International Journal of Control and Automation
Vol. 11, No. 1 (2018), pp.75-90
http//dx.doi.org/10.14257/ijca.2018.11.1.07

Adaptive Tracking Control Based on Recurrent Wavelet Fuzzy CMAC for Uncertain Nonlinear Systems

ThanhQuyen Ngo[1, a], Tuan. N. A. Nguyen[1, b], Nam T. P. Le[2, 3, c,*], D. C. Pham[1, d] and Nghia D. Ngo[1, e]

[1]*Faculty of Electrical Engineering Technology, Industrial University of Ho Chi Minh City, Vietnam*
[2]*Division of Computational Mathematics and Engineering, Institute for Computational Science, Ton Duc Thang University, Ho Chi Minh City, Vietnam*
[3]*Faculty of Civil Engineering, Ton Duc Thang University, Ho Chi Minh City, Vietnam*
[a]*ngothanhquyen@iuh.edu.vn,* [b]*nguyenngocanhtuan@iuh.edu.vn*
[c]*letuanphuongnam@tdt.edu.vn,* [d]*dph@iuh.edu.vn,* [e]*ngodinhnghia@iuh.edu.vn*

Abstract

This paper presents a control system based on the recurrent wavelet fuzzy cerebellar model articulation controller (RWFCMAC) for a class of multiple-input–multiple-output (MIMO) uncertain nonlinear systems to achieve the high-precision position tracking. The proposed control system is applied to imitate an ideal controller because it incorporates the advantages of the wavelet decomposition property with a fuzzy CMAC fast learning ability and an adaptive smooth compensator (SC) is designed to attenuate the effect of the approximation error caused by the RWFCMAC approximator. Furthermore, the online tuning laws of RWFCMAC and SC parameters are derived according to gradient descent method and Lyapunov function so that the stability of the system can be guaranteed. The experimental results of 2 DoF Helicopter and tank level system are provided to verify the robustness and effectiveness of the proposed control methodology. The proposed control system gives good agreements with the setpoint values including the external loading. Morever, it can be used for the unknown dynamic systems.

***Keywords**: Wavelet, Cerebellar model articulation controller (CMAC), Nonlinear Systems, MIMO*

1. Introduction

In recent years, several researches have devoted to the fuzzy control or fuzzy neural network control of nonlinear systems [1-5]. The fuzzy neural networks have been proposed by combining a fuzzy rule base system with and a neural network [2, 3]. A lot of applications using fuzzy neural networks have been presented in [4, 5]. The present study aims to propose a more generalizing fuzzy neural network and then applies it to control the uncertain nonlinear systems.

Recently, many applications have been successfully implemented based on wavelet neural networks (WNNs) which combine the learning ability of neural network and capability of wavelet decomposition property [6–9]. Difference from conventional NNs, the membership functions of WNN is wavelet functions which are spatially localized. This result in the WNNs are capable of learning more efficiently than conventional NNs for control and system identification demonstrated in [14, 16]. As a result, WNNs have

Received (July 8, 2017), Review Result (November 22, 2017), Accepted (December 2, 2017)
* Corresponding Author

ISSN: 2005-4297 IJCA

been considered interest in the applications to deal with uncertainties and nonlinearity control system shown in [6–7].

To deal with disadvantages of NNs, cerebellar model articulation controller (CMAC) was proposed by Albus in 1975 [10] for the identification and control of complex dynamical systems, due to its advantage of fast learning property, good generalization capability and ease of implementation by hardware [11–13]. The conventional CMACs, regarded as non-fully connected perceptron-like associative memory network with overlapping receptive fields which used constant binary or triangular functions. The disadvantage is that their derivative information is not preserved. For acquiring the derivative information of input and output variables, Chiang and Lin [14] developed a CMAC network with a differentiable Gaussian receptive-field basis function and provided the convergence analysis for this network. The advantages of using CMAC over neural network in many applications were well documented [15–20]. However, in the above CMAC literatures, the structure of CMAC are not merited of the high-level human knowledge representation and thinking of fuzzy theory.

In this article, we propose the adaptive recurrent wavelet fuzzy CMAC (RWFCMAC) control system for a class of multiple-input–multiple-output (MIMO) uncertain nonlinear systems to achieve the high-precision position tracking. This control system combines advantages of fuzzy inference system with CMAC and wavelet decomposition capability and a delayed self-recurrent unit in the association memory space and the adaptive single input fuzzy compensator which is designed to deal with the approximation errors between the estimating RWFCMAC and the ideal controller to the stability of system is guarantied. The online tuning laws of RWFCMAC and SC parameters are derived according to gradient descent method and Lyapunov function so that the stability of the system can be guaranteed.

This paper is organized as follows: System description is described in Section II. Section III presents RWFCMAC control system. Experiment results of 2 DoF hellicopter and tank level systems are provided to demonstrate the tracking control performance of the proposed RWFCMAC system in Section IV. Finally, conclusions are drawn in Section V.

2. Problem Formulation

Consider a class of MIMO nonlinear dynamic system described in the following form:

$$\begin{cases} x^{(n)} = f_0(\underline{x}) + G_0(\underline{x})u + L(\underline{x}) \\ y = x \end{cases} \tag{1}$$

Where $x \in \Re^m$ is the state, $u \in \Re^m$ is the control input, and $y \in \Re^m$ is the system output. Define $\underline{x} = \begin{bmatrix} x^T & \dot{x}^T & \cdots & x^{(n-1)^T} \end{bmatrix}^T \in \Re^{nm}$ as the system state vector. It is assumed to be available for measurement. In addition, $f_0(\underline{x}) \in \Re^m$ and $G_0(\underline{x}) \in \Re^m$ are system nominal nonlinear vector-and matrix-valued functions, respectively, and they are assumed to be bounded and available. Meanwhile, assume the nonlinear system of (1) is controllable and $G_0^{-1}(\underline{x}) \in \Re^m$ exists for all $\underline{x}$. $L(\underline{x}) \in \Re^m$ denotes the unknown uncertainty, which is assumed to be bounded. If there exist mismodelings between practical systems and the nominal functions, they can be absorbed into the uncertainty.

The control purpose is to design a control system such that the system output can track a desired trajectory signal $y_d \in \Re^m$. Define the tracking error as

$$e = y_d - y \tag{2}$$

and the system tracking error vector is defined as

$$\underline{e} \triangleq \left[e^T, \dot{e}^T, ..., e^{(n-1)T} \right]^T \in \Re^{nm} \tag{3}$$

Define an integrated sliding function as

$$s \triangleq e^{n-1} + K_1 e^{n-2} + \cdots K_n \int_0^t e(\tau) d\tau \tag{4}$$

where $K_i \in \Re^{m \times m}$, $i = 1, 2, \cdots n$, are positive constant matrices and define $K = \left[K_1^T \quad \cdots \quad K_n^T \right]^T \in \Re^{nm \times m}$. If the nominal functions $f_0(\underline{x}) \in \Re^m$ and $G_0(\underline{x}) \in \Re^m$ and the uncertainty $L(\underline{x}) \in \Re^m$ are exactly known, then an ideal controller can be designed as

$$u^* = G_0^{-1}(\underline{x}) \left[y_d^{(n)} - f_0(\underline{x}) - L(\underline{x}) + K^T \underline{e} \right] \tag{5}$$

By substituting the ideal controller (5) into (1), the error dynamic equation is given as follows:

$$\dot{s} = e^{(n)} + K^T \underline{e} = 0 \tag{6}$$

It is obvious that errors will be asymptotically tend to zero if the gain matrices of $K = \left[K_1^T \quad \cdots \quad K_n^T \right]^T \in \Re^{nm \times m}$ is determined so that the roots of the characteristic polynomial $P(\lambda) = I\lambda^n + K_1 \lambda^{n-1} + \cdots + K_n$ lie strictly in the open left haft of complex plane. However, the ideal controller in (5) can not determine, because of $L(x)$ is exactly unknown for practical applications. So, in order to this problem, a proposed adaptive RWFCMAC control system is shown in Figure 1 which comprises a RWFCMAC $u_{RWFCMAC}$ and a smooth compensator u_{SC} as follows:

$$u = u_{RWFCMAC} + u_{SC} \tag{7}$$

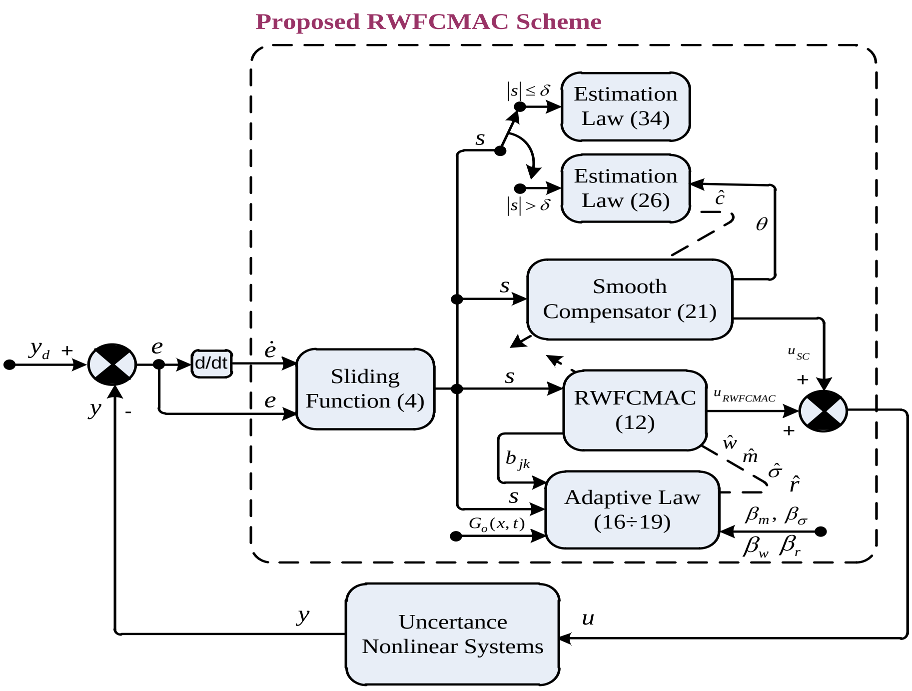


Figure 1. Block Diagram of the RWFCMAC Feedback Control System

3. Adaptive RWFMAC Control System Design

3.1. Brief of the RWFCMAC

The main difference between the FCMAC and the original CMAC is that association layer in the FCMAC is the rule layer which is represented as follows.

R^l : if X_1 is μ_{1jk} and X_2 is $\mu_{2jk}, \cdots, X_{n_i}$ is μ_{ijk} then For $i=1,2,\cdots,n_i$, $j=1,2,\cdots,n_j$, and $l=1,2,\cdots,n_k n_j$. (8)

Where n_i is the number of the input dimension, n_j is the number of the layers for each input dimension, n_k is the number of blocks for each layer, $l=n_k n_j$ is the number of the fuzzy rules and μ_{ijk} is the fuzzy set for *i*th input, *j*th layer and *k*th block, w_{jk} is the output weight in the consequent part.

Based on the [21] a novel RWFCMAC is represented and shown in Figure 2. It is combines a wavelet function with the FCMAC including input, association memory, receptive field, and output spaces, is proposed to implement the RWFCMAC estimate in RWFCMAC control system shows in Figure 1. The signal propagation is introduced according to functional mapping as follows:

The first mapping $X: X \rightarrow A$: assume that each input state variable $X=[X_1 \quad X_2 \quad \cdots \quad X_{n_i}]$ can be quantized into n_e discrete states and that the information of a quantized state is regarded as region a wavelet receptive-field basic function for each layer. The mother wavelet is a family of wavelets. The first derivative of basic Gaussian function for each layer is given here as a mother wavelet which can be represented as follows:

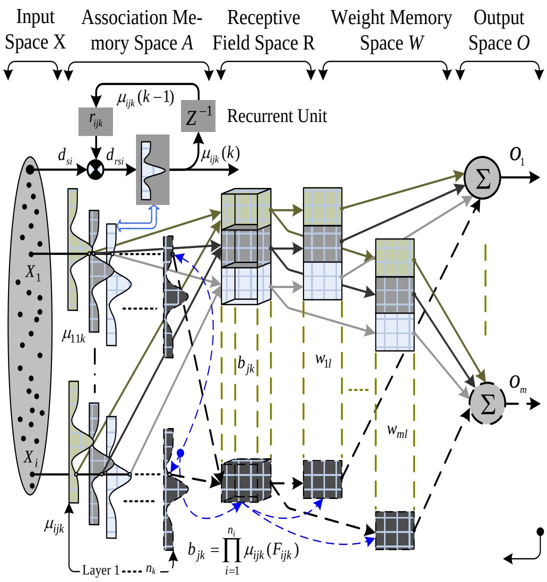


Figure 2. Architecture of a RWFCMAC

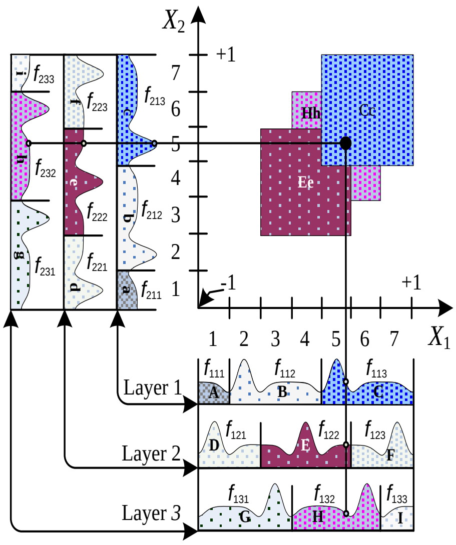


Figure 3. Block Division of RWFCMAC with Wavelet Function

$$\mu_{ijk}(F_{ijk}) = -F_{ijk} \exp\left[-\frac{F_{ijk}^2}{2}\right] \quad i=1,2,\cdots,n_i, \quad k=1,2,\cdots,n_k \tag{9}$$

Where $F_{ijk}=(d_{rsi}(k)-m_{ijk})/\sigma_{ijk}$, m_{ijk} is a translation parameter and σ_{ijk} is dilation. In addition, the input of this block can be represented as

$$d_{rsi}(k) = d_{si}(k) + r_{ijk}\mu_{ijk}(k-1) \tag{10}$$

Where r_{ijk} is the recurrent gain, k is denotes the time step, and $\mu_{ijk}(k-1)$ denotes the value of $\mu_{ijk}(k)$ through a time delay. Clearly, the input of this block contains the memory term $\mu_{ijk}(k-1)$, which stores the past information of the network and presents the dynamic mapping.

The second mapping $A: A \to R$: the information μ_{ijk} of each kth block and each jth layer relates to each location of receptive field space. The Figure 3 illustrates a structure of two-dimension $(n_i = 2)$ RWFCMAC with wavelet basic function with $n_j = 3$ and $n_k = 3$ case. Areas of receptive field space is formed by multiple-input regions are called hypercube; i.e. in the fuzzy rules in (9), the product is used as the "and" computation in the consequent part. The firing of each state in jth each layer and kth each block can be obtained the weigh of each hypercube corresponding. Assume that in 2-D RWFCMAC case is shown in Figure 4, where input state vector is (6, 3), then, the content of lth hypercube can be obtained as follows:

$$b_{jk} = \prod_{i=1}^{n_i} \mu_{ijk}(F_{ijk}) \quad \text{For } j = 1, 2, \cdots, n_j \text{ and } k = 1, 2, \cdots, n_k \tag{11}$$

Finally, The RWFCMAC output is the algebraic sum of the activated weighs with the hypercube elements. The output mathematic form can be expressed as follows:

$$u = \sum_{j=1}^{n_j}\sum_{k=1}^{n_k} w_{jk} b_{jk}\left(F_{ijk}\right) = \sum_{j=1}^{n_j}\sum_{k=1}^{n_k} w_{jk} \prod_{i=1}^{n_i} \mu_{ijk}(F_{ijk})$$
$$\text{For } j = 1, 2, \cdots, n_j,\ k = 1, 2, \cdots, n_k \text{ and } i = 1, 2, \cdots, n_i. \tag{12}$$

3.2. On-line Learning Algorithm

By taking the time derivative of (4) and using (3), (8). We have

$$\dot{s} = e^{(n)} + K^T \underline{e} = -f_0(x) - G_0(\underline{x})u + y^{(n)}{}_d - L(\underline{x}) + K^T e \tag{13}$$

The energy function is defined as

$$V(s(t)) = \frac{1}{2}s^2(t) \tag{14}$$

Substituting equation (7) into equation (13) and multiplying both sides by $s(t)$ yield

$$s\dot{s} = -sf_0(\underline{x}) - sG_0(\underline{x})\left(u_{SOWCM} + u_{sc}\right) + s\left(y_d^{(n)} - L(\underline{x}) + K^T \underline{e}\right) \tag{15}$$

With the energy function $V(s(t))$, the parameters updating law based on the normalized gradient descent method can be derived as follows

The updating law for the kth weight memory can be derived according to

$$\dot{\hat{w}}_{jk} = -\beta_w \frac{\partial s(t)\dot{s}(t)}{\partial u_{RWFCMAC}} \frac{\partial u_{RWFCMAC}}{\partial \hat{w}_{jk}} = \beta_w\, s(t) G_0(x,t) \hat{b}_{jk}(F_{ijk}) \tag{16}$$

Where β_w is positive learning rate for the output weight memory w_{jk}.

The translations, dilations and recurrent gain of the kth mother wavelet function can be also updated according to

$$\dot{\hat{m}}_{ijk} = -\beta_m \frac{\partial s(t)\dot{s}(t)}{\partial u_{RWFCMAC}} \frac{\partial u_{RWFCMAC}}{\partial \hat{b}_{jk}} \frac{\partial b_{jk}}{\partial f_{ijk}} \frac{\partial f_{ijk}}{\partial \hat{m}_{ijk}} = -\beta_m s(t) G_0(x,t) w_{jk} b_{jk} \frac{1-F_{ijk}^2}{(X_i - \hat{m}_{ijk})} \tag{17}$$

$$\dot{\hat{\sigma}}_{ijk} = -\beta_\sigma \frac{\partial s(t)\dot{s}(t)}{\partial u_{RWFCMAC}} \frac{\partial u_{RWFCMAC}}{\partial \hat{b}_{jk}} \frac{\partial b_{jk}}{\partial f_{ijk}} \frac{\partial f_{ijk}}{\partial \hat{\sigma}_{ijk}} = -\beta_\sigma s(t) G_0(x,t) w_{jk} b_{jk} \frac{1-F_{ijk}^2}{\sigma_{ijk}} \tag{18}$$

$$\dot{\hat{r}}_{ijk} = -\beta_r \frac{\partial s(t) s(t)}{\partial u_{RWFCMAC}} \frac{\partial u_{RWFCMAC}}{\partial \mu_{ij}} \frac{\partial \mu_{ij}}{\partial F_{ij}} \frac{\partial F_{ij}}{\partial r_{ij}} = \beta_r s(t) G_0(x,t) w_{jk} b_{jk} \frac{1-F_{ijk}^2}{(d_s - \hat{m}_{ijk})} \mu_{ijk}(k-1) \tag{19}$$

Where β_m, β_σ and β_r are positive learning rates for the translation $\hat{m}_{ijk}$, dilation $\hat{\sigma}_{ijk}$ and recurrent gain $\hat{r}_{ijk}$.

3.3. Smooth Compensator

The update laws of equations (15), (16), (17) and (18) require a proper choice of the learning rates β_w, β_m, β_σ and β_r in order to the convergence of the output errors are guaranteed; however, this is not easy which depends on each person's experience. In addition, the RWFCMAC is used to approximate the imprecise model or un-model of nonlinear system through learning. However, there exist errors between the estimating RWFCMAC and the ideal controller. So, to deal with these problems, the smooth compensator is designed to cope with the approximation errors and the stability of system is guarantied.

Assume that, the approximation error between the ideal controller and the estimating RWFCMAC is $\varepsilon(t)$. Thus; the ideal controller can be represented as the following form:

$$u^* = u_{RWFCMAC} + \varepsilon(t) \tag{20}$$

Where the approximation error term $\varepsilon(t)$, It is assumed that this is bounded by $0 \le \varepsilon(t) \le \rho^+$ in which is a positive constant.

The smooth compensator is designed as

$$u_{sc} = \begin{cases} -G_0^{-1}(x)\hat{\rho}^+ \operatorname{sgn}(s) & if\ |s| > \delta \quad \text{(a)} \\ -G_0^{-1}(x)\hat{\rho}^- s & if\ |s| \le \delta \quad \text{(b)} \end{cases} \tag{21}$$

Where $\hat{\rho}^+$ is the estimated approximation error bound, $\hat{\rho}^-$ is a free controller parameter, and δ is a positive constant revealing the linear region which is a trade-off between the chattering attenuation versus convergence speed. If δ is chosen small, it will easily result in chattering in the control force; on the contrast, if δ is chosen large to avoid chattering, the convergence speed will become too slow.

Substituting (7) into (1) yields

$$x^{(n)} = f_0(x) + G_0(x)(u_{RWFCMAC} + u_{sc}) + L(x). \tag{22}$$

After some straightforward manipulations, the error equation governing the system can be obtained through (5), (7), (20), and (1) as follows:

$$e^{(n)} + K^T \underline{e} = G_0(x) u_{sc} + \varepsilon = \dot{s}. \tag{23}$$

In order to guarantee the stability of the AWFCB control system for the situation, $|s| > \delta$, a Lyapunov function is defined as

$$V(s,\,\tilde{\rho}^{+}) = \frac{1}{2}s^{T}\dot{s} + \frac{1}{2\eta_{1}}\tilde{\rho}^{+2} \tag{24}$$

Where η_1 is a learning rate with a positive constant and $\tilde{\rho}^{+} = \rho^{+} - \hat{\rho}^{+}$ Using the time derivative of the Lyapunov function (24) and using (23), (21a) yields:

$$\dot{V}(s,\tilde{\rho}^{+}) = s\dot{s} + \frac{\tilde{\rho}^{+}\dot{\tilde{\rho}}^{+}}{\eta_{D}} = s(\varepsilon - \hat{\rho}^{+}\mathrm{sgn}(s)) + \frac{\tilde{\rho}^{+}\dot{\tilde{\rho}}^{+}}{\eta_{1}} = (s^{T}\varepsilon - \rho^{+}|s|) + \frac{\tilde{\rho}^{+}\dot{\tilde{\rho}}^{+}}{\eta_{1}}. \tag{25}$$

If the smooth compensator is designed for the situation, $|s| > \delta$ as shown in (21a), with the approximation error bound estimation law:

$$\dot{\tilde{\rho}}^{+} = -\dot{\hat{\rho}}^{+} = -\eta_{1}|s| \tag{26}$$

Then, from (25) becomes:

$$\begin{aligned}\dot{V}(s,\,\tilde{\rho}^{+}) &= s\varepsilon - \hat{\rho}^{+}|s| - \left(\rho^{+} - \rho^{+}\right)|s| = \left(s\varepsilon - \rho^{+}|s|\right) \le \left(|s||\varepsilon| - \rho^{+}|s|\right) \\ &= -\left(\rho^{+} - |\varepsilon|\right)|s| \le 0.\end{aligned} \tag{27}$$

Since $\dot{V}(s(t),\rho^{+}(t))$ is a negative semi-definite function, i.e. $V(s(t),\rho^{+}(t)) \le V(s(0),\rho^{+}(0))$, it implies that $s(t)$ and $\tilde{\rho}^{+}$ is bounded functions. Let function $h(t) \equiv \left(\rho^{+} - \|\varepsilon\|_{1}\right)s \le \left(\rho^{+} - \|\varepsilon\|_{1}\right)\|s\|_{1} \le -\dot{V}(s,\tilde{\rho}^{+})$ and integrate function $h(t)$ with respect to time

$$\int_{0}^{t} h(t)d\tau \le V(s(0),\,\rho^{+}(t)) - V(s(t),\,\rho^{+}(t)) \tag{28}$$

Because $V(s(0),\,\rho^{+}(0))$ is a bounded function, and $V(s(t),\,\rho^{+}(t))$ is a non-increasing and bounded function, the following result can be concluded:

$$\lim_{t\to\infty}\int_{0}^{t} h(\tau)\,d\tau < \infty \tag{29}$$

In addition, $\dot{h}(t)$ is bounded; thus, by Barbalat's lemma can be shown that $\lim_{t\to\infty} h(t) = 0$. It can imply that s will be converging to zero as time tends to infinite.

The compensator in (21a) uses a sign function to guarantee the system's stability; its output tracks the desired trajectory, even in the unknown plant model. However, the compensator is usually discontinuous across s. This leads to control input chattering. In order to guarantee the stability of the RWFCMAC control system for the situation $|s| \le \delta$ a Lyapunov function is defined as

$$J(s,\,\tilde{\rho}^{-}) = \frac{1}{2}s^{T}\dot{s} + \frac{1}{2\eta_{2}}\tilde{\rho}^{-2} \tag{30}$$

Where η_2 is a learning rate with a positive constant. Ideally, there exists an optimal constant, ρ^{-*} which matches the robust stability condition in (21b) as

$$\rho^{-*}|s| > |\varepsilon| \tag{31}$$

However, this optimal constant cannot be obtained, so an online estimation of this constant is proposed. The estimation error is defined as

$$\tilde{\rho}^{-} = \rho^{-} - \hat{\rho}^{-}. \tag{32}$$

Using the time derivative of the Lyapunov function (30) and using (22), (21b) yields:

$$\begin{aligned}\dot{J}(s,\tilde{\rho}^{-}) &= s\dot{s} + \frac{\tilde{\rho}^{+}\dot{\tilde{\rho}}^{+}}{\eta_D} = s(\varepsilon - \rho s) + \frac{\tilde{\rho}^{-}\dot{\tilde{\rho}}^{-}}{\eta_2} = (s\varepsilon - \rho^{-}\left|s^2\right|) - \frac{\tilde{\rho}^{-}\dot{\hat{\rho}}^{-}}{\eta_2} + \rho^{-*}\left|s^2\right| - \rho^{-*}\left|s^2\right| \\ &= s\varepsilon + \tilde{\rho}^{-}\left|s^2\right| - \frac{\tilde{\rho}^{-}\dot{\hat{\rho}}^{-}}{\eta_2} - \rho^{-*}\left|s^2\right| \\ &= s\varepsilon - \tilde{\rho}^{-}\left(\left|s^2\right| - \frac{\dot{\hat{\rho}}^{-}}{\eta_2}\right) - \rho^{-*}\left|s^2\right|.\end{aligned} \tag{33}$$

The parameter estimation law is chosen as

$$\dot{\hat{\rho}}^{-} = \eta_2\left|s^2\right| \tag{34}$$

and therefore, (33) becomes

$$\begin{aligned}&\dot{J}(s,\tilde{\rho}^{-}) = s\varepsilon - \tilde{\rho}^{-}\left(\left|s^2\right| - \frac{\dot{\hat{\rho}}^{-}}{\eta_2}\right) - \rho^{-*}\left|s^2\right| = s\varepsilon - \rho^{-*}\left|s^2\right| \le |s||\varepsilon| - \rho^{-*}\left|s^2\right| \\ &= -|s|\left(\rho^{-*}|s| - |\varepsilon|\right) \le 0.\end{aligned} \tag{35}$$

Similarly to the discussion in the previous section, it is concluded that **s** converge to zero, as t→∞. As a result, the RWFCMAC control system for the situation $|s| \le \delta$ asymptotically stabilizes the system.

4. Experimental Results

4.1. 2 DoF Hellicopter System

A experimental results of 2 *DoF* Helicopter are examined to illustrate the effectiveness of the proposed control method. A photograph of the experimental system is shown in Figure 4. The control algorithm is implemented using a Pentium computer and the control software is Matlab 2013b. The interface device is implemented by the motion control card STM32F4, which can measure the angular positions with a resolution of 2500 counts/revolution for pitch and yaw angle at the same time. The nonlinear dynamic equation of 2 *DoF* Helicopter system are given by [22].

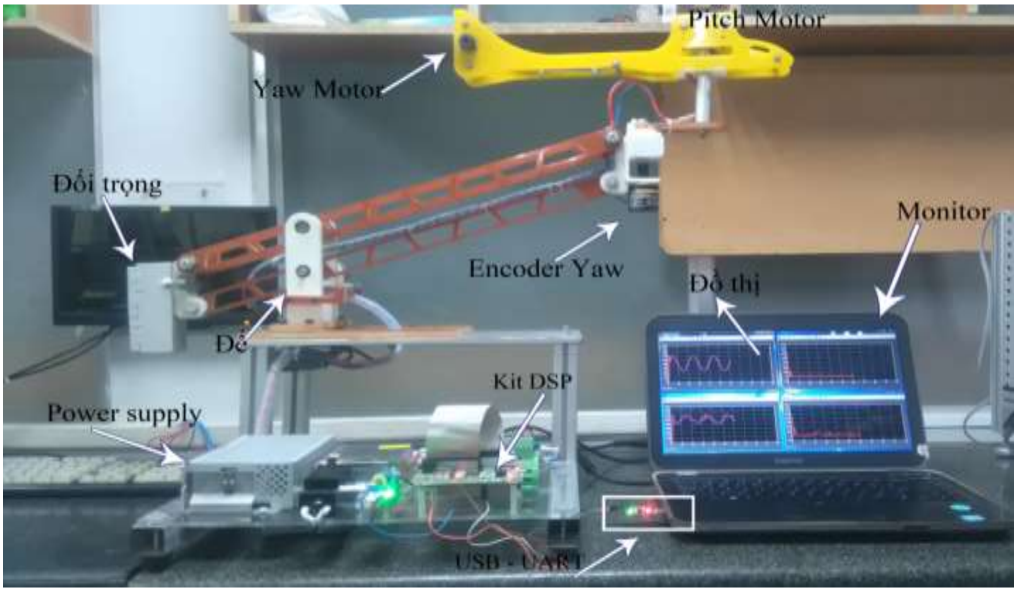
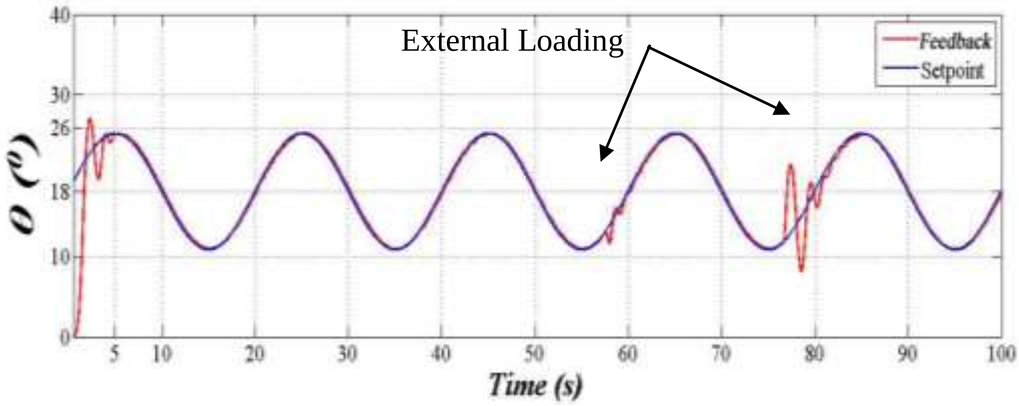


Figure 4. PC based 2 DoF Hellicopter Position Control System

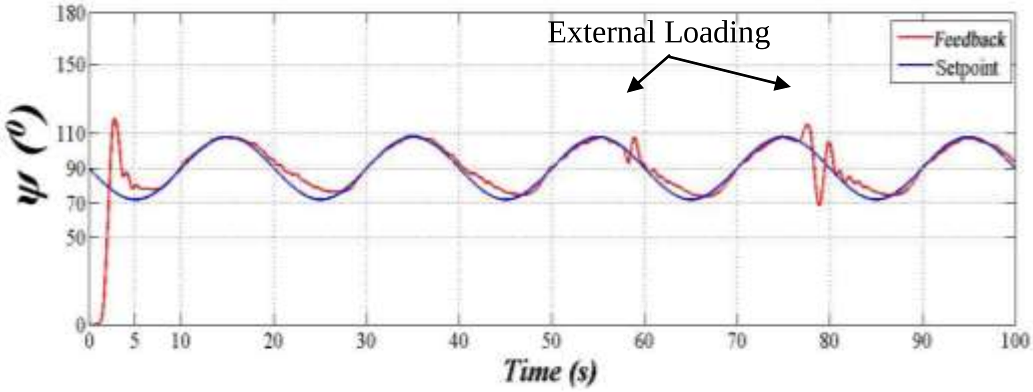
$$\ddot{x} = f\left(\underline{x}\right) + G\left(\underline{x}\right)u + L\left(x\right) \tag{36}$$

where $x = \left[x^T \quad \dot{x}^T\right], x = [\theta \quad \psi], \dot{x} = [\dot{\theta} \quad \dot{\psi}]$ represent the position and velocity of the pitch and yaw angle, respectively; $G\left(\underline{x}\right)$ is the gain of the 2 DoF Hellicopter; $f\left(\underline{x}\right)$ denotes a nonlinear dynamic function; u is the input voltage; and $L\left(\underline{x}\right)$ is the normalized lump force of the uncertain nonlinearities such as friction, and external disturbance. Since the dynamic characteristic of 2 DoF hellicopter is difficult to obtain, the dynamic functions $f\left(\underline{x}\right)$, $G\left(x\right)$ and $L\left(\underline{x}\right)$ are assumed to be unknown. The proposed RWFCMAC system is applied to control the system by letting $f_0\left(\underline{x}\right) = 1$ and $G_0\left(\underline{x}\right) = 1$.

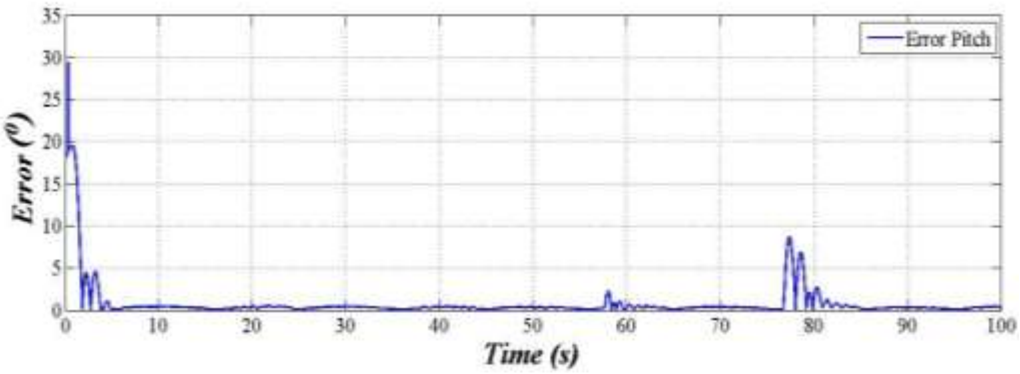
In this section, the proposed RWFCMAC control system is used for 2 DoF Hellicopter trajectory tracking control. The proposed recuurent wavelet fuzzy CMAC is shown in Figure 2 and is characterized by: number of input state variables are s_1, s_2, number of elements for each input state variable: $n_e = 5$, generalization: $\rho = 4$, number of layers for each input dimension: $n_j = 4$, number of blocks for each layer: $n_k = 2$, number of rules: $n_l = 8$. The parameters of the proposed RWFCMAC are selected as $k_1 = k_2 = 6$, $\beta_w = 0.1,$ $\beta_m = \beta_\sigma = \beta_r = \beta_1 = \beta_2 = 0.01$. All the parameters are determined through some trials in order to guarantee the desired control performance. The experimental results of the proposed RWFCMAC system due to a sinusoidal and constant commands are shown in Figure 5 and Figure 6 for no loading and 1kg loading at $t = 57$ and 2kg loading at $t = 77$, respectively. The experimental results indicate that highly-accurate trajectory tracking responses have been achieved without control chattering and by the proposed RWFCMAC control. Moreover, in the 2 DoF hellicopter control system, its dynamic functions and external load are unknown. This shows that the proposed design method can handle this unknown dynamic system.



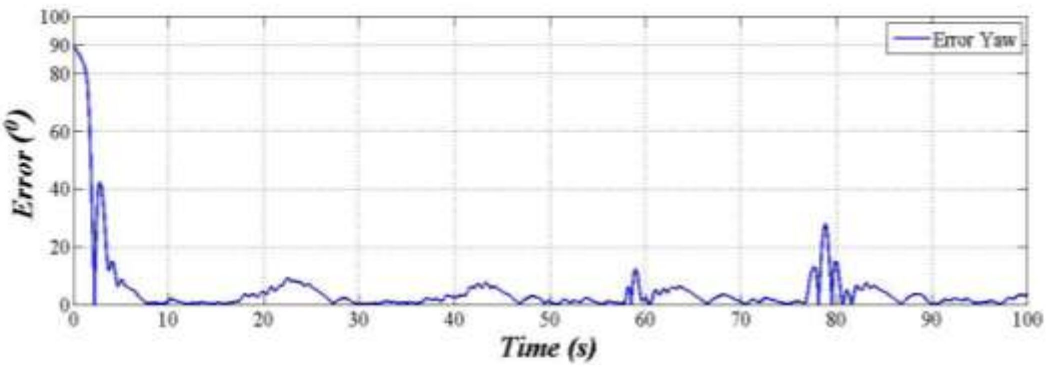
(a) Tracking responses of pitch axis



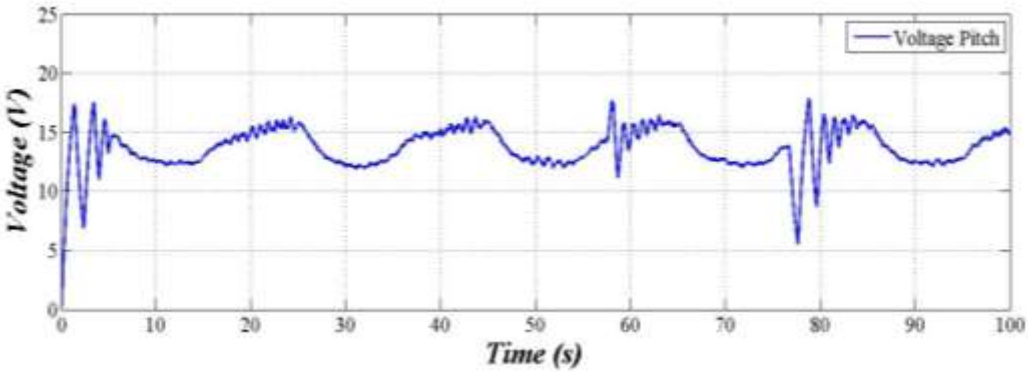
(b) Tracking responses of yaw axis



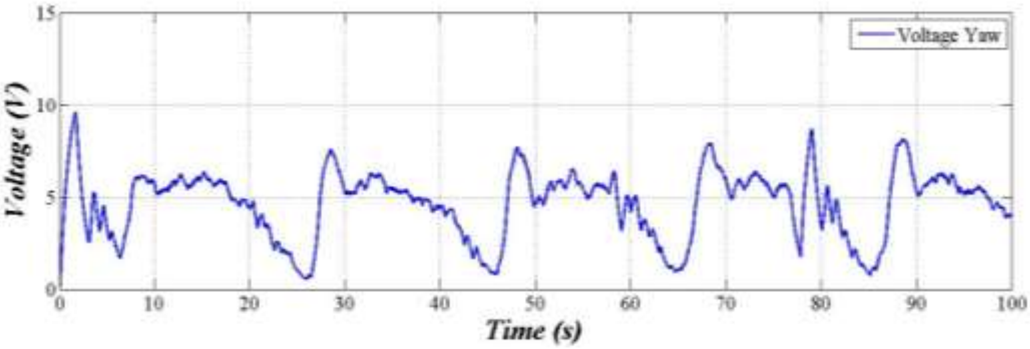
(c) Tracking error of pitch axis



(d) Tracking error of yaw axis

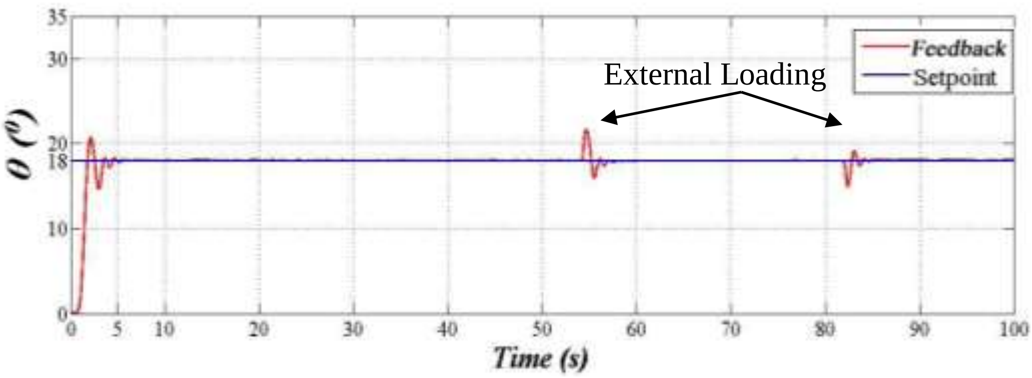


(e) Control effort of pitch axis

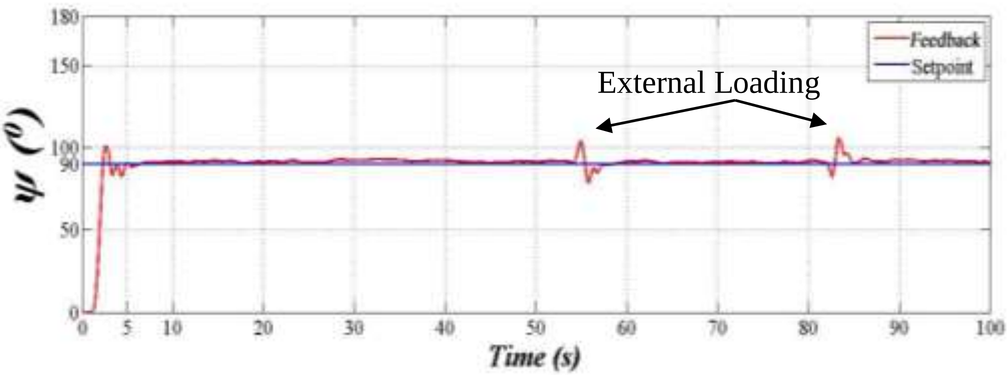


(f) Control effort of yaw axis

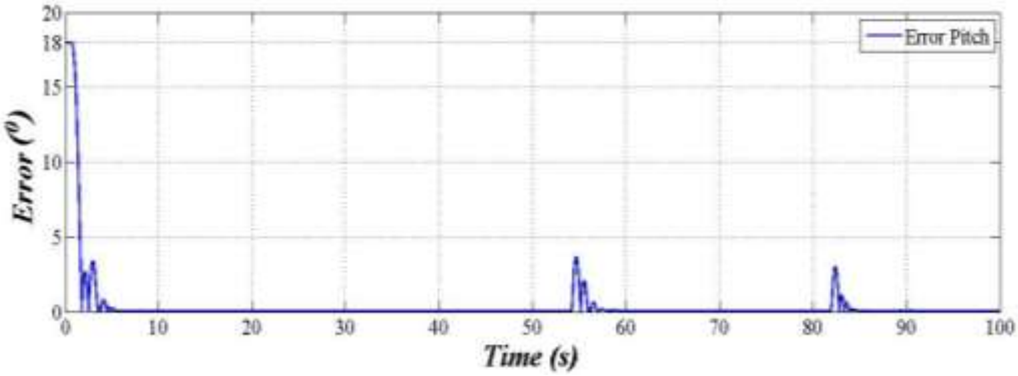
Figure 5. Experimental Result of Proposed RWFCMAC Due to a Sinusoidal Command for 2 DoF Hellicopter: No Loading and with 1kg Loading at $t = 57$ and 2kg Loading at $t = 77$



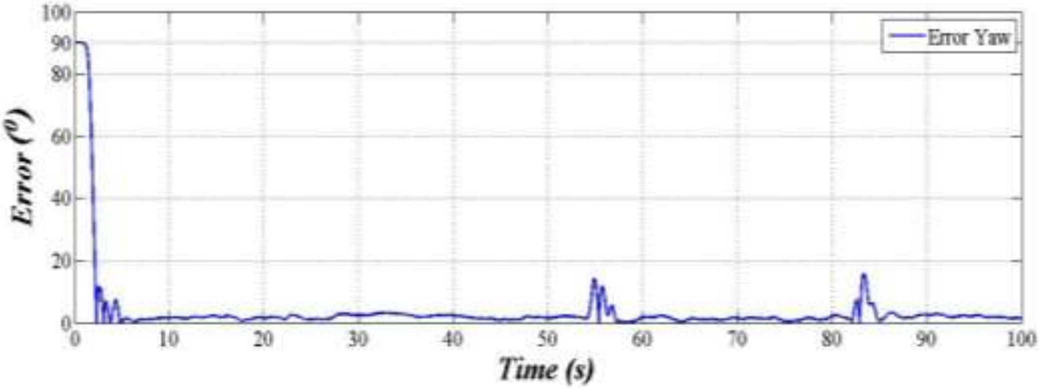
(a) Tracking responses of pitch axis



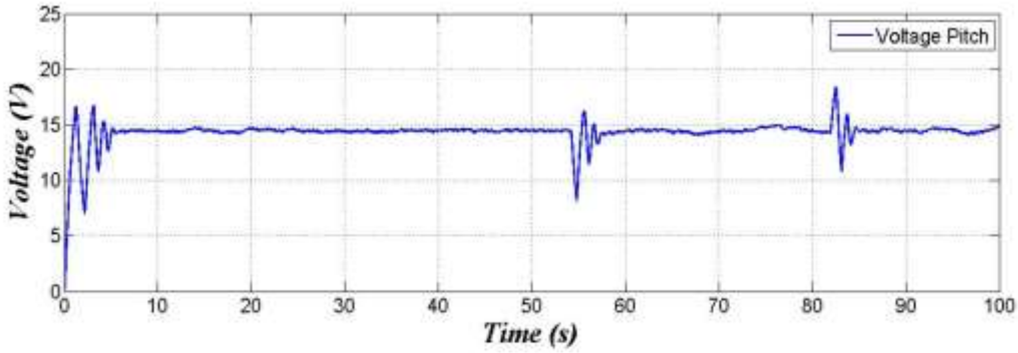
(b) Tracking responses of yaw axis



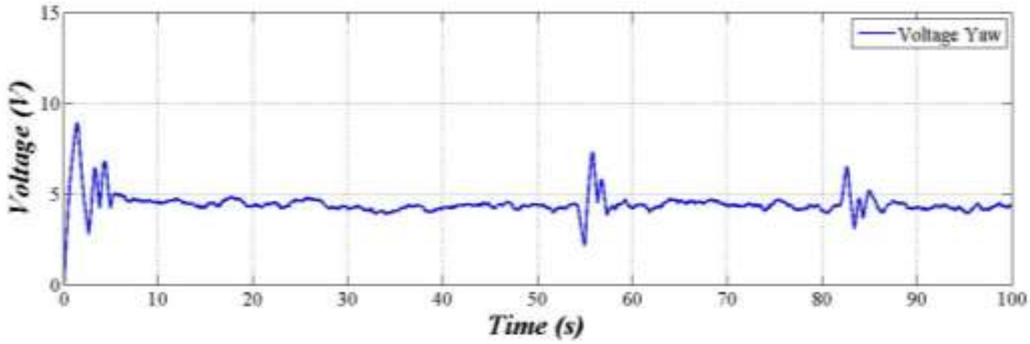
(c) Tracking error of pitch axis



(d) Tracking error of yaw axis



(e) Control effort of pitch axis



(f) Control effort of yaw axis

Figure 6. Experimental Result of Proposed RWFCMAC Due to a Constant Command for 2 DoF Hellicopter: No Loading and with 2kg Loading at $t = 54$ **and 2kg Loading at** $t = 83$

4.2. Tank level System

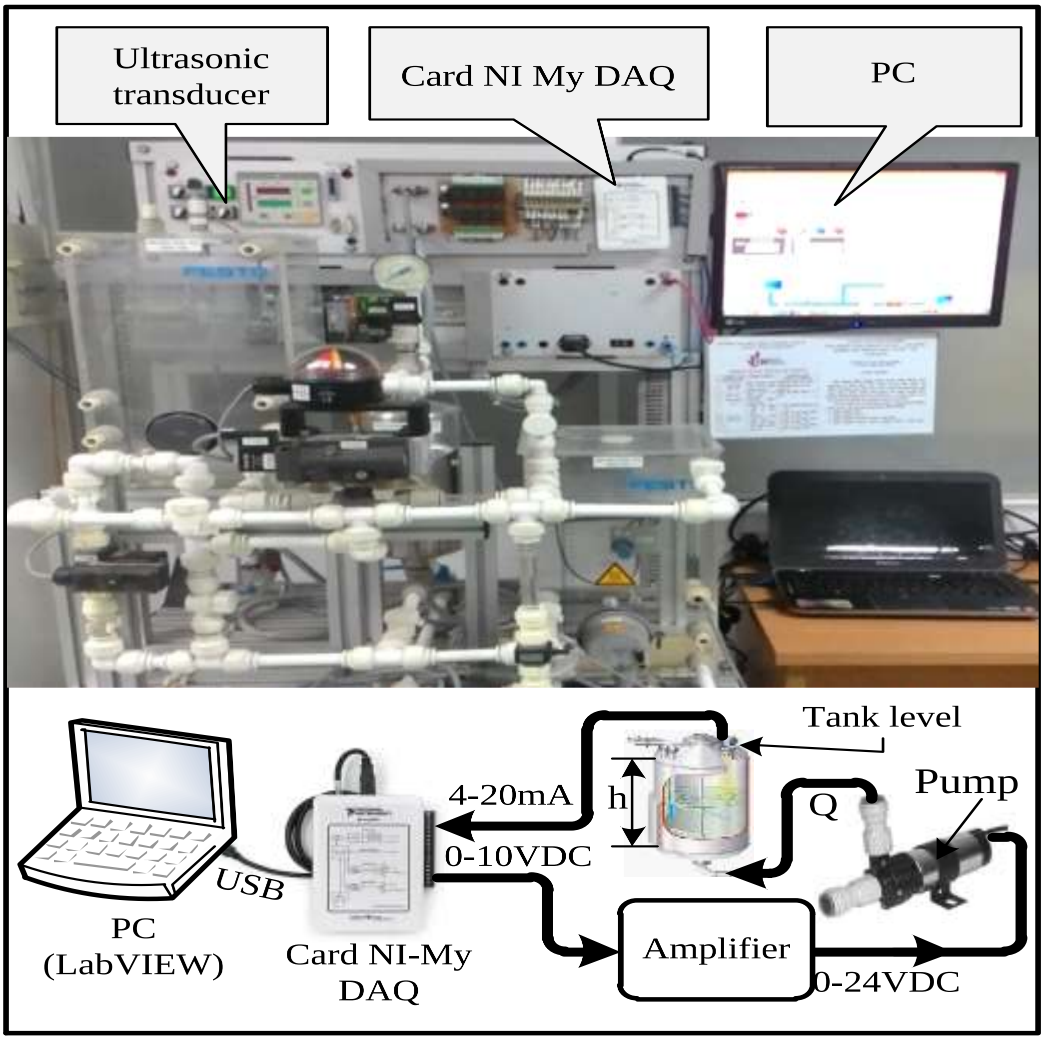
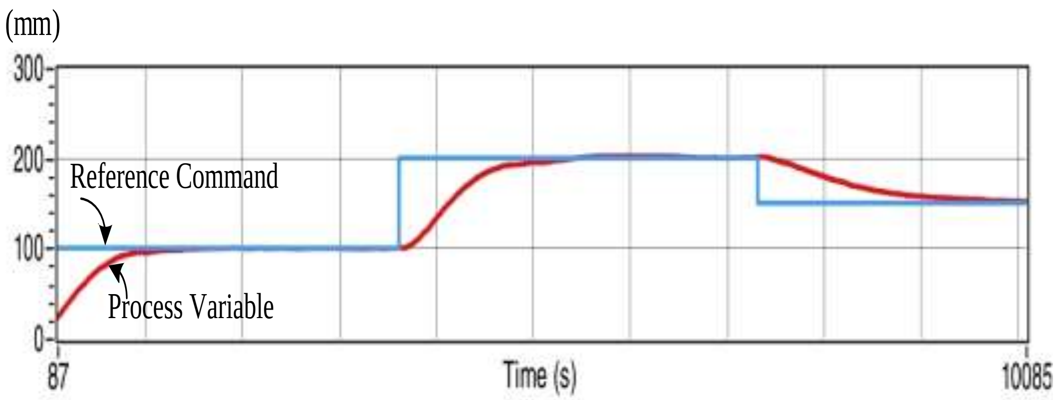


Figure 7. PC based Tank Level Position Control System

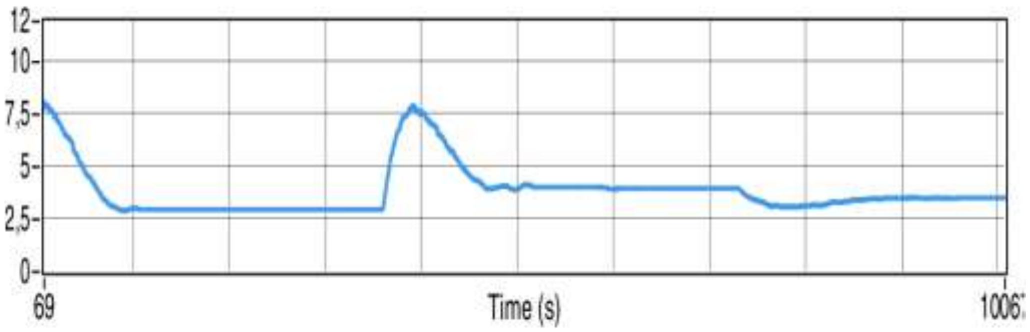
A other experimental results of tank level are examined to illustrate the effectiveness of the proposed control method. A photograph of the experimental system is shown in Figure 7. For the purpose of comparison, the experimental results for a PID control and the proposed RWFCMAC control for a tank level are given. Firstly, a PID controller is applied to control this system. The PID gains are selected as $k_c = 4$, $T_i = 0,75$ and $T_d = 0.01$; they are determined through trial-and-error to achieve satisfactory tracking performance. The experimental results of the PID controller are shown in Figure 8. The tracking response is shown in Figure 8(a); the associated control effort and tracking error are shown in Figure 8(b) and 8(c). Finally, the proposed RWFCMAC control is also applied to this system. The control parameters are selected the same 2 DoF hellicopter control system, where the number of input state variable is s_1. The experimental results of the proposed RWFCMAC system due to a periodic step commands are shown in Figure 9. The tracking response is shown in Figure 9(a); the associated control effort and tracking error are shown in Figure 9(b) and 9(c). The experimental results indicate that highly-accurate trajectory tracking responses have been achieved without control chattering by the proposed RWFCMAC control. A comparison of performance measures of the PID control and RWFCMAC control system are tabulated in T able 1 which indicate that, the root mean square error of RWFCMAC control can achieve better tracking performance than the PID control system.

Table 1. Performance Measures of PID Control and Proposed RWFCMAC Control System

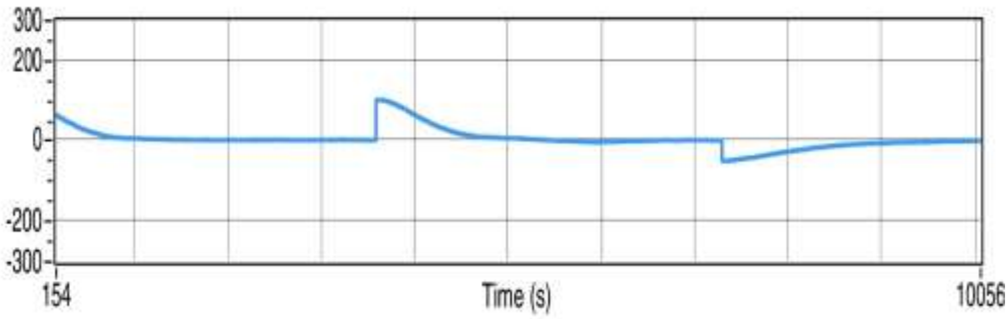
Tracking error	PID Control System	Proposed RWFCMAC Control System
Total Root Mean Square Error (mm)	1,8	1,2



(a) Tracking responses of tank level

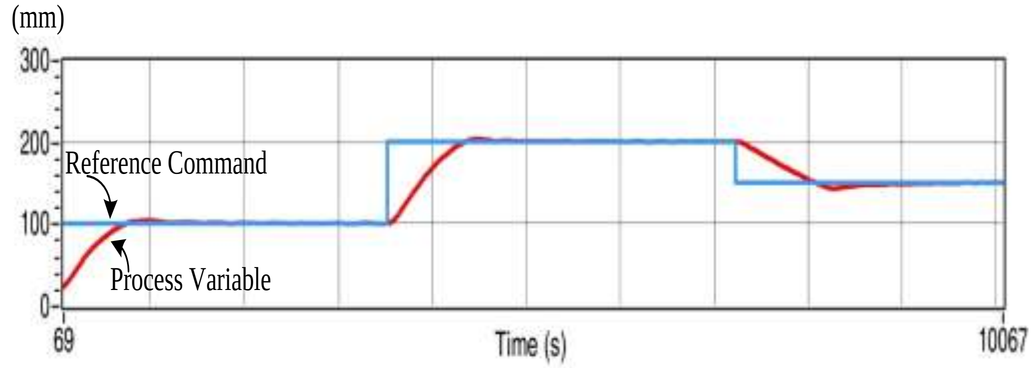


(b) Control effort

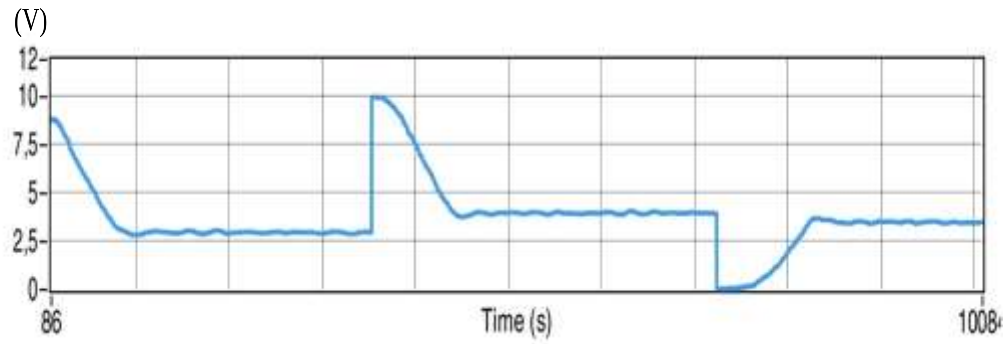


(c) Tracking error of tank level

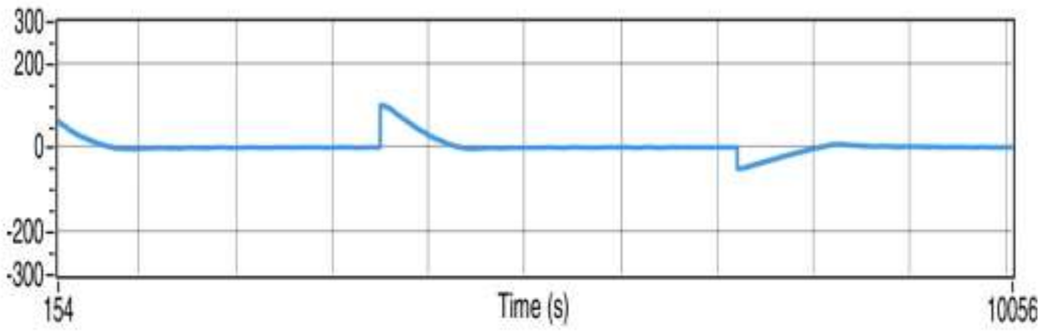
Figure 8. Experimental Result of PID Due to a Periodic Step Command for Tank Level Control System



(a) Tracking responses of tank level



(b) Control effort



(c) Tracking error of tank level

Figure 9. Experimental Result of Proposed RWFCMAC due to a Periodic Step Command for Tank Level Control System

5. Conclusion

Due to dynamical system has a non-linear characteristic and time-varying behavior. It is difficult to establish exactly mathematical model for the design of a model-based control system. To due with these problems, the most of the control system was proposed based on the intelligent control theory to approximate non-linear function. In this paper, the novel RWFCMAC approximation with SC compensator is also developed and successfully used to control the 2 DoF hellicopter and tank level systems. In this proposed scheme, the main RWFCMAC controller incorporates the advantages of the wavelet decomposition property, dynamic response with fuzzy CMAC fast learning ability and the SC compensator is designed to attenuate the effect of the approximation error. The online tuning laws of RWFCMAC and SC parameters are derived based on gradient descent method and Lyapunov function. Finally, though the experimental results of the proposed RWFCMAC system can achieve favorable tracking performance for two these systems. Moreover, in the these control system, its dynamic functions are unknown. This shows that the proposed design method can handle this unknown dynamic system.

References

[1] A. Vemuri, M.M. Polycarpou, S.A. Diakourtis, "Neural network based fault detection in robotic manipulators," IEEE Robotics Automation, vol. 14, no. 2, **(1998)**, pp. 342-348.

[2] Wenzhi. Gao, R.R. Selmic, "Neural network control of a class of nonlinear systems with actuator saturation," IEEE Trans., Neural Net., vol. 17, no. 1, **(2006)**, pp. 147-156.

[3] Yi Zou, Yaonan Wang, XinZhi Liu, "Neural network robust H∞ tracking control strategy for robot manipulators," Applied Mathematical Modelling, vol. 34, **(2010)**, pp. 1823-1838.

[4] B. S. Chen, H. J. Uang, and C. S. Tseng, "Robust tracking enhancement of robot systems including motor dynamics: A fuzzy-based dynamic game approach," IEEE Trans. Fuzzy syst., vol. 11, no. 4, **(1998)**, pp. 538-552.

[5] H. X. Li and S.C. Tong, "A hybrid adaptive fuzzy control for a class of nonlinear MIMO systems," IEEE Fuzzy Syst., vol. 11, no. 1, **(2003)**, pp. 24-34.

[6] R. J. Wai, "Development of new training algorithms for neuro-wavelet systems on the robust control of induction servo motor drive," IEEE Trans. Ind. Electron., vol. 49, no. 6, **(2002)**, pp. 1323-1341.

[7] F.F.M. EI-Sousy, "Robust wavelet-neural network sliding-mode control system for permanent magnet synchronous motor drives," IET Electr. Power Appl., vol. 5, Iss. 1, **(2011)**, pp. 113-132.

[8] C. H. Lu, "Design and application of stable predictive controller using recurrent wavelet neural networks," IEEE Trans. Ind. Electron., vol. 56, no. 9, **(2009)**, pp. 3733-3742.

[9] F.-J. Lin, S.-Y. Chen, Y.-C. Hung "Field-programmable gate array-based recurrent wavelet neural network control system for linear ultrasonic motor," IET Electr. Power Appl., vol. 3, Iss. 4, **(2009)**, pp. 289-312.

[10] J. S. Albus, "A new approach to manipulator control: The cerebellar model articulation controller (CMAC)," J. Dyn. Syst. Meas. Control, vol. 97, no. 3, **(1975)**, pp. 220–227.

[11] H. Shiraishi, S. L. Ipri, and D. D. Cho, "CMAC neural network controller for fuel-injection systems," IEEE Trans. Control Syst. Technol., vol. 3, no. 1, **(1995)**, pp. 32–38.

[12] S. Jagannathan, S. Commuri, and F. L. Lewis, "Feedback linearization using CMAC neural networks," Automatica, vol. 34, no. 3, **(1998)**, pp. 547–557.

[13] Y. H. Kim and F. L. Lewis, "Optimal design of CMAC neural-network controller for robot manipulators," IEEE Trans. Syst. Man Cybern. C, Appl. Rev., vol. 30, no. 1, **(2000)**, pp. 22–31.

[14] C. T. Chiang and C. S. Lin, "CMAC with general basis functions," J. Neural Netw., vol. 9, no. 7, **(1996)**, pp. 1199–1211.

[15] C. M. Lin and Y. F. Peng, "Adaptive CMAC-based supervisory control for uncertain nonlinear systems," IEEE Trans. Syst. Man Cybern. B, Cybern., vol. 34, no. 2, **(2004)**, pp. 1248–1260.

[16] S. F. Su, T. Tao, and T. H. Hung, "Credit assigned CMAC and its application to online learning robust controllers," IEEE Trans. Syst. Man Cybern. B, vol. 33, no. 2, **(2003)**, pp. 202–213.

[17] H. C. Lu, C. Y. Chuang, M. F. Yeh, "Design of hybrid adaptive CMAC with supervisory controller for a class of nonlinear system," Neurocomputing, vol. 72, no. 7-9, **(2009)**, pp. 1920-1933.

[18] Y. F. Peng and C. M. Lin, "Intelligent hybrid control for uncertain nonlinear systems using a recurrent cerebellar model articulation controller," IEE Proc. Control Theory Appl., vol. 151, no. 5, **(2004)**, pp. 589-600.

[19] S.-Y. Wang, C.-L. Tseng, C.-C Yeh, "Adaptive supervisory Gaussian-cerebellar model articulation controllers for direct torque control induction motor drive," IET Electr. Power Appl., vol. 5, Iss. 3, **(2011)**, pp. 295-306.

[20] M. F. Yeh and C. H. Tsai, "Standalone CMAC control systems with online learning ability," IEEE Trans. Syst. Man Cybern. B, vol. 40, no. 1, **(2010)**, pp. 43-53.

[21] Chih-Min Lin, and Hsin-Yi Li, "A Novel Adaptive Wavelet Fuzzy Cerebellar Model Articulation Control System Design for Voice Coil Motors" IEEE Trans. Ind. Electron., vol. 59, no. 4, **(2012)**, pp. 2024-2033.

[22] P. K. Huang, P. H. Shieh, F. J. Lin and H. J. Shieh, "Sliding-mode control for a two-dimensional piezo-positioning stage," IET Control Theory Appl., vol. 4, no. 1, **(2007)**, pp. 1104-1113.

[23] Elumalai Vinodh Kumar, Ganapathy Subramanian Raaja, Jovitha Jerome, "Adaptive PSO for optimal LQR tracking control of 2 DoF laboratory helicopter" Appl. Soft Comput. J., vol. C, no. 41, **(2015)**, pp. 77-90.

