network allows the network inputs to be connected directly to the output nodes via some weighted connections to form a linear model in parallel with the nonlinear original MLP model. These additional linear input connections do not significantly increase the complexity of the MLP network since the connections are linear. It has been proved that HLMP network only requires very small number of neurons to perform the control action. Simple RLS algorithm was used to train the network since the parameters of the network are appear linearly within the network model. Thus, the HMLP network with a simple RLS algorithm can be selected to be implemented as an Adaptive Neuro-controller.

A HMLP network with one hidden layer is shown in Figure 2. It can be expressed by the following equation

$$\hat{y}_k(t) = \sum_{j=1}^{n_h} w_{jk}^2 F\left(\sum_{i=1}^{n_i} w_{ij}^1 v_i^0(t) + b_j^1\right) + \sum_{i=0}^{n_i} w_{ik}^l v_i^0(t) \tag{7}$$

for $1 \leq k \leq m$, 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 v_i^0 denote to 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

$$F\left(v(t)\right) = \frac{1}{1 + e^{-v(t)}} \tag{8}$$

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

$$\varepsilon_k = y_k(t) - \hat{y}_k(t) \tag{9}$$

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

3.3. Estimation Algorithm

The least square algorithm is one of the most used parameter estimator. Basically, the algorithm minimizes the cost function of the controlled output. The corrective adjustments are designed to make the output signal approach to the desired response. The recursive least squares algorithms,

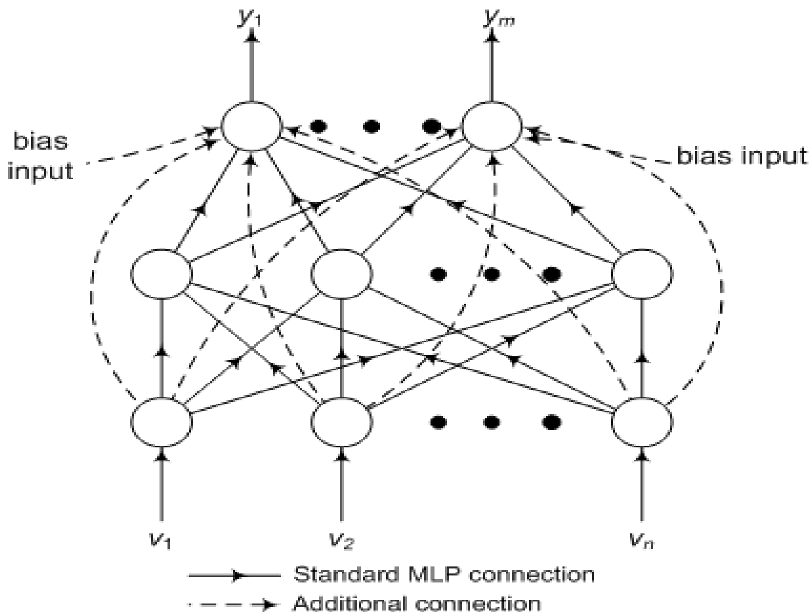


Figure 2: Hybrid Multi Layered Perceptron Network

when applied to parameters or state estimation, presents two advantages: avoids matrix inversion in the presence of uncorrelated measurement errors; and needs smaller matrices sizes, which means less need of memory storage [25]. In order to deal with parameter varying plant, a weighted recursive least square (WRLS) will be used. Some modifications are required for WRLS algorithm to able to estimate the controller parameters instead of the conventional estimation of plant parameters.

For all $t \geq t_0$, given $\hat{\Theta}(t_0)$ and set $P(t) = \alpha[\mathbf{I}]$, the WRLS estimate $\hat{\Theta}(t)$ using the following recursive equations [22]

$$\begin{aligned} \hat{\Theta}(t) &= \hat{\Theta}(t-1) + K(t)\left[y(t) - \varphi^{\top}(t)\hat{\Theta}(t-1)\right] && (10) \\ K(t) &= P(t-1)\varphi(t)\left[\lambda(t)\mathbf{I} + \varphi^{\top}P(t-1)\varphi(t)\right]^{-1} && (11) \\ P(t) &= \left[\mathbf{I} - K(t)\varphi^{\top}(t)\right]P(t-1)/\lambda(t) && (12) \end{aligned}$$

Equation (10) need to be modified to become

$$\hat{\Theta}(t) = \hat{\Theta}(t-1) + K(t)e(t-1) \tag{13}$$

where e is the difference between plant output and reference input. $\varphi(t)$ is the information vector that consists of the controller inputs and $\hat{\Theta}(t)$ is the vector of controller parameters. Other symbols are defined and assigned according to the standard WRLS algorithm as in [26]. Another modification that is required to speed up the learning process is by resetting the covariant matrix $P(t)$ and forgetting factor $\lambda(t)$, if the model following error becomes significantly large. The resetting is based on the following equation

$$\begin{aligned} P(t) &= 10[\mathbf{I}] \\ \lambda(t) &= 0.95 && (14) \end{aligned}$$

4. PID CONTROLLER

PID controller is the most widely used conventional controllers. The acronyms of PID stand for proportional-integral-derivative control. The gains of proportional, integral and derivative control have to be tuned and fixed throughout the control simulation. Generally, proportional control is used to reduce the rise time, integral control is used to reduce the steady state error and derivative control is to improve the transient response. PID can work well for first and second order system but for system with long time delays, large uncertainties and harmonic disturbances a more sophisticated control is needed [27].

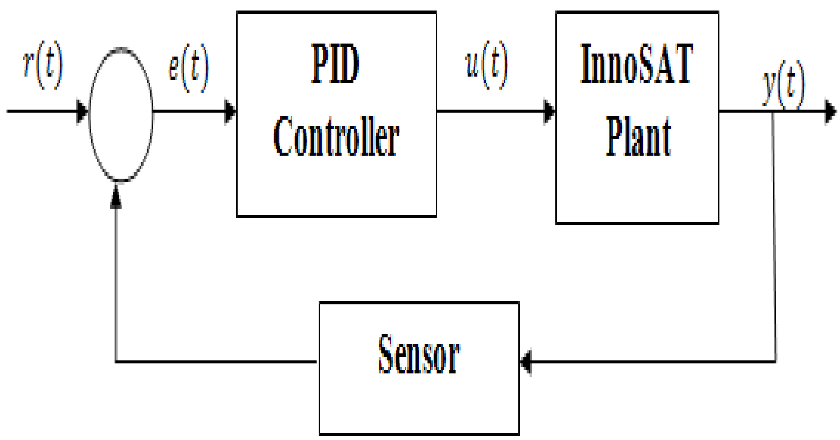


Figure 3: Block Diagram of PID Controller

A discrete PID controller is shown in Figure 3 [28], where it is defined by relationship between the error signal $e(t)$ and the control output signal, $u(t)$. The error signal is used to generate the proportional, integral, and derivative actions, with the resulting signals weighted and summed to form the control output signal. The output of the PID controller in terms of gain can be written as [3]

$$u(t) = K_p * err(t) + K_d * Derr(t) + K_i * Terr(t) \tag{15}$$

K_p = proportional gain; K_i = integral gain; K_d = derivative gain

The error signal $err(t)$ represents the difference of actual orientation angle $y(t)$ and the reference model $r(t)$. The proportional control multiplies the error $err(t)$ by a gain K_p, the derivative control multiplies the different of error $Derr(t)$ by a gain K_d to reduce the overshoot and the rise time, and the integral control multiplies the total of error $Terr(t)$ by a gain K_i to correct the steady state error.

5. RESULTS AND DISCUSSION

In this section, simulation results of InnoSAT plant are presented. The simulation results were produced for the controllers using some operating conditions such as varying gain, noise and disturbance. The performances of the controllers will be evaluated based on time response and tracking performance in response to the model reference output. The effectiveness of the proposed ANC based on HMLP network is compared to conventional PID controller. 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 @ 0.6274 deg/s
Initial angular velocity $\dot{\emptyset}_o$	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

The transfer function for Roll, Pitch and Yaw axes after substituting the parameter value of InnoSAT are become

$$\phi(s) = \frac{30.58T_{dx} + 30.58T_{cx} + 5}{s^2} \tag{16}$$

$$\theta(s) = \frac{20.08T_{dy} + 20.08T_{cy} + 5}{s^2} \tag{17}$$

$$\psi(s) = \frac{30.21T_{dz} + 30.21T_{cz} + 5}{s^2} \tag{18}$$

For this comparison, the InnoSAT plants can be described by a difference equation of the discrete form

$$\begin{aligned} x(t) &= 2 * x(t-1) - x(t-2) + K_p(t) * 15.29 * (u_{sx}(t-1) + u_{sx}(t-2)) \\ &+ 15.29 * (u_{dx}(t-1) + u_{dx}(t-2)) \end{aligned} \tag{19}$$

$$\begin{aligned} y(t) &= 2 * y(t-1) - y(t-2) + K_p(t) * 10.04 * (u_{sy}(t-1) + u_{sy}(t-2)) \\ &+ 10.04 * (u_{dy}(t-1) + u_{dy}(t-2)) \end{aligned} \tag{20}$$

$$\begin{aligned} z(t) &= 2 * x(t-1) - x(t-2) + K_p(t) * 15.1 * (u_{sz}(t-1) + u_{sz}(t-2)) \\ &+ 15.1 * (u_{dz}(t-1) + u_{dz}(t-2)) \end{aligned} \tag{21}$$

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

$$y_m(t) = y_m(t-1) - 0.15y_m(t-2) + 0.15r(t-1) \tag{22}$$

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. The cost functions for model following was set to

$$e_m(t) = 0.7e(t) + 0.2\Delta e(t) \tag{23}$$

where $e(t)$ is the proportional error and $\Delta e(t)$ is the differential error.

The time response of the system with ANC and PID controllers are shown in Figure 4. The gains for the PID controller were tuned to the best performance for fixed plant parameters, which are $K_p = 0.095$, $K_d = 0.07$ and $K_i = 0.009$. Figure 4 shows that at early stage ANC produced faster response compare to PID controller for Roll and Pitch axis, even though the PID controller already have the best tuning gains. The figure also shows that overshoot of PID controller is higher than ANC controller especially for Y axis with overshoot more than 25%. In terms of settling time, the output response of ANC controller is slightly better than PID controller. The numerical analysis for time response of ANC and PID controller can be referred to Table 2 - Table 4.

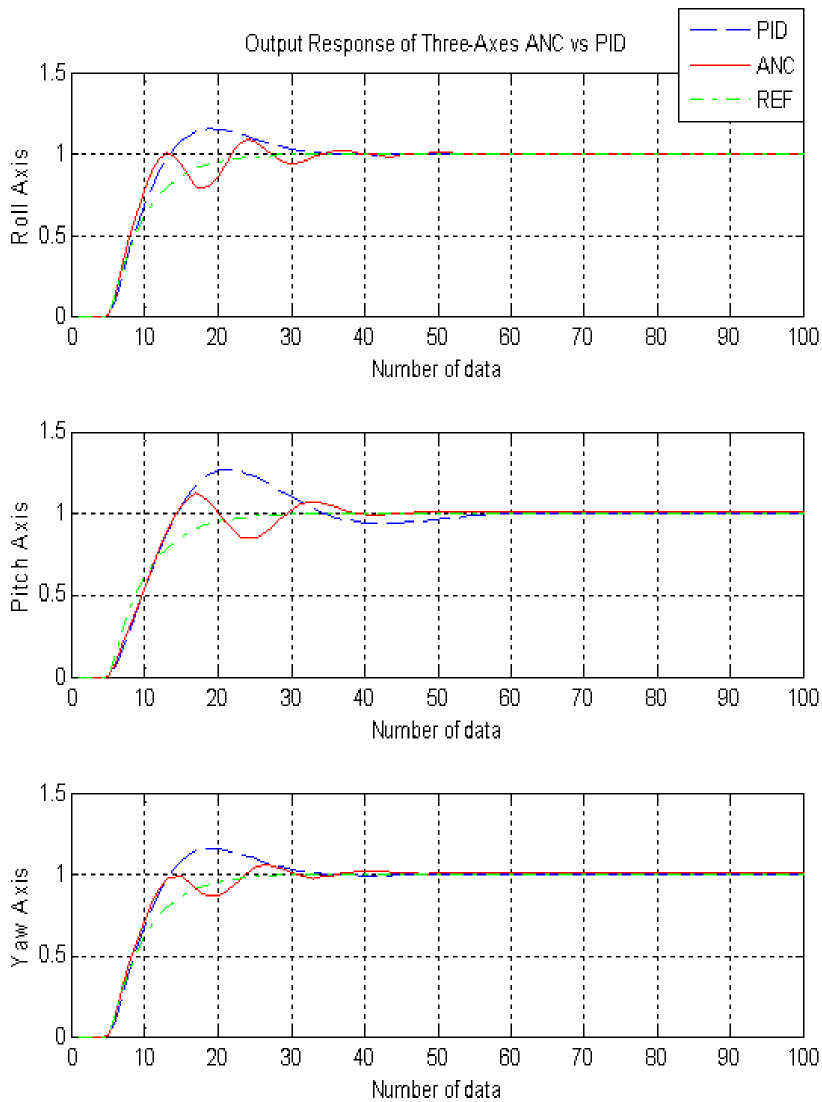
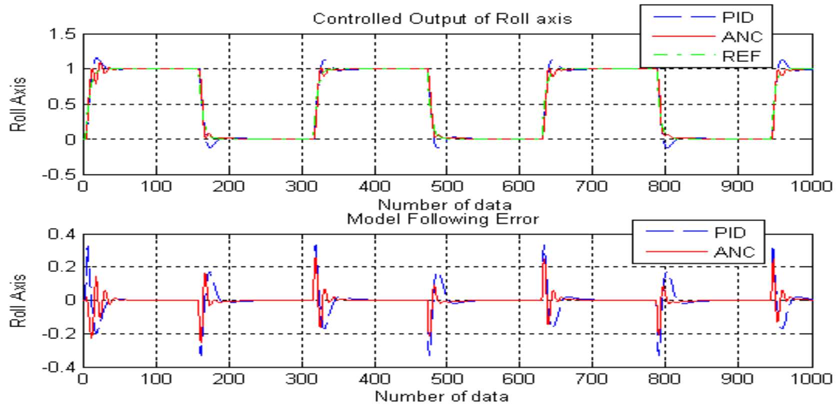
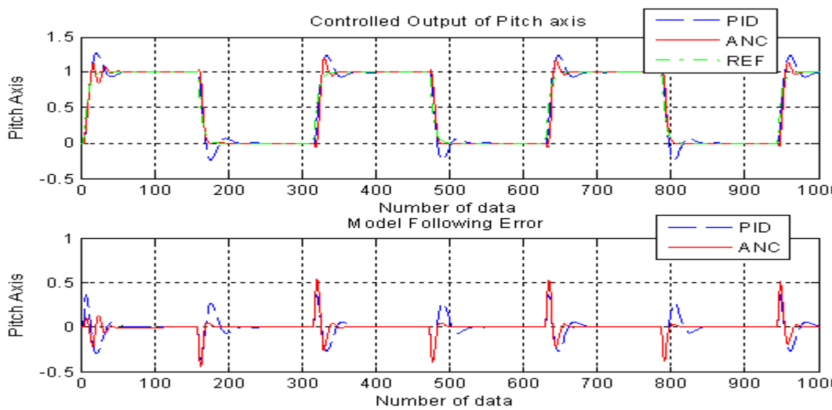


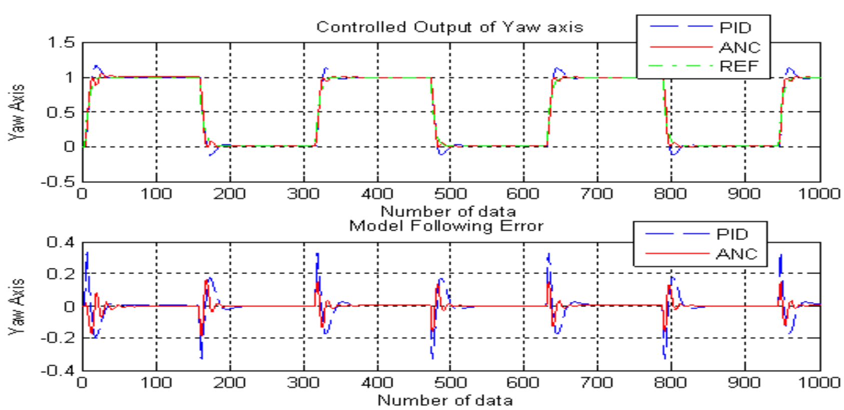
Figure 4: Step response of ANC and PID controllers for unity gain



(a)



(b)



(c)

Figure 5: Comparison results with unity gain for (a) Roll, (b) Pitch and (c) Yaw axis

Based on Figure 5(a), (b) and (c), the simulation results show that ANC significantly provides faster response time with reduced overshoot while the PID controller continuously has the same pattern of overshoot for all cycle. This can be proved by model following error figure showed at each axis. The performances comparison system between the ANC and PID controllers were computed and compared in Table 2 to Table 4. It can be observed that the performances of ANC for all axes are better than the PID controller in terms of percentage of overshoot and rise time. In terms of settling time, PID controller shows good performance compare to ANC but only at the first cycle for Roll and Yaw axes. On the other hand, output response of PID has a long settling time and percentage of overshoot is more than 25% for Pitch axis. For ANC controller, overshoot at the first cycle is quite bad during the initial learning but it can reduce the overshoot until 0% especially for Roll and Yaw axis. It shows that the controller can adapt with the dynamic of the system.

Table 2: Performance comparison between ANC and PID controllers for Roll Axis

System Characteristics	ANC			PID
	1st cycle	2nd cycle	3rd cycle	All cycle
Rise time (Tr)	5.26 s	5.55 s	5.71 s	6.05 s
Settling time (Ts)	37.74 s	28.97 s	28.51 s	31.08 s
Percent Overshoot	8.65 %	1.28 %	0 %	15.37 %

Table 3: Performance comparison between ANC and PID controllers for Pitch Axis

System Characteristics	ANC			PID
	1st cycle	2nd cycle	3rd cycle	All cycle
Rise time (Tr)	6.96 s	5.04 s	5.37 s	6.84 s
Settling time (Ts)	37.33 s	30.14 s	29.95 s	52.92 s
Percent Overshoot	11.76 %	19.58 %	16.16 %	26.90 %

Table 4: Performance comparison between ANC and PID controllers for Yaw Axis

System Characteristics	ANC			PID
	1st cycle	2nd cycle	3rd cycle	All cycle
Rise time (Tr)	6.10 s	6.48 s	6.55 s	6.07 s
Settling time (Ts)	42.14 s	20.52 s	20.41 s	31.12 s
Percent Overshoot	5.30 %	0.73 %	0.61 %	15.68 %

The simulation results for operating conditions such as varying gain, noise and disturbance are shown in Figure 6, 8 and 10. As illustrate in Figure 7, the output response for all axes of ANC and PID controller asymptotically follows the desired response at the high gain. However, the output response of ANC degrades with small oscillations at the low gain while output response for PID controller is even worst.

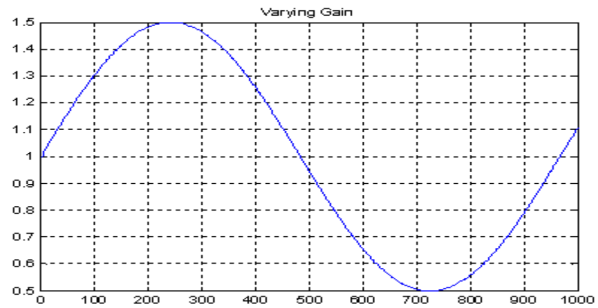
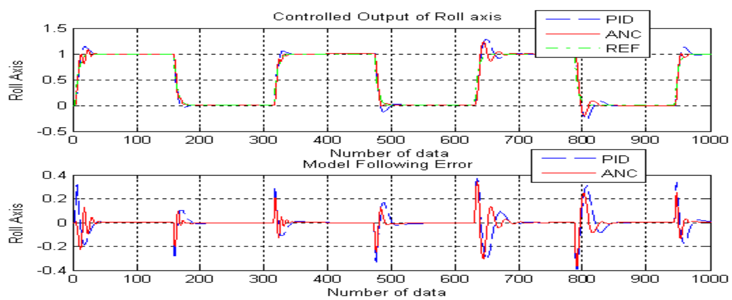
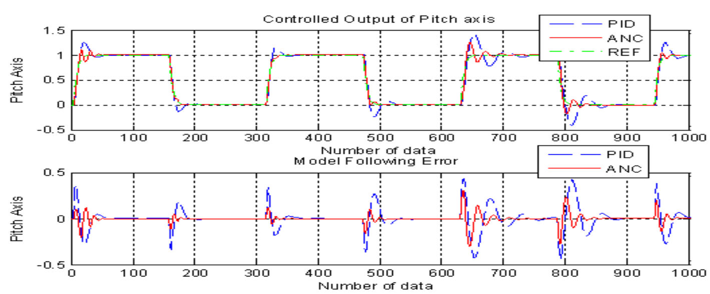


Figure 6: Varying gain



(a)



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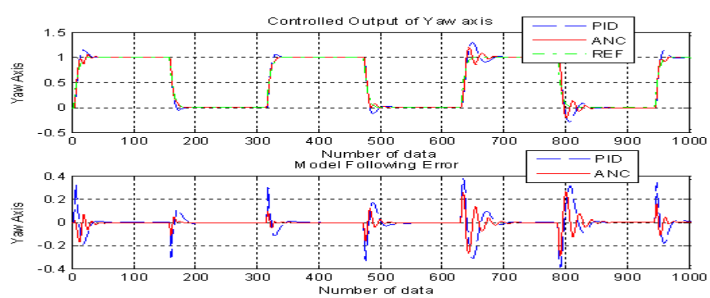

(c)

Figure 7: Comparison results with varying gain for (a) Roll, (b) Pitch and (c) Yaw axis

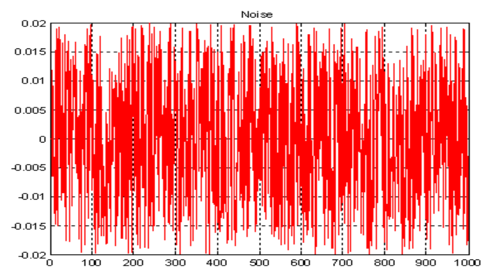

Figure 8: Additive noise at the plant output

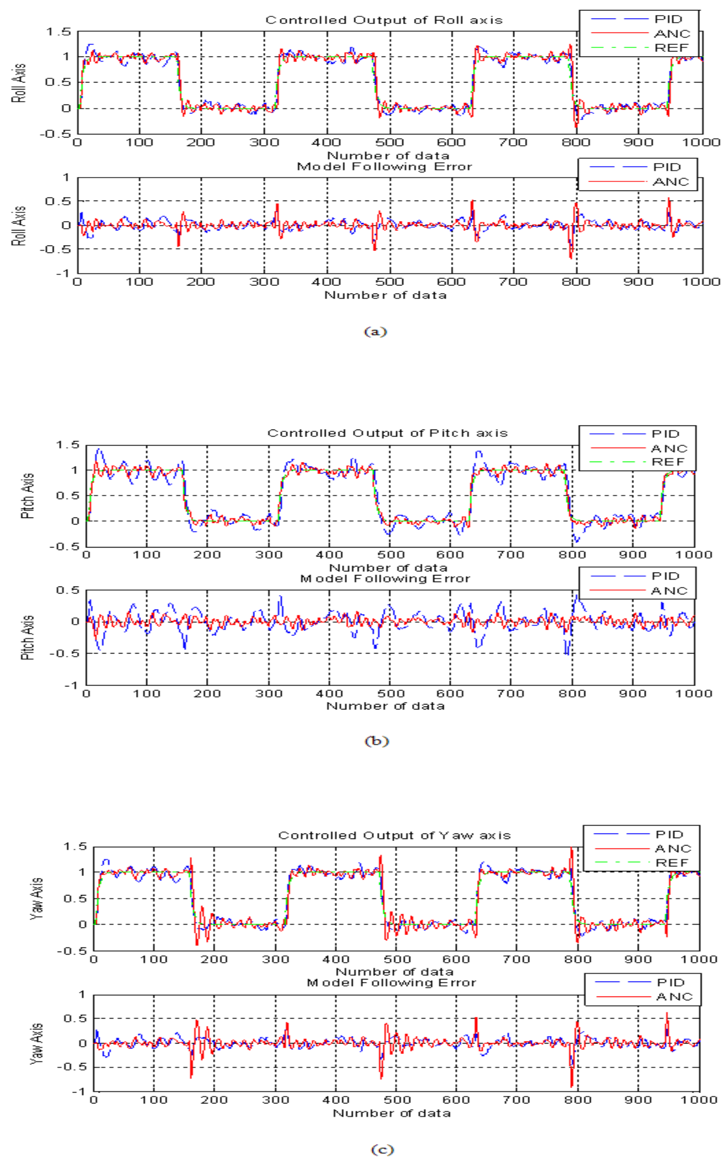

Figure 9: Comparison results with measurement noise for (a) Roll, (b) Pitch and (c) Yaw axis

Figure 9(a), (b) and (c) shows the system is subjected to measurement noise known as Gaussian white noise sequence with zero mean and variance 0.00013. For these figures, it is rather difficult to distinguish the performance between the ANC and PID controllers. This is because the plots show that the PID controller can produce result as good as the ANC controller. For Pitch axis, output response of ANC is slightly better than PID controller but the response for the Roll and Yaw axes are degraded. Based on the model following error figure, the error cannot be eliminated from the system but the average of error is about 0. It also can be observed that the simulation results for ANC and PID controllers are capable to follow the output of reference model and remain stable under measurement noise.

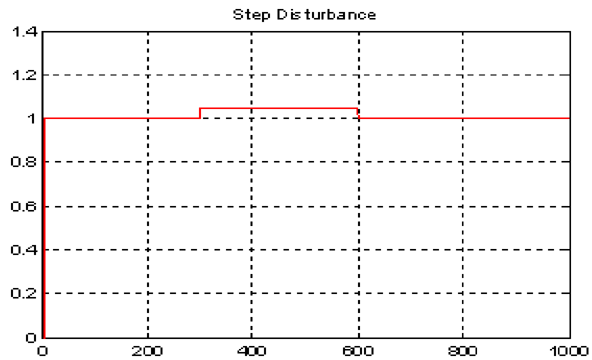

Figure 10: Step disturbance of 0.05 between 300 s to 600 s

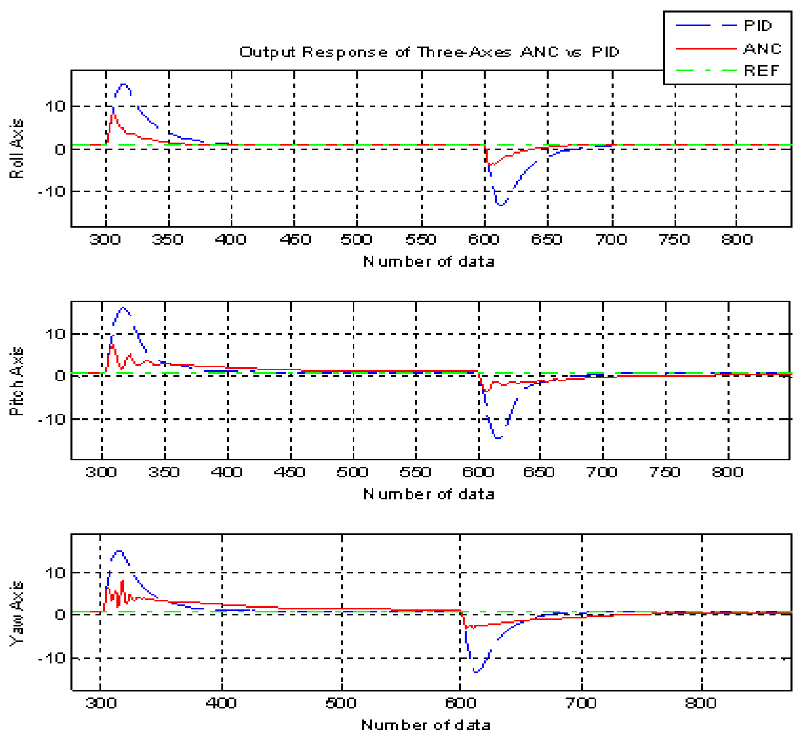

Figure 11: Output response of ANC and PID controllers with step disturbance

From the simulation result in Figure 11, it can be said that the ANC can improve the efficiency of attitude stabilization better than the classical controller, PID. When step disturbance with strength 0.05 is added to the system at 300s and 600s, the percentage of overshoot for PID controller is higher than ANC controller. The figure also shows that the output response for both controllers settle to a steady state rapidly when the satellite encounters disturbances. Overall, the controlled output for both controllers still follow the model reference output after certain time. It points out that performance of ANC is significantly better than PID controllers for all axes when dealing with disturbance.

6. CONCLUSIONS

An adaptive neuro-controller based on model reference adaptive control for the dynamical plants has been presented. The controller structure is a direct type and can employ the feedforward neural network such as hybrid multi layered perceptron network to compensate adaptively the parameter varying in the plant, disturbance torque and varying operating conditions. The MRAC's scheme has special characteristic of not requiring explicit identification of the process or plant parameters makes the scheme robust to the sudden plant parameter changes. Its performance was compared to a conventional PID controller to control 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 response time with reduced overshoot and its performance getting better with more simulation times while PID controller continuously has the same pattern of response. However, the output response of ANC controller is slightly degraded at certain condition (noise) for Roll and Yaw axes compared to PID controller. Based on the simulation results and performance analysis for both controllers, it can be signify that the ANC based on HMLP network is sufficient to control the plants with unpredictable conditions. It is also observed that ANC based on HMLP network is controllable and more stable than PID controller.

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REFERENCES

1. K. Woellert, P. Ehrenfreund, A.J. Ricco and H. Hertzfeld, "Cubesats: Cost-effective science and technology platforms for emerging and developing nations," *Advances in Space Research* , 47, 663–684, 2011.
2. T. Inamori, N. Sako and S. Nakasuka, "Magnetic dipole moment estimation and compensation for an accurate attitude control in nano-satellite missions," *Acta Astronautica* , 2010.
3. M.J. Sidi, *Spacecraft Dynamics and Control* , Cambridge University Press, 2001.
4. J.R. Wertz, *Spacecraft Attitude Determination and Control* , Holland: Kluwer Academic Publishers, 1978.
5. M.I. Martinelli and R.S.S. Pena, "Passive 3 axis attitude control of MSU-1 pico-satellite," *Acta Astronautica* , 56, 507–517, 2005.
6. C.H. Cheng, S.L. Shu and P.J. Cheng, "Attitude control of a satellite using fuzzy controllers," *Expert Systems with Applications* , 36, 6613–6620, 2010.
7. C. Ouchine, "Modeling and Simulation of Active Attitude Control for Satellites," *M.S. Thesis* , Faculty of Engineering, Universiti Putra Malaysia, 2004.

8. A. Gonzalez and R. Ordonez, "Adaptive Control Scheme for Plants with Time-Varying Structure Using On-Line Parameter Estimation," *IEEE Conference on Discussion and Control* , Barcelona, Dec 2005.
9. J. Zhang et al., "Application of Neuro-fuzzy Control for Satellite AOCS," *Seventh International Conference on Control, Automation, Robotic and Vision* , Singapore, Dec 2002.
10. A. M. Zou and K. Kumar, "Adaptive fuzzy fault-tolerant attitude control of spacecraft," *Control Engineering Practice* , 19, 10–21, 2011.
11. C. H. Cheng and S. L. Shu, "Application of GA-based neural network for attitude control of a satellite," *Aerospace Science and Technology* , 14, 241–249, 2010.
12. H.A. Talebi and R.V. Patel, "Neural Network-Based Fault Detection Scheme for Satellite Attitude Control Systems," Proceedings of IEEE Conference on Control Applications , Toronto, Canada, August 2005.
13. H. Hao, Z. Sun and Y. Zhang, "Fault Diagnosis on Satellite Attitude Control with Dynamic Neural Network," *Proc. of ISNN (2)* , 537–542, 2004.
14. K. KrishnaKumar, S. Rickard and S. Bartholomew, "Adaptive neuro-control for spacecraft attitude control," *Journal Neurocomputing* , 131–148, 1995.
15. N. Sivaprakash and J. Shanmugam, "Neural Network Based Three Axis Satellite Attitudes Control Using Only Magnetic Torquers," *24th Digital Avionics Systems Conference* , October 2005.
16. A.R. Mehrabian and M.B. Menhaj, "A real-time neuro-adaptive controller with guaranteed stability," *Applied Soft Computing* , 8, 530–542, 2008.
17. J. Rajasekaran, A. Chunodkar and R. Padhi, "Structured model-following neuro-adaptive design for attitude maneuver of rigid bodies," *Control Engineering Practice* , 17, 676–689, 2009.
18. R. Mohd-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, 249–254, 2002.
19. B.S. Gregory, "Attitude Control System For ION, The Illinois Observing Nanosatellite," ıM.S. Thesis , Faculty of Electrical Engineering, University of Illinois, 2004.
20. Q. Sang and G. Tao, "Gain Margin of Model Reference Adaptive Control Systems," *Proceedings of the 7th World Congress on Intelligent Control and Automation* , 2008.
21. H.D. Patino and D. Liu, "Neural Network-Based Model Reference Adaptive Control System," *Systems, Man and Cybernetics, Part B, IEEE Transactions* , 30, 198–204, 2000.
22. M.Y. Mashor, "Indirect Model Reference Parametric Adaptive Controller", *International Conference on Control, Instrumentation and Mechatronics Engineering* , Johor Bahru, Malaysia, May 2007.
23. N.A. Mat-Isa and W.M.F.W. Mamat, "Clustered-Hybrid Multilayer Perceptron network for pattern recognition application," *Journal of Applied Soft Computing* , 11, 1457–1466, 2010.
24. M.Y. Mashor, "Hybrid Multilayered Perceptron Network," *International Journal of System Science* , 31, 771–785, 2000.
25. P.C.R.P.M. Pardal, H.K. Kuga and R.V.D. Moraes, "Implications of the Application of Recursive Least Squares Algorithms to Satellite Orbit Determination Using GPS Measurements", *WSEAS Transaction on Systems* , 8(3), March 2009.
26. K.J. Astrom and B. Witternmark, *Adaptive Control* , 2nd Ed., Sweeden: Addison-Wesley Publishing Company, Inc.1995.
27. R.A. Pazm, "The Design of PID Controller," Klipsch School of Electrical and Computer Engineering, 2001.
28. M.F. Rahmat and M.M. Ghazaly, "Performance Comparison between PID and Fuzzy Logic

Controller in Position Control System of DC Servomotor," *Jurnal Teknologi* , Universiti Teknologi Malaysia, 1–17, 2006.