POSITION AND ORIENTATION CONTROL OF A MOBILE ROBOT USING INTELLIGENT ALGORITHMS BASED HYBRID CONTROL STRATEGIES

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الملخص

تم تطوير هذا البحث والتحقيق من أداء الخوارزميات الذكية من أجل تثبيت الروبوت عند تتبعه لاشارة مرجعية محددة. أحد أنواع الروبوتات هو روبوت متحرك ذو عجلتي (TWBMR) حيث يتطلب التحكم في هذا النوع من الربوت التحكم فى كلا من الموازنة والمناورة باستخدام المتحكم الهجين. ايضا في هذه الورقة تم استخدام لوغاريتمات الذكاء الاصطناعي وهى الشبكات العصبية (NN)والتحكم المنطقي الضبابي (FLC) كأدوات رئيسية لتحسين أداء نظام الروبوت غير الخطي دون استخدام أي نموذج رياضي. يتم استخدام بيانات الإدخال والإخراج الخاصة بـ TWBMR الناتجة عن نظام التحكم في الحلقة المغلقة لتكوين نموذج الشبكة العصبية الذى يحاكي النظام الاخطى للربوت. في هذه الدراسة ، يمكن تدريب نموذج الشبكات العصبية في وضع عدم الاتصال ثم نقله إلى عملية يتم فيها تنفيذ التعلم التكيفي Online باستخدام نظام الاستدلال الضبابي المتكيف ANFIS وذلك لتحسين أداء النظام. اثبتت نتائج المحاكاة من أن استراتيجيات التحكم الذكية يمكن أن تحقق أداء تحكم مناسبًا بالاضافة للحصول على نتائج دقيقة جدا حتى فى وجود بعض المؤثرات لاغير مرغوب بها.

ABSTRACT

This paper investigates the balancing and tracking control of the mobile robot using a strongly integrated controller. The two independently motorized wheels in this mechatronic system track the target reference and investigate a balancing at the gravity center above the axis of the wheels' rotation where model fluctuations and an external disruption are included in the consideration. In this work, the innovative controller is presented and tested as a coupling controller based on the notions to satisfy considered design objectives. The proposed controller depends on linking several algorithms with each other, where the integrated controller design passes through three phases that are sequential and dependent on each other. The input-output data of TWBMR generated from the closed loop control system is used to develop a neural network model. In this study, the neural networks model can be trained offline and then transferred into a process where adaptive online learning is carried out using Adaptive Network-Based Fuzzy Inference System ANFIS to improve the system performance. The simulation results verify that the considered identification and control strategies can achieve favorable control performance. The ANFIS control design approach does not require an accurate model of the plant. In addition, high-level knowledge of the system is not needed to build a set of rules for a fuzzy controller. ANFIS achieved acceptable tracking accuracy in compared to FLC. Evaluation of navigation and balance abilities for TWMR are tested with different scenarios, the designed controller is investigated to observe the behavior of the robot on various targets, and its effectiveness is validated. The most significant advantages of designed controllers are that it renders the control system insensitive to external disturbances and model uncertainty.

KEYWORDS: ANFIS; FLCA; FLCP; TWBMR; NN; LQRIC; IUI; FLC.

INTRODUCTION

Development and control of two wheeled balancing mobile robot or wheeled inverted pendulum is a popular research topic in verifying various control theories over the last decade, the motion control problem of a robot that can self-balancing on wheels has received much attention in both academic and industry worldwide. Two wheeled robot system is not only an intricate multiple-input multiple-output nonlinear system but also a kind of typical non-holonomic system with time-varying dynamics [1]. It is also a complicated coupled dynamic system with non-linear saturation dynamic characteristics [2]. In real movement, TWBMR suffers from uncertain factors, such as load change and road conditions and external interference, this will bring great difficulties to motion control for TWBMR. The control objective of the robot is to perform control motion of the wheels while stabilizing the Intermediate Body (IB) around the upright position [3]. Fuzzy logic control and Adaptive Networks based Fuzzy Inference system is designed and implemented to stabilize the neural network model of TWBMR system [4,5]. The work in this paper can be arranged as follows. In section two, the mathematical model of TWBMR is written, in section three, the system analysis is considered, the neuro model of TWBMR, fuzzy logic controller, and ANFIS is designed in section four, and finally, the conclusion is presented.

MATHEMATICAL MODEL OF TWBMR

The performance of a balancing robot depends on the efficiency of the control algorithms and the dynamic model of the system. By adopting the coordinate system shown in Figure (1) using Newtonian mechanics, it can be shown that the dynamics of the TWBMR under consideration is governed by the following equations of motion, Linear displacement of the vehicle is denoted by x, angular rotation about the y-axis (pitch) by θ, and angular rotation about the z-axis (yaw) by δ [6,7].

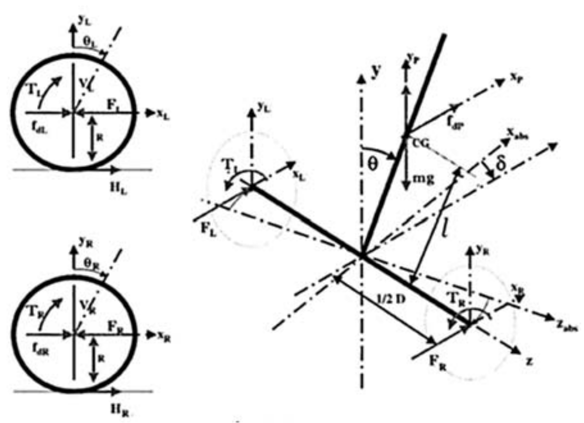


Figure 1: Diagram of forces and moments acting on the TWBMR system [6,7]

The definitions of parameters are listed in Table (1). A mechanical 3 DOF system can be modeled using six state space variables. The following variables have been chosen:

x:	position (m)	ν:	speed (m/s)	θ:	pitch angle (rad)
ω:	pitch rate (rad/s	δ:	yaw angle (rad)	$\dot{\delta}$:	yaw rate (rad/s)

Based on these parameters the state space equation for the system is obtained as [5-7]:

$$\dot{x} = \nu \qquad (1)$$

$$\dot{\nu} = \frac{T_L}{\alpha R} + \frac{T_R}{\alpha R} + \frac{F_{dL}}{\alpha} + \frac{F_{dR}}{\alpha} + \frac{f_p}{\alpha} - m\,l\cos\theta\,\left(\frac{m\,g\,l\sin\theta + f_p\;l\cos\theta}{\alpha(J_{mo}+J_{po})}\right) \qquad (2)$$

$$\dot{\theta} = \omega \tag{3}$$

$$\dot{\omega} = \frac{(m\,g\,l \sin\theta + f_p\, l \cos\theta)\left(M + m + 4M_w + \frac{2J_w}{R^2}\right)}{\beta} + \frac{m\, l \cos\theta\left(\frac{T_L}{R} + \frac{T_R}{R} + F_{dL} + F_{dR} + f_p\right)}{\beta} \tag{4}$$

$$\dot{\delta} = \Omega \tag{5}$$

$$\dot{\Omega} = \frac{D}{2}\left[\frac{\frac{T_L}{R} - \frac{T_R}{R} + F_{dL} - F_{dR}}{J_\delta + \frac{D^2}{2}\left[\frac{J_w}{R^2} + M_w\right]}\right] \tag{6}$$

With α and β are defined as following:

$$\alpha = M + m + 4M_w + \frac{2J_w}{R^2} + \left(\frac{m^2\, l^2 \cos^2\theta}{(J_{mo} + J_{po})}\right)$$

$$\beta = (J_{mo} + J_{po})\left(M + m + 4M_w + \frac{2J_w}{R^2}\right) + m^2\, l^2 \cos^2\theta$$

Table 1: Definition of system parameters [6,7]

Parameter	**Definition**
m	Mass of robot body
R	Radius of wheel
D	Distance between wheels
f_p	Disturbances applied CG
CG	Center of gravity of robot body
l	Distance between CG and wheel axis.
J_δ	Moment of inertia of chassis with respect to Y-axis
J_{mo}	Moment of inertia of chassis
J_{po}	Moment of inertia of pendulum
F_P	Horizontal force
T_L, T_R	Torques generated from the motors
θ_L, θ_R	Rotation angles of wheels
H_L, H_R	Friction forces with ground surface
F_{dL}, F_{dR}	Outside Disturbances applied to wheels
F_L, F_R	Interacting forces between wheels and chassis
J_L, J_R	Moment of inertia of left and right wheels with respect to Z-axis
M_L, M_R	Mass of each wheel

Due to small variation about operating conditions at $\theta = 0$ [5], the above equations are linearized to get the following linearized model.

$$\dot{x} = v \tag{7}$$

$$\dot{v} = \frac{T_L}{\alpha R} + \frac{T_R}{\alpha R} + \frac{F_{dL}}{\alpha} + \frac{F_{dR}}{\alpha} + \frac{(J_{mo} + J_{po}) - ml^2}{\alpha(J_{mo} + J_{po})} f_p - \frac{m^2 g\, l^2}{\alpha(J_{mo} + J_{po})}\theta \; \frac{m^2 g\, l^2}{\alpha(J_{mo} + J_{po})}\theta \tag{8}$$

$$\dot{\theta} = \omega \tag{9}$$

$$\dot{\omega} = \frac{\left(\frac{mlT_L}{R} + \frac{mlT_R}{R} + mlF_{dL} + mlF_{dR}\right)}{\beta} + \frac{(mg\, l\theta + f_p l)\left(M + m + 4M_w + \frac{2J_w}{R^2}\right) + ml\, f_p}{\beta} \tag{10}$$

$$\dot{\delta} = \Omega \tag{11}$$

$$\dot{\Omega} = \frac{D}{2}\left[\frac{\frac{T_L}{R}-\frac{T_R}{R}+F_{dL}-F_{dR}}{J_\delta+\frac{D^2}{2}\left(\frac{J_w}{R^2}+M_w\right)}\right] \tag{12}$$

The above general state-space representation of a continuous LTI system can be expressed in the following form:

$$\begin{bmatrix}\dot{x}\\ \dot{v}\\ \dot{\theta}\\ \dot{\omega}\\ \dot{\delta}\\ \ddot{\delta}\end{bmatrix} = \begin{bmatrix}0 & 1 & 0 & 0 & 0 & 0\\ 0 & 0 & x_{23} & 0 & 0 & 0\\ 0 & 0 & 0 & 1 & 0 & 0\\ 0 & 0 & x_{43} & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 1\\ 0 & 0 & 0 & 0 & 0 & 0\end{bmatrix}\begin{bmatrix}x\\ v\\ \theta\\ \omega\\ \delta\\ \dot{\delta}\end{bmatrix} + \begin{bmatrix}0 & 0 & 0 & 0 & 0\\ y_{21} & y_{22} & y_{23} & y_{24} & y_{25}\\ 0 & 0 & 0 & 0 & 0\\ y_{41} & y_{42} & y_{43} & y_{44} & y_{45}\\ 0 & 0 & 0 & 0 & 0\\ y_{61} & y_{62} & y_{63} & y_{64} & 0\end{bmatrix}\begin{bmatrix}T_L\\ T_R\\ F_{dL}\\ F_{dR}\\ f_p\end{bmatrix} \tag{13}$$

Where

$x_{23} = -\frac{m^2 g\, l^2}{\alpha(J_{mo}+J_{po})}$, $x_{43} = \frac{\left(M+m+4M_w+\frac{2J_w}{R^2}\right)mgl}{\beta}$, $y_{21} = y_{22} = \frac{1}{R\alpha}$, $y_{23} = y_{24} = \frac{1}{\alpha}$

$y_{25} = \frac{(J_{mo}+J_{po})-m\, l^2}{\alpha(J_{mo}+J_{po})}$, $y_{41} = y_{42} = \frac{ml}{R\beta}$, $y_{43} = y_{44} = \frac{ml}{\beta}$, $y_{45} = \frac{\left(M+m+4M_w+\frac{2J_w}{R^2}\right)l+ml}{\beta}$

$y_{61} = \frac{D}{2R}\left[\frac{1}{J_\delta+\frac{D^2}{2}\left(\frac{J_\omega}{R^2}+M_\omega\right)}\right]$, $y_{62} = -\,y_{61}$, $y_{63} = \frac{D}{2}\left[\frac{1}{J_\delta+\frac{D^2}{2}\left(\frac{J_\omega}{R^2}+M_\omega\right)}\right]$, $y_{64} = -\,y_{63}$

ANALYSIS OF THE SYSTEM

However, before discussing control system design, the following section will cover the conversion process from state-space to transfer function representation and conduct an open-loop analysis of the system for each input. Multiple-input multiple-output (MIMO) systems require one transfer function for every input to output combination. Interactive User interface (IUI) design is the process of making interfaces in software or computerized devices with a focus on looks or style. Designers aim to create designs users will find easy to use and pleasurable. IUI design typically refers to graphical user interfaces (GUI) but also includes others, such as voice-controlled ones. In this section, we will design an Interactive User Interface for the users of TWBMR that simplify and implement control system theories through the simulation. The IUI implemented through a MATLAB program with designed user function, which computes transfer function matrixes (TFM), root-locus, bode plot and state-space model with a full-state output. This program generates a menu of choices for user input as shown in Figure (2), which reduced the effort and simplify the mathematical calculation [6,7]. Additionally, Figure (3) shows the simulated results for the TWBMR open loop response to a step and impulse input.

Figure 2: Interactive user interface design for TWBMR

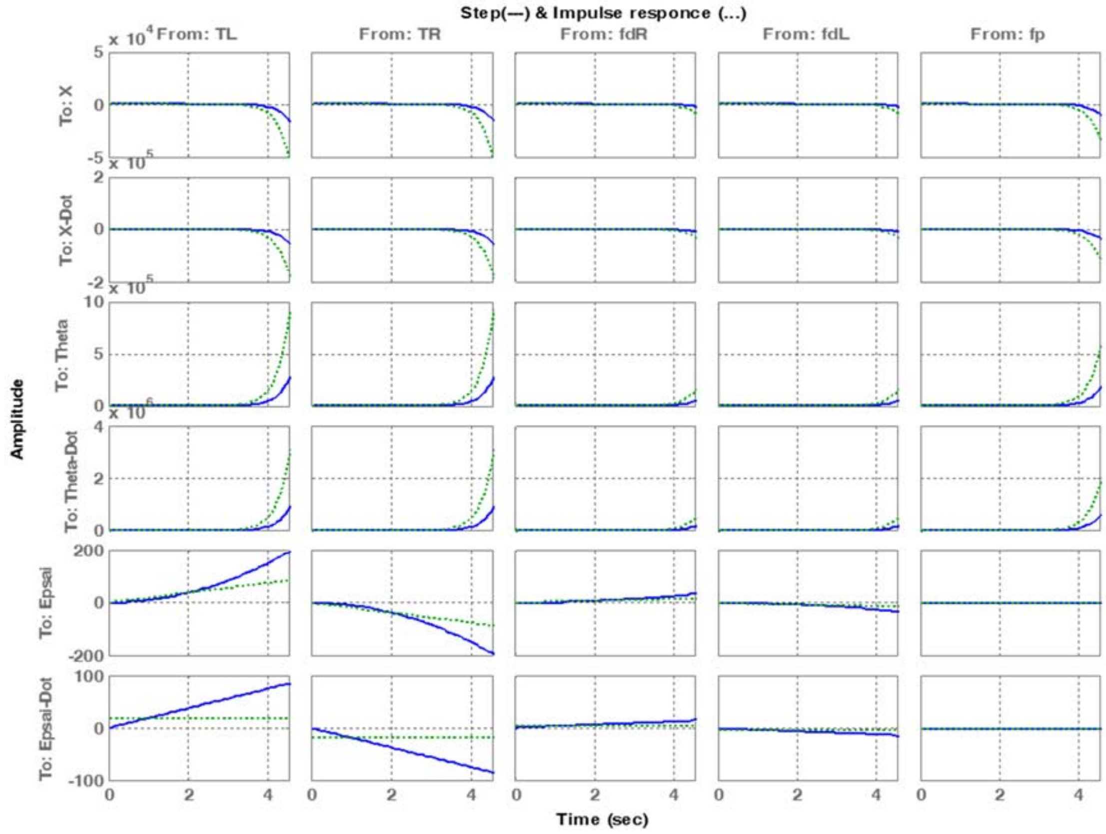


Figure 3: Open loop unit step and impulse response of the transfer function matrix

Control Design Approaches for the TWBMR

The core idea of the integrated controller design for TWMR in this work is based on the overlapping phases that shown in Figure (4).

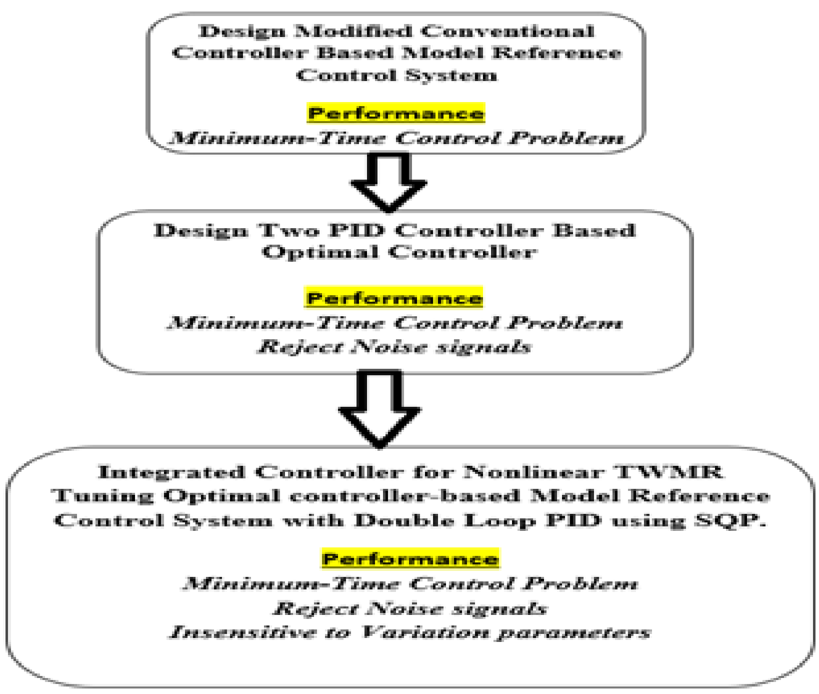


Figure 4: Strategy of integrated controller design for TWBMR [9]

In stage one LQR is designed with an IC-based reference control system (LQRIC Based MRCS). Stage two, a dual-loop parallel control of PID-based LQRIC (PCDL-PID) is designed, and in the final stage in this design, the sequential quadratic programming (SQP) is used to set parameters of the final designed control [7,8].

Stage One: Modified Optimal Controller Based on Model Reference Control System (MRCS)

It is possible to develop the controller based on a linearized system in a design of nonlinear control systems, and then apply the created controller to the nonlinear system for assessment or redesign using computer simulation. The linearized system is utilized as a reference model for the genuine nonlinear system in this paper. Both linearized and nonlinear systems run at the same time. This section explains how to combine feed forward control algorithms like Integral Control (IC) with state feedback control techniques like LQR. The state space model of linearized TWMR is

$$\dot{x} = Ax + Bu \tag{14}$$

$$\dot{X}_i = \dot{e} = r - y = r - Cx \tag{15}$$

A new state is e, where r is set point and y is the actual output.

$$\begin{bmatrix} \dot{x} \\ \dot{X}_i \end{bmatrix} = \begin{bmatrix} A & 0 \\ -C & 0 \end{bmatrix} \begin{bmatrix} x \\ X_i \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u + \begin{bmatrix} 0 \\ 1 \end{bmatrix} r \tag{16}$$

The new system matrix is $A_a = \begin{bmatrix} A & 0 \\ -C & 0 \end{bmatrix}$, In addition, the new input matrix is $B_a = \begin{bmatrix} B \\ 0 \end{bmatrix}$

The output equation is

$$y = C_a X = \begin{bmatrix} C & 0 \end{bmatrix} \begin{bmatrix} x \\ X_i \end{bmatrix} \tag{17}$$

The new output matrix $C_a = \begin{bmatrix} C & 0 \end{bmatrix}$

The state feedback can be written as:

$$u = -\begin{bmatrix} K & -K_i \end{bmatrix} \begin{bmatrix} x \\ X_i \end{bmatrix} = -K_a X_a \tag{18}$$

Where $K_a = \begin{bmatrix} K & -K_i \end{bmatrix}$

K: State feedback gain based LQR

Ki : Integral gain.

The closed-loop state equation with the state feedback control u(t) is

$$\begin{bmatrix} \dot{x} \\ \dot{X}_i \end{bmatrix} = \begin{bmatrix} A & 0 \\ -C & 0 \end{bmatrix} \begin{bmatrix} x \\ X_i \end{bmatrix} - \begin{bmatrix} B \\ 0 \end{bmatrix} \begin{bmatrix} K & -K_i \end{bmatrix} \begin{bmatrix} x \\ X_i \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} r$$

$$\begin{bmatrix} \dot{x} \\ \dot{X}_i \end{bmatrix} = (A_a - B_a K_a) \begin{bmatrix} x \\ X_i \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} r \tag{19}$$

$$\det(\lambda I - (A_a - B_a K_a)) = det\left(\lambda I - \begin{bmatrix} A - BK & BK_i \\ -C & 0 \end{bmatrix}\right) = 0$$

Figure (5) shows the wheel smoothly approaches the required setpoint with a tiny overshoot and the body angular stays around zero. The optimum control-based MRCS had higher TWMR tracking performance with varied references. Figure (6) depicts the results in the presence of the disturbance. As illustrated in this figure, a position and angle continue to vibrate about the required targets, which is an unsatisfactory reaction and indicates the designed controller poor resilience. Different strategies are used in the second stage, and the controller algorithm is modified in stage one to make the system practically insensitive to noise signals [9].

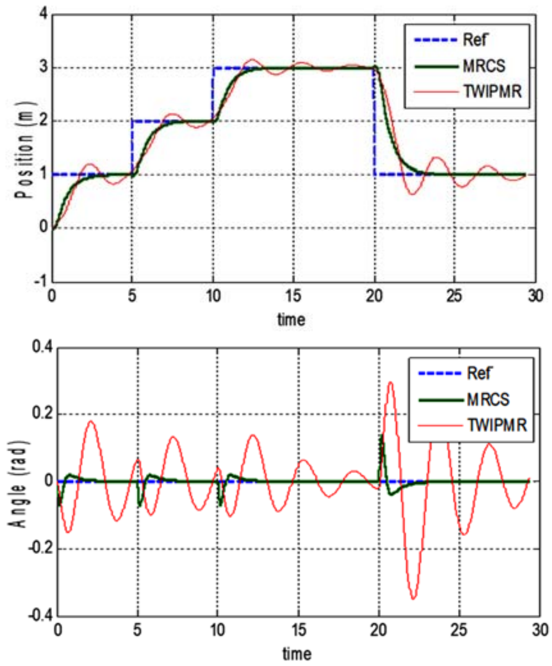


Figure 5: States of TWMR using optimal controller-based MRCS

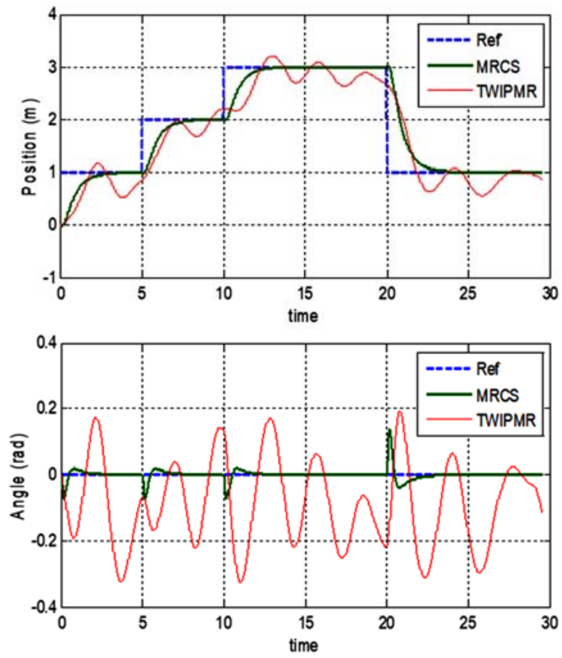


Figure 6: States of TWMR using optimal controller with disturbance

STAGE TWO: PARALLEL PID BASED ON OPTIMAL CONTROLLER

The ideal controller that was designed in stage one will be utilized to tune PID controllers in this step, and the double loops PID will work together to give a strong anti-interference capacity of the system. The control signal can be represented as,

$$u(s) = \left[\theta_{ref}(s) - \theta(s)\right]PID_A(s) + \left[x_{ref}(s) - x(s)\right]PID_P(s) \tag{20}$$

In addition, the characteristic equation of closed loop with two-loop PID controller's is as follows [7-9].

$$1 + PID_A G_a(s) + PID_P G_x(s) = 0$$

$$1 + \frac{K_{da}s^2+K_{pa}s+K_{ia}}{s}\cdot\frac{a_1}{s^4+a_2s^3+a_3s^2+a_4s} + \frac{K_{dx}s^2+K_{px}s+K_{ix}}{s}\cdot\frac{b_1s^2+b_2}{s^4+a_2s^3+a_3s^2+a_4s} = 0 \tag{21}$$

$G_a(s)$ and $G_x(s)$ indicate the transfer functions from angle and position to input voltage, respectively. The following characteristic equation is obtained by substituting the equations of PID_A, PID_P, $G_a(s)$, and $G_x(s)$ in Eq.10 and simplifying to yield the following equation.

$$s^5 + (a_2 + b_1K_{dx})s^4 + (a_3+b_1K_{px})s^3 + (a_4 + a_1K_{da} + b_1K_{ix} + b_2K_{dx})s^2 + (a_1K_{pa} + b_2K_{px})s + (a_1K_{ia} + b_2K_{ix}) = 0 \tag{22}$$

The ideal state-feedback gains with integral gain are stated as PID controller gains. The following intended characteristic equation will be compared to this:

$$s^5 + \alpha_1 s^4 + \alpha_2 s^3 + \alpha_3 s^2 + \alpha_4 s + \alpha_5 = (s-\gamma_1)(s-\gamma_2)(s-\gamma_3)(s-\gamma_4)(s-\gamma_5) \tag{23}$$

$\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5$ are the eigenvalues which derived from stage one (LQRIC based MRCS).

$\alpha_1, \alpha_2, \alpha_3, \alpha_4$, α_5 are the characteristic polynomials coefficients. Were,

$$\begin{bmatrix} K_{px} \\ K_{ix} \\ K_{dx} \\ K_{pa} \\ K_{da} \end{bmatrix} = \begin{bmatrix} 0 & 0 & b_1 & 0 & 0 \\ b_1 & 0 & 0 & 0 & 0 \\ 0 & b_1 & b_2 & 0 & a_1 \\ b_2 & 0 & 0 & a_1 & 0 \\ 0 & b_2 & 0 & 0 & 0 \end{bmatrix}^{-1} \begin{bmatrix} \alpha_1 - \alpha_2 \\ \alpha_2 - \alpha_3 \\ \alpha_3 - \alpha_4 \\ \alpha_4 \\ \alpha_5 - \alpha_1 . K_{ia} \end{bmatrix}$$

From stage two, the performance in the time domain have improved, and trajectory-tracking capability has enhanced, as shown in Figure (7).

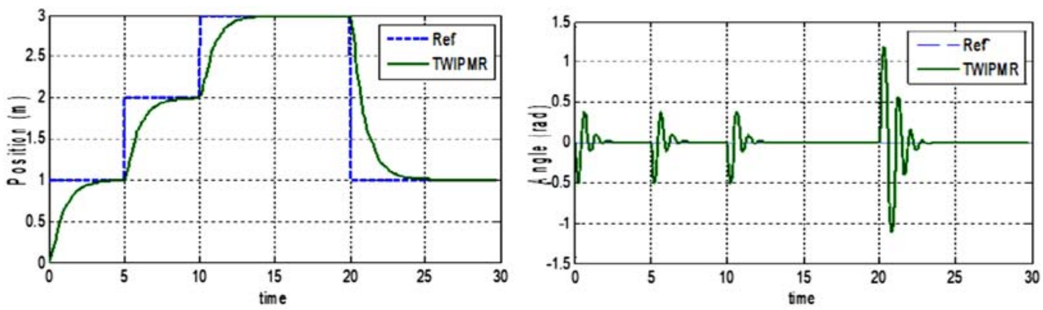


Figure 7: States of TWMR using Two loop PID based optimal control

Stage Three: Feedforward and Feedback Control Strategy Based on NCD

The control of nonlinear TWIPMR in this technique has been integrated by combining forward and feedback control algorithms to design a Hybrid Control Strategy (HCS). As illustrated in Figure (8), HCS controller consists of an outer parallel feedforward PID, and an interior feedback loop based LQR with IC. The integrated controller based HCS tuning using nonlinear control design (NCD).

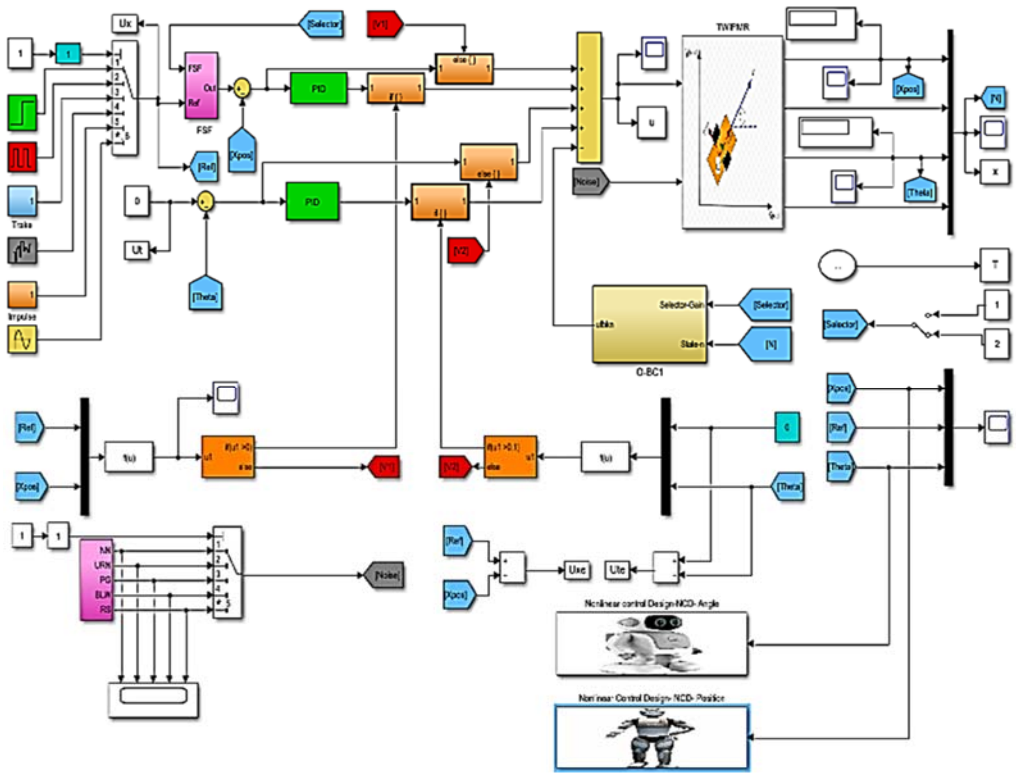


Figure 8: Integrated controller with NCD robot

NCD block set translates the nonlinear simulink model of TWMR time-domain constraints into a constrained optimization problem, which is solved using a nonlinear optimization approach called Sequential Quadratic Programming (SQP) [9-11]. NCD compares the simulation results to the constraint targets, and adjusts tunable parameters of $PID_{Position}$ (K_{px}, K_{ix}, and K_{dx}), PID_{Angle} (K_{pa}, K_{ia}, and K_{da}), and LQR-IC (K and K_i) controllers using SQP. When using this method, the main issue is how to determine the initial values of the controller variables of HCS. If the number of these variables is too much, the process of altering these variables will take a long time without attaining the system's needed specifications in many times. The following approach was used to address this issue: -

1- The optimization problem can be given constraints concerning the closed loop system performance such as overshoot, rise time and settling time.
2- The initial values (K_{LQR-IC}, K_{px}, K_{ix}, K_{dx}, K_{pa}, K_{ia} and K_{da}) of the controller's parameters are chosen as the obtained result from stage one and stage two of the designed integrated controller to prevent the long repetition of the SQP algorithm.
3- The closed loop system is simulated, and the cost function is assessed at each iteration using the provided controller parameters. After that, a termination test is run to determine whether the iteration should be continued. If the test fails, the SQP optimization algorithm uses the optimization constraints to adjust the controller settings. According to the obtained results as shown in Figure (9). The integrated controller HCS is an effective control technique for improving the time domain specification of system response and reducing the amount of oscillation in the error.

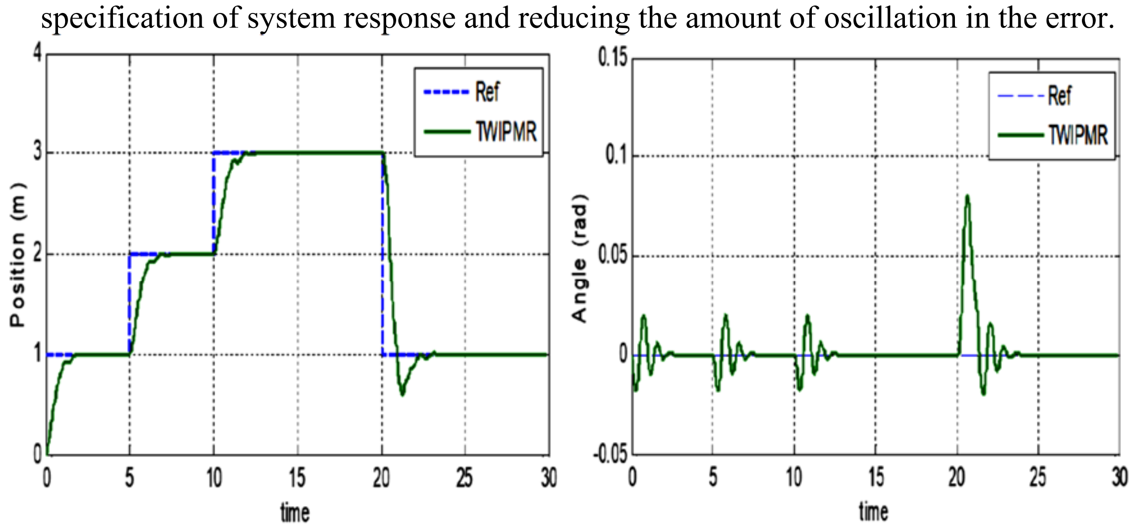


Figure 9: States of TWMR using integrated controller

Intelligent Techniques for TWBMR

Neural networks and fuzzy logic systems are often considered as a part of soft computing area hybrid intelligent systems combining fuzzy logic and neural networks are proving their effectiveness in a wide variety of real-world problems. Fuzzy logic and neural networks have computational properties that make them suited for problems and not for others [12].

Neural Module of TWBMR

The science of artificial neural networks is based on a collection of simple processing units (neuron) that are massively interconnected to produce meaningful behavior. The main advantage of neural networks is that it is possible to be trained to perform a particular function by adjusting the values of connections (weights) between elements [13,14]. System identification is the process of deriving a mathematical model of a system using observed data. To provide a set of targets for the neural network to learn, the Simulink model of the robot with feedback control is used to generate input output samples. Multi-output neural networks were developed, the input being the control signal and the outputs $(x, \dot{x}\ ,\ \theta\ and\ \dot{\theta})$. The types of neural network to be devolved are Feed-Forward (FF) and Cascade-Forward (CF). The MATLAB code creates a multi- layers FF and CF neural network model (neuro model) as shown in Figure (10). The mean square error (MSE) gives a good indication of the accuracy of the neuro model. At the start of the training, the error between the neuro model and the output plant is high. As the number of epochs increases the mean square error decrease. From GUI of ***nntools*** of MATLAB it is possible to determine the correct number of epochs for training [7,15]. During testing, neural networks with a range of hidden layer neurons were simulated as presented in Table (2).

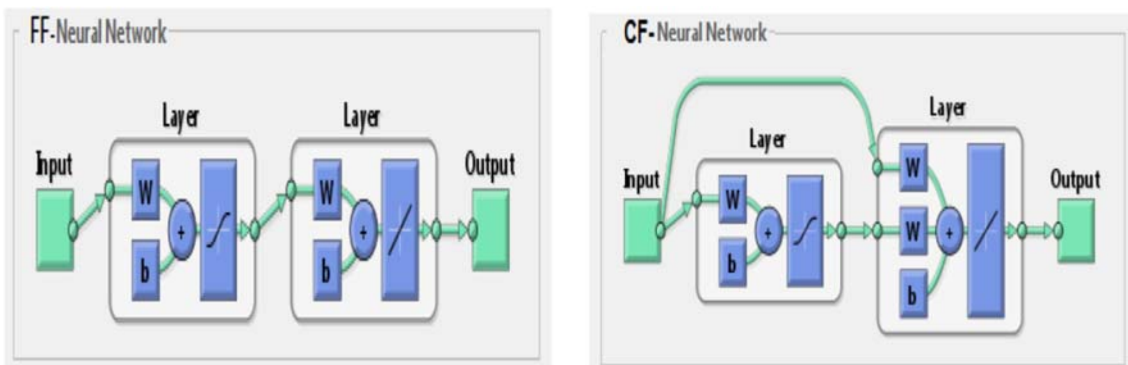


Figure 10: FF and CF neuro model of TWBMR using GUI

Table 2: Setup results of the FF and CF networks

NN	Num. of Neurons	Simulation Time (Sec)	$\mathbf{MSE(x)}$	$\mathbf{MSE(\dot{x})}$	$\mathbf{MSE(\theta)}$	$\mathbf{MSE(\dot{\theta})}$
FF	5	5	0.008	0.023	0.001	0.009
	10	10	0.007	0.021	0.001	0.009
	50	55	0.007	0.021	0.001	0.008
	100	137	0.007	0.019	0.001	0.008
CF	5	6	0.009	0.022	0.0002	0.009
	10	10	0.008	0.022	0.0001	0.009
	50	55	0.007	0.021	0.0001	0.009
	100	146	0.007	0.019	0.0001	0.008

The quality of the neural network model is checked by comparing the four outputs from the neural network model with the four outputs of the process. Figure (11) shows the response from the process and neuro model (10 neurons in hidden layer) for each state. Where the MSE is very low, and the neural model predicts the target with high accuracy when the number of hidden layer neurons is increased [7,9].

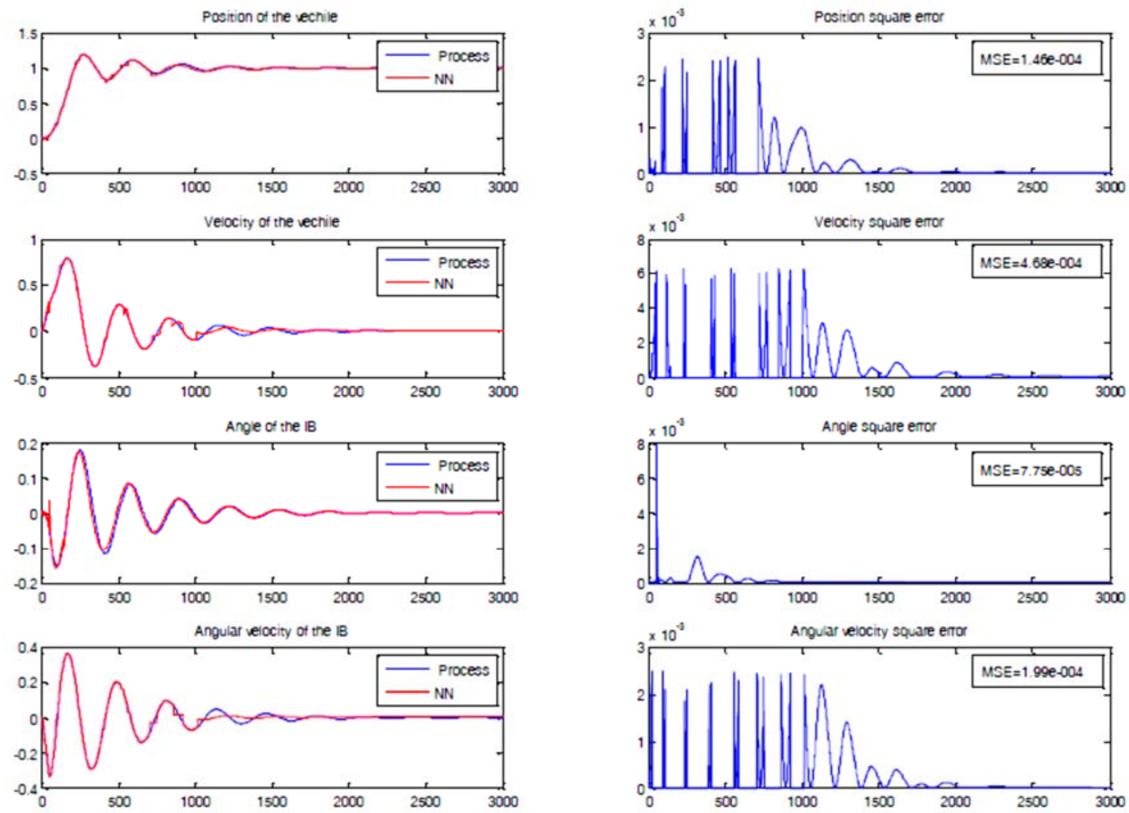


Figure 11: FF neural network (10 Neuron) model of robot

NNEURO Model Control Using FLC

Fuzzy logic control (FLC) has attracted considerable attention as a tool for novel control approaches because of the variety of advantages that it offers over classical control techniques. One of the major limitations of conventional control systems is their inability to cope with changes in the TWBMR dynamics with time and actuator saturation, which add to the nonlinearity of the system. An interesting alternative that could be investigated is the use of FLC methods [11]. FLC does not require a mathematical model of the plant and will be applied directly to neuro model constructed in above section. FLC has been designed for stabilization and tracking of the robot. This will result in a multi-input multi-output (MIMO) fuzzy controller, which will incur a huge time-consuming rule-base. Therefore, for simplicity and reducing the processing time, the fuzzy controller was split into two fuzzy controllers, utilizing the error and the derivative of error for both the measured tilt angle of IB and linear displacement of the vehicle. This will reduce the rule-base drastically and the associated processing time. The FLC was divided into FLCP and FLCA as illustrated in Figure (12). The FLCP controls the linear position on x-axis, FLCA controls the title angle of the robot about y-axis. For the required displacement of the vehicle, sufficient torque needs to be applied to the wheels. The FLCP can be designed to produce the torque using the error and change of error of the vehicle displacement. However, there is still the effect of the disruption applied to the IB with the disturbance force. As the torque produced by the FLCP will not be enough for achieving the upright position of the IB, an additional torque needs to be produced to bring the IB back to the upright position using the tilt angle information as inputs to the FLCA [7]. The control variables of FLCP and FLCA were summed together which is further used as input to a neuro model of mobile system as shown in Figure (12).

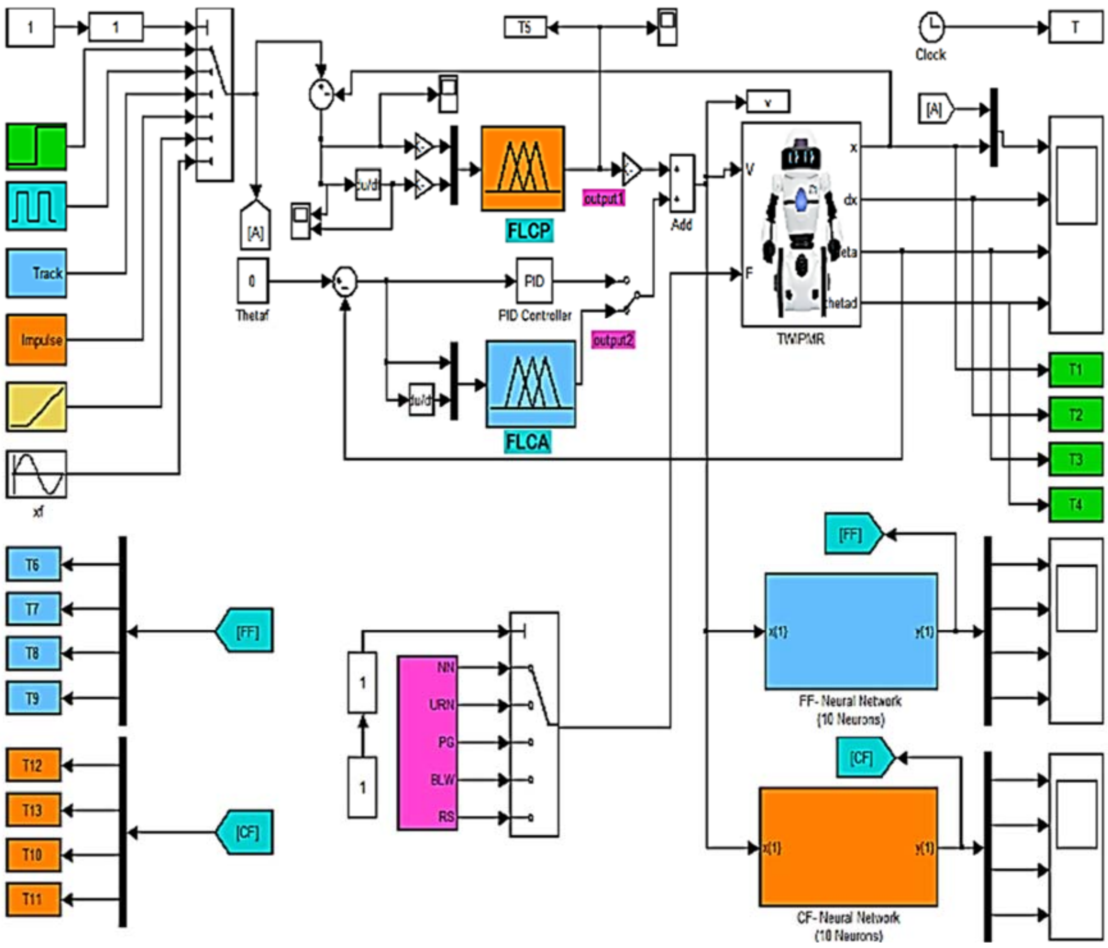


Figure 12: Simulink model of actual and neuro model with FLC

The fuzzy inference system (FIS) file is created using the fuzzy logic toolbox [12]. To design the FLCs, it requires the choice of membership functions and the rule base. Five linguistic variables for the error and derivative of error shown in Table (3). The linguistic variables are chosen for each input and outputs: negative big (NB), negative small (NS), zero (Z), positive small (PS), and positive big (PB). Triangular membership functions (MFs) for inputs and outputs are chosen for each linguistic variable. The membership functions of error and derivative of error for vehicle and IB is shown in Figure (13).

Table 3: Fuzzy control rules for FLCP and FLCA

		Change of Error									
		FLCP					FLCA				
		NB	**NS**	**Z**	**PS**	**PB**	**NB**	**N S**	**Z**	**P S**	**PB**
Error	**NB**	NB	NB	NS	NS	Z	NB	NB	NB	N S	Z
	NS	N B	NB	Z	Z	P S	NB	NB	N S	Z	P S
	Z	NB	NS	P S	P S	PB	N S	N S	Z	P S	
	PS	NS	Z	PB	PB	PB	N S	N S	Z		
	PB	Z	PS	PB	PB	PB	Z	Z			

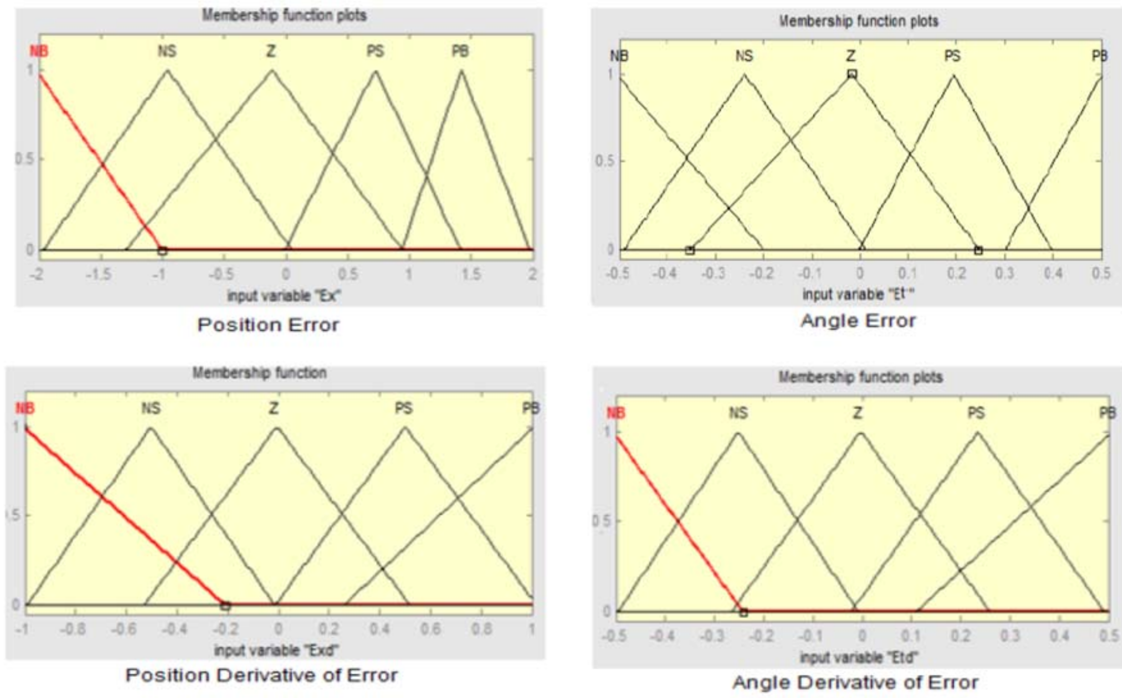
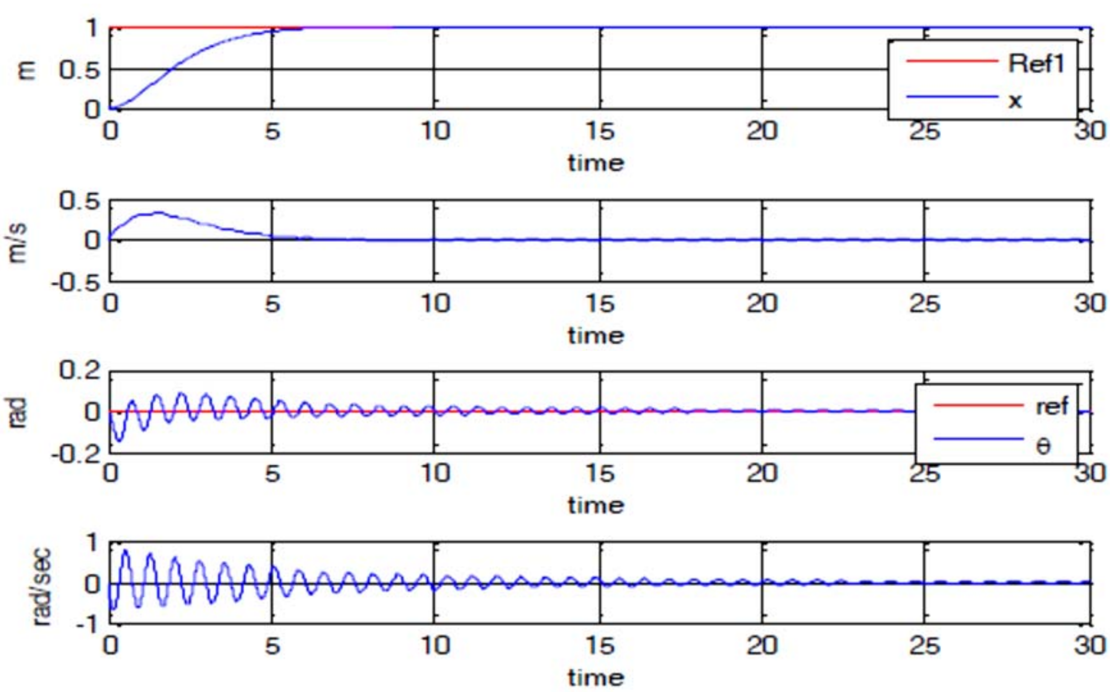


Figure 13: Membership functions of FLCP and FLCA

The simulation results of fuzzy controllers for neuro model of TWBMR are shown in Figure (14). It is clearly seen that the tracking capability of TWBMR with given unit step (Ref. 1) and different step level reference (Ref. 3) is acceptable and the IB angle is seen making smooth movements. In addition, the sinusoidal type of reference (Ref. 2) is applied. Tracking capability is not good as (Ref. 1 and Ref. 3). However, to improve the performance and make the system faster the number of rules used in the fuzzy system needs to be optimized. Neural networks along with fuzzy logic control can be applied to construct ANFIS controller.



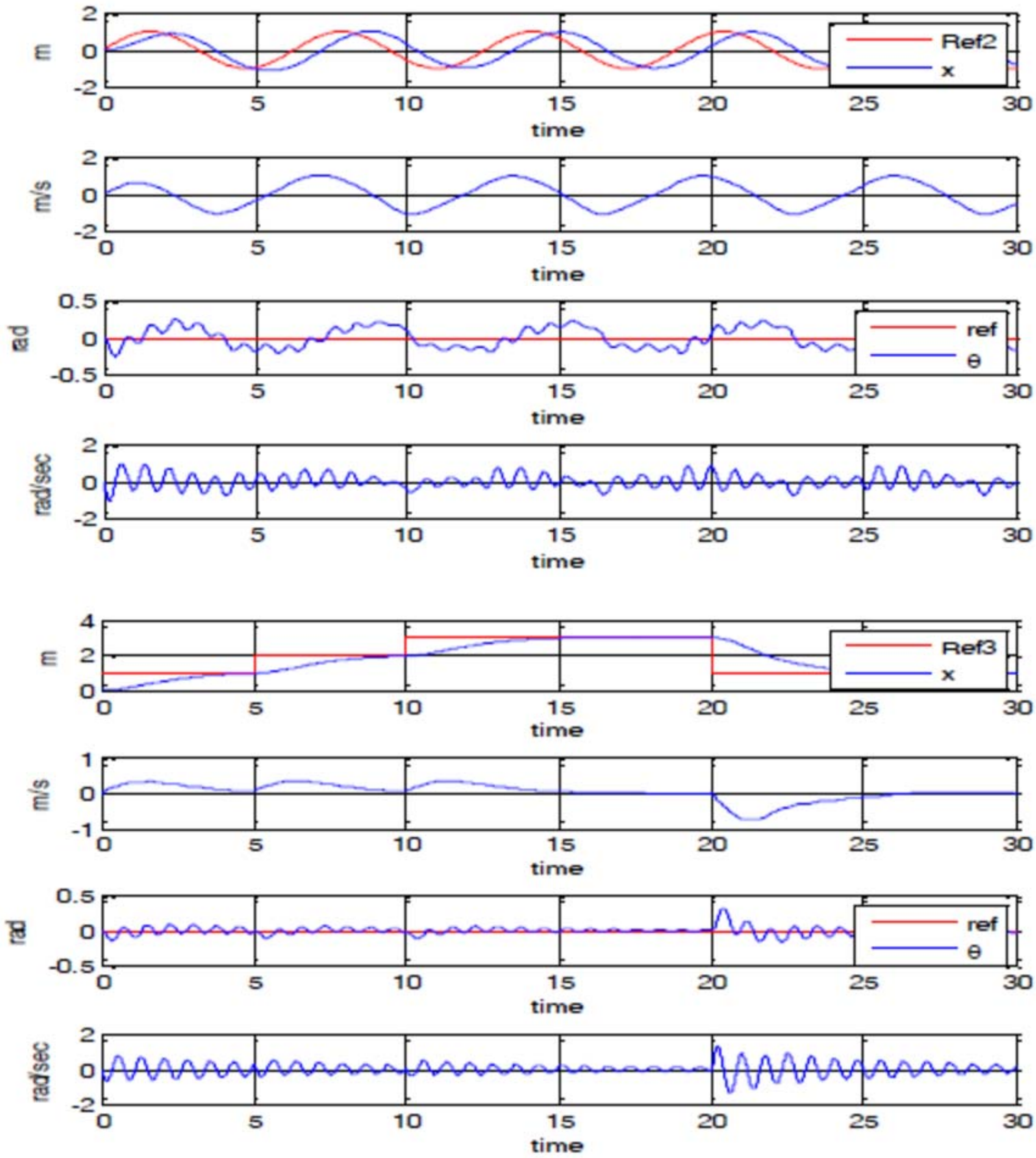


Figure 14: Simulation results of FLC for neuro TWBMR

Adaptive Network Based (ANFIS)

The merged technique of the learning power of the NNs with the knowledge representation of FL has created a new hybrid technique, called the term Neuro fuzzy networks [13]. The novel design of an ANFIS for controlling TWBMR is presented in this section. An ANFIS is learning technique that uses fuzzy logic to transform given inputs into the desired output through highly interconnected neural network processing elements and information connections, which are weighted to map the numerical inputs into an output [14]. To start the ANFIS learning, first, a training data set that contains the desired input and output data pairs of the target system is to be required. The design parameters required for any ANFIS controller are, number of data pairs, training data set, checking data sets and fuzzy inference systems for training, the number of epochs to be chosen to start the training, [15,16]. The basic flow diagram of computations in ANFIS using MATLAB toolbox is presented in Figure (15).

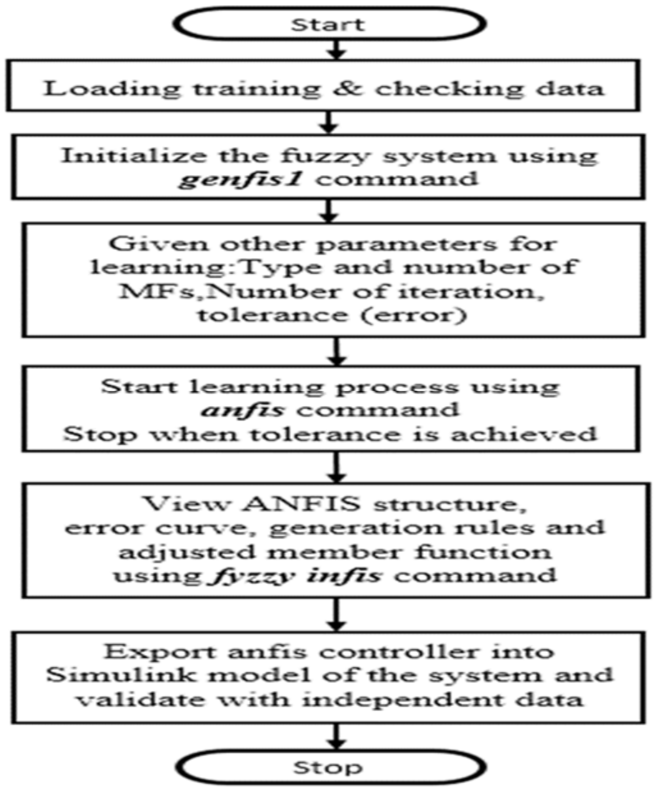


Figure 15: Computations in ANFIS using MATLAB toolbox

The ANFIS trains for the inputs, angle, angular velocity, position, and velocity and the output is the voltage control signal. The fuzzy controller for neuro model of TWBMR was used to generate input and output data for training. A total of 3000 datasets were collected which were further divided into training and checking data sets as shown in Figure (16). After the training has ended, we can export ANFIS model to Simulink file or workspace and use it directly to control the system.

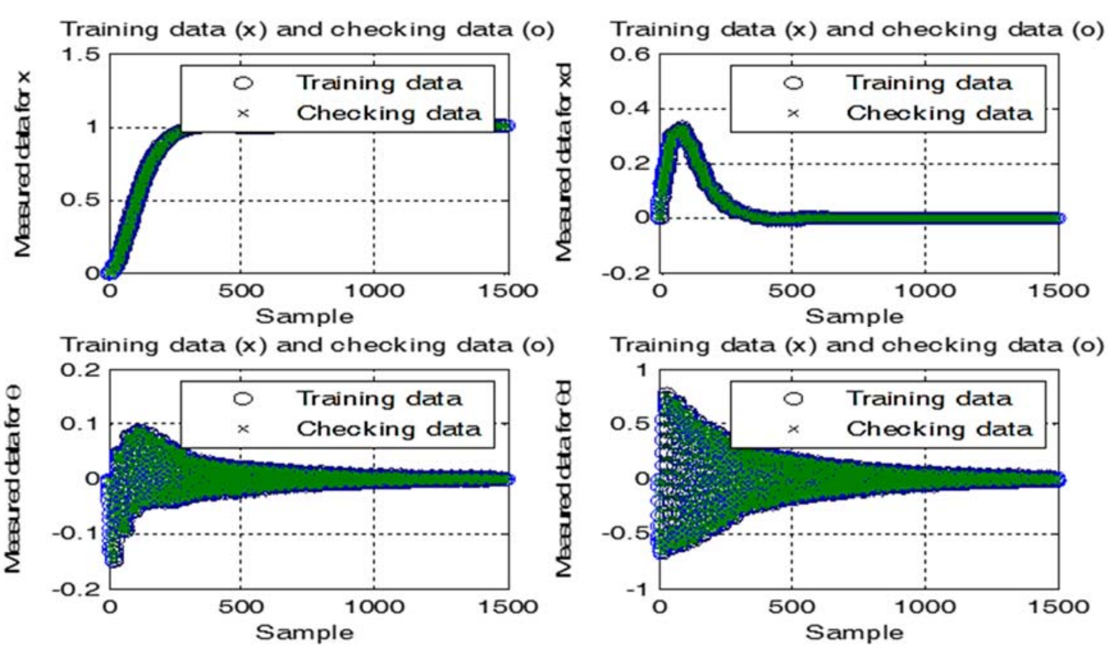


Figure 16: Training and checking data for ANFIS controller

The simulink structure of TWBMR with ANFIS controller is shown in Figure (17). The simulation results are depicted in Figure (18). The results showed better performance of ANFIS controller over the FLC. According to the comparison of the simulation curves, the ANFIS controller can improve the dynamic performance of the TWBMR system, and it also shows the good adaptability when presence of undesirable signals and varying the parameter of the system. ANFIS provides better performance when it comes to a relationship that is nonlinear between input and output. The ANFIS controller learns the training data quickly with a very low amount of error tolerance. In the case of FLC the rules, are large in number. Therefore, by using neuro fuzzy system the numbers of rules are reduced [17-18].

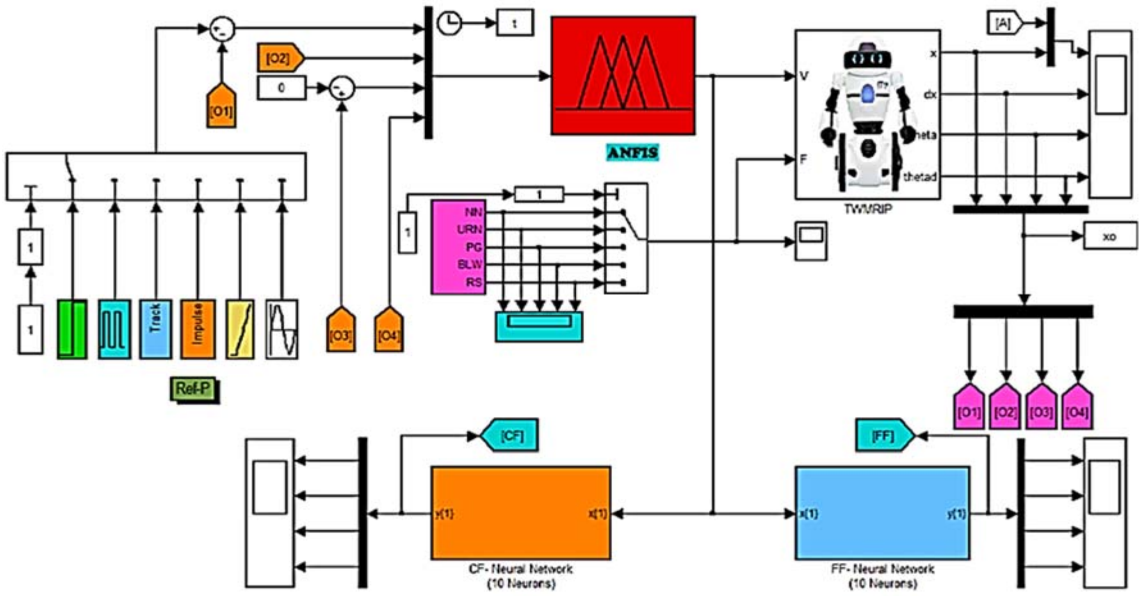
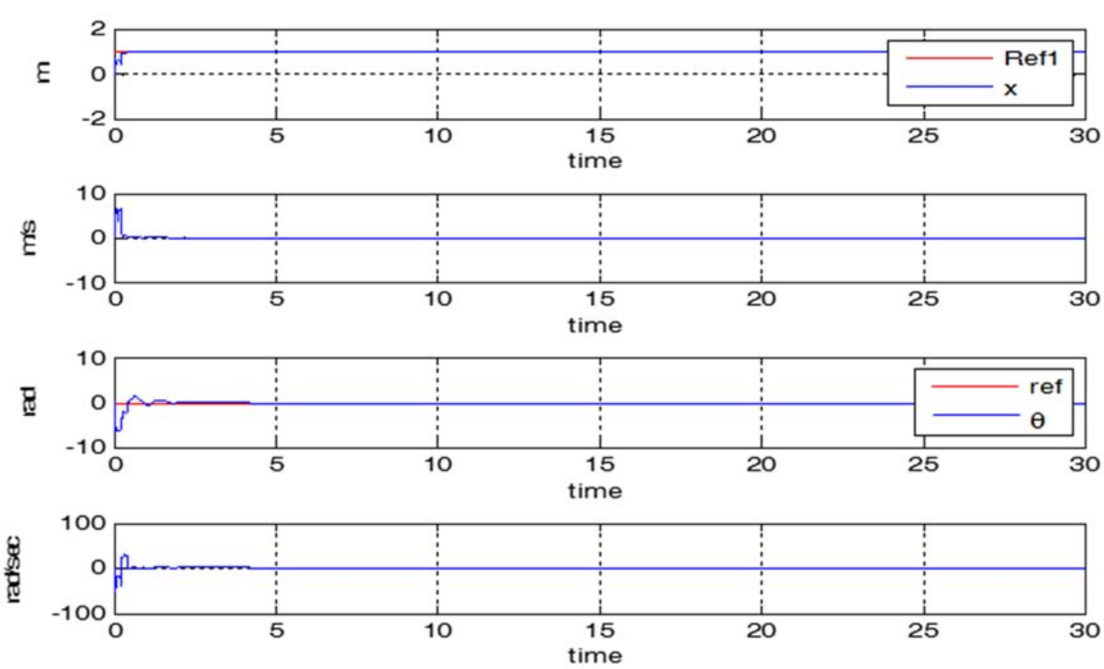


Figure 17: Simulink model of TWBMR with ANFIS scheme



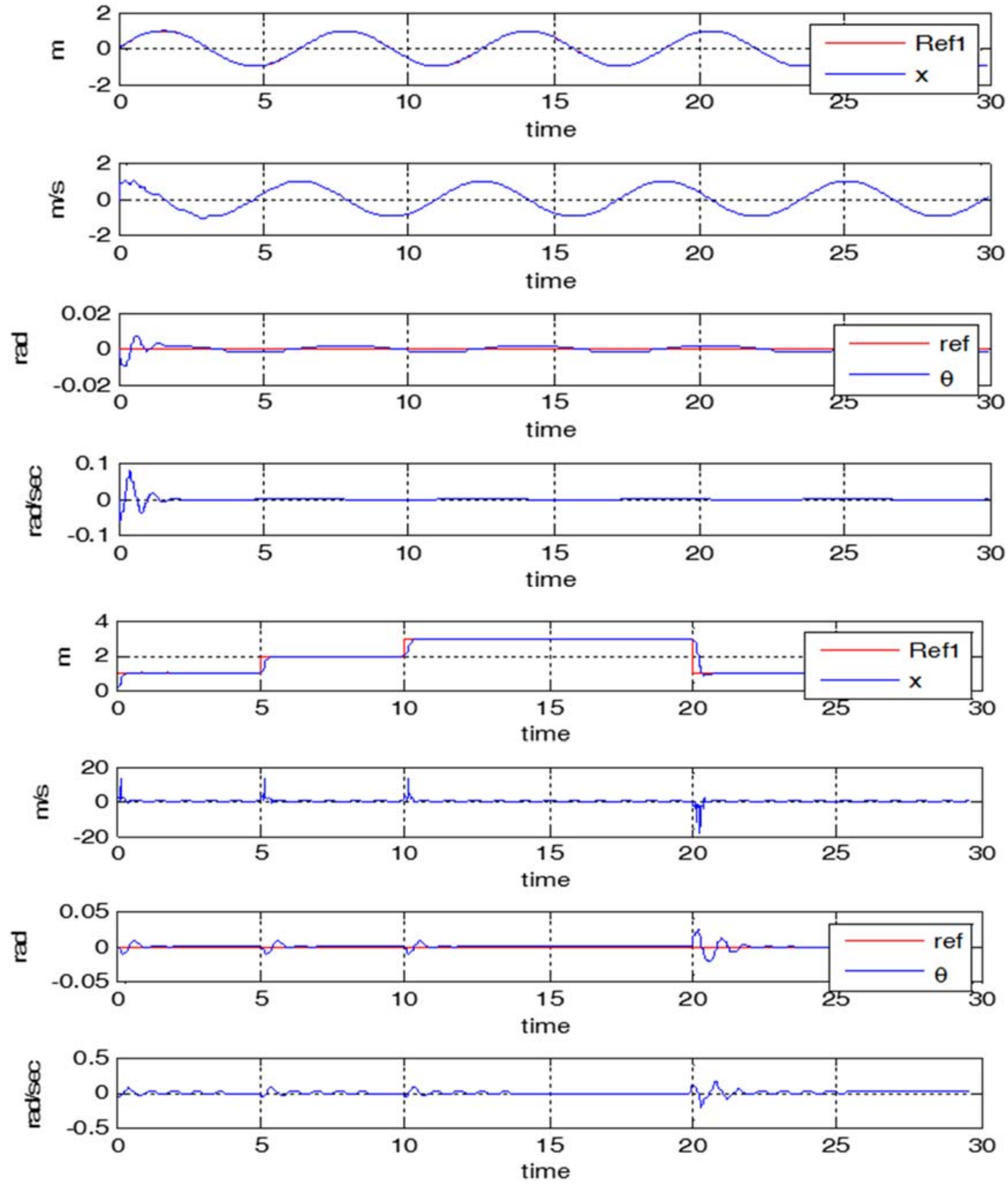


Figure 18: Performance of TWBMR with ANFIS controller

To confirm the proposed controller has excellent learning in all regions based on the desired paths. The controller has the ability to resist the external disturbances as demonstrated in Figure (19), The control design can obtain a good balance effect and has good anti-disturbance. Changing the beginning state and seeing how it influences the simulation results using the designed controller would also be beneficial. As a result, the initial condition for the vertical angle of the robot's body is adjusted from 10^o to 50^o degrees. The overshoot in the state variables also increases, as shown in the results in Figure (20). The controller, on the other hand, provided us the required results in every case.

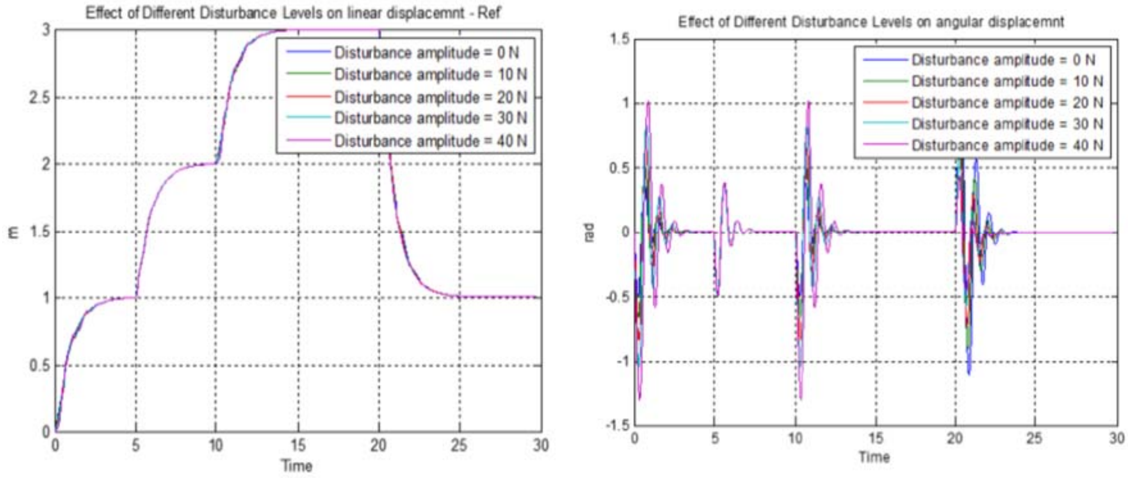


Figure 19: States of TWMR using integrated controller with disturbances

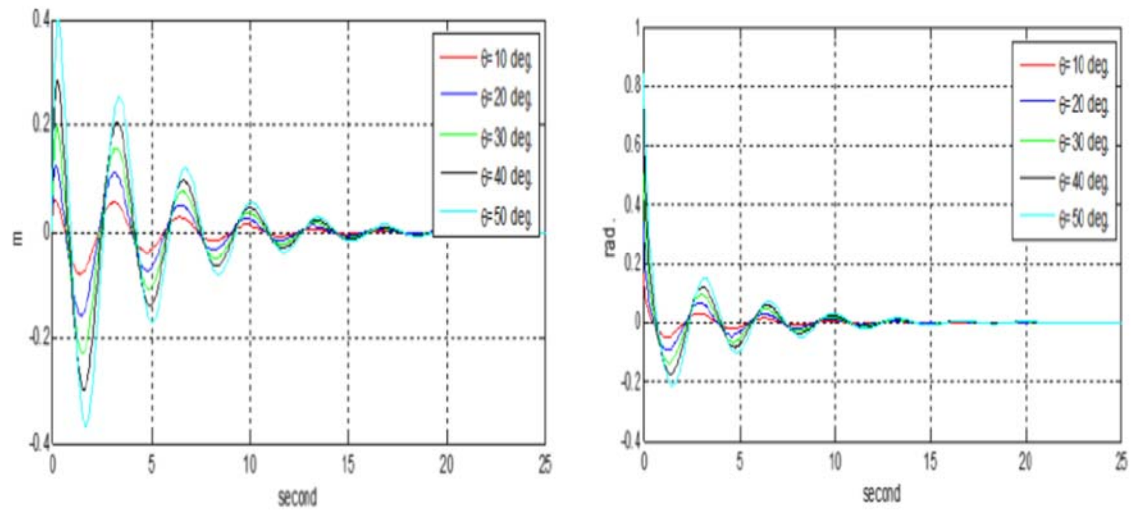


Figure 20: Response of TWIPMR for various initial conditions

CONCLUSION

The field of electromechanical technology may be for all intents and purposes characterized as the study, plan, and utilization of robot frameworks for manufacturing. Industrial mechanical autonomy plays a key part in robotization which requires contemplations for planning. The key challenge in independent robot routes is robust planning of ways and dodge the existing inactive and dynamic obstacles. This paper has focused on modeling, simulation, and control of dynamical unstable TWBMR. More specifically, the stability and tracking performance behavior of the system for different references trajectory have been studied and improved by designing intelligent control algorithms. The nonlinearities behaviors degrade the performance of the control system that can be improved by using an adaptive technique represented by the intelligent technique, which is developed in this paper and used for identification and control of the robot system. Feed-forward (FF) and Cascade-Forward (CF) networks were developed with a wide range of hidden layer neurons. The feedforward networks modeled the non-linear robot with high accuracy, where the MSE between the process and the neuron model was very low. In addition, ANFIS has been applied as a controller to improve the system performance according to an optimal control parameters adjustment. Different input reference signals have been applied to test the effectiveness of this controller and it is demonstrated that an acceptable tracking accuracy can be achieved compared to FLC. It is concluded that under the influence of these signals the intelligent controller is successful to achieve a high tracking performance in transient and steady state time.

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