International Journal of Control, Automation and Systems 18(9) (2020) 2423-2434
http://dx.doi.org/10.1007/s12555-019-0513-7
ISSN:1598-6446 eISSN:2005-4092
http://www.springer.com/12555

Adaptive Trajectory Neural Network Tracking Control for Industrial Robot Manipulators with Deadzone Robust Compensator

La Van Truong, Shou Dao Huang, Vu Thi Yen, and Pham Van Cuong*

Abstract: This paper proposed a novel adaptive tracking neural network with deadzone robust compensator for Industrial Robot Manipulators (IRMs) to achieve the high precision position tracking performance. In order, to deal the uncertainty, the unknown deadzone effect, the unknown dynamics, and disturbances of robot system, the Radial Basis function neural networks (RBFNNs) control is presented to control the joint position and approximate the unknown dynamics of an n-link robot manipulator. The online adaptive control training laws and estimation of the dead-zone are determined by Lyapunov stability and the approximation theory, so that the stability of the entire system and the convergence of the weight adaptation are guaranteed. In this controller, a robust compensator is constructed as an auxiliary controller to guarantee the stability and robustness under various environments such as the mass variation, the external disturbances and modeling uncertainties. The proposed control is the verified on a three-joint robot manipulators via simulations and experiments in comparison with PID and Neural networks (NNs) control.

Keywords: Adaptive control, RBF network, robot manipulator, unknown deadzone.

1. INTRODUCTION

Recently, Robot manipulators have been widely applied in the industrial. In fact, Industrial Robot manipulators are multivariable nonlinear systems and they suffer from various uncertainties in their dynamics, which deteriorate the system performance and stability, such as external disturbance, nonlinear friction, highly time-varying, and payload variation. Therefore, achieving high performance in trajectory tracking is a very challenging task. So, many researchers were proposed adaptive controller, robust adaptive controller, fuzzy logic control, neural network control, etc. [1–8]. In [9], the vector control method of induction motor using an MRAS-fuzzy logic observer was presented. This type of observer combines the Model Reference Adaptive Systems (MRAS) technique with the fuzzy logic to design an MRAS-fuzzy logic observer which can at first estimate the rotor speed and second the rotor resistance. In [10], adaptive model control and neural network based trajectory planner were designed for dynamic balance and motion tracking of desired trajectories. However, this control needed the knowledge of dynamics. In [11], an adaptive controller based neural networks was proposed to deal uncertainties and input saturation of robotic manipulators. The RBFNNs controller was used to approximate the unknown dynamic and an auxiliary system was designed to solve the input saturation. In [12–16], adaptive neural network controllers were presented by using output feedback methods, and in [17–26], artificial neural networks were widely used for the control design of nonlinear systems. In addition, in practical control system, Deadzone that is a natural and nonlinear item, widely exists and takes adverse effects on the whole system. In the robotic control, the performance of control systems is generally influenced by deadzone, such as poor transient response, large overshoot, and excessive steady state. To deal these problems, some deadzone rejection technologies have proposed to enhance the performance of robotic system. In [27–30], a compensation scheme was presented for nonlinear actuator deadzone. These techniques provided a procedure for using neural networks to determine the preinverse of an unknown right-invertible. In [28], an adaptive tracking control was designed for a class of nonlinear discrete time systems with deadzone input. In this control, the neural network was used to approximate the unknown function in the transformed system, and the tracking error converged to neighborhood of zero. In [31], the adaptive control of nonlinear dynamic systems with an

Manuscript received July 9, 2019; revised October 26, 2019; accepted December 5, 2019. Recommended by Associate Editor Yang Tang under the direction of Editor Hamid Reza Karimi.

La Van Truong and Shou Dao Huang are with the College of Electrical and Information Engineering, Hunan University, Hunan Changsha, China (e-mails: latruongnute@gmail.com, hsd1962@hnu.edu.cn). La Van Truong is also with Faculty of Electrical-Electronic Engineering, NamDinh University of Technology Education, Vietnam. Vu Thi Yen and Pham Van Cuong are with the Faculty of Electrical Engineering Technology, Hanoi University of Industry, Hanoi, Vietnam (e-mails: havi2203@gmail.com, cuongpv0610@haui.edu.vn).
* Corresponding author.

Springer

unknown deadzone was focused on. The effective deadzone estimation technique was proposed by using neural network for a wide range of system. To tackle effects of deadzone, multilayers neural network is also used. Adaptive control based on multilayers neural network by combining dynamic surface control and backstepping techniques was developed for nonlinear system [32]. Although multilayers neural network has approximating capabilities, but no method exists to select the network structure to achieve the desired approximation accuracy, and multilayers neural network tends to forget old information that has results in bad approximation of data. Furthermore, in comparing with multilayers neural network, RBFNNs controllers that usually consume relatively less calculation resources are simpler in both designing and application. In this paper, we propose a novel adaptive tracking RBFNNs to control the joint position and to deal the problem of compensation dead- zone, unknown dynamic and external disturbance for three link IRMs which the conventional controllers cannot properly handle. By using Lyapunov stability theory, the weights of RBFNNs are update online, and the robustness and stability of the RBFNNs are guaranteed. Comparing with the existing results in the literatures, our proposed controller is more flexible, and the time consuming training process is not necessary.

This paper is organized as follows: The preliminaries are described in Section 2. Section 3 presents Control design and Stability Analysis. The simulation and experimental results are proposed in Section 4. Finally, in Section 5, concluding remarks are given.

2. PRELIMINARIES

2.1. Model of robotic manipulators

In this paper, the dynamics of an n- link industrial robot manipulator with external disturbance can be described in the Lagrange equation as follows:

$$M_R(q)\ddot{q}+C_R(q,\dot{q})\dot{q}+G_R(q)+F_R(\dot{q})=\tau-\tau_0 \tag{1}$$

with $q=[q_1\ q_2\ \dots\ q_n]\in R^{n\times 1}$ is the joint position vector, $\dot{q}=[\dot{q}_1\ \dot{q}_2\ \dots\ \dot{q}_n]\in R^{n\times 1}$ is the velocity vector and $\ddot{q}=[\ddot{q}_1\ \ddot{q}_2\ \dots\ \ddot{q}_n]\in R^{n\times 1}$ is the acceleration vector. $M_R(q)$ expresses the $n\times n$ symmetric inertial matrix. $C_R(q,\dot{q})$ denotes the $n\times n$ vector of Coriolis and Centripetal forces. $G_R(q)\in R^{n\times n}$ denotes the Gravity vector. $F_R(\dot{q})$ denotes the $n\times 1$ vector of the frictions. τ_0 expresses the $n\times 1$ vector of the input unknown disturbances. And τ is the $n\times 1$ control input vector of joints torque. For designing controller, several properties of the robot dynamics (1) have been assumed as follows:

Property 1: $M_R(q)$ is the $n\times n$ symmetric inertial Matrix and bounded:

$$m_1\|x\|^2\le x^T M_R(q)x\le m_2\|x\|^2,\ \ \forall x\in R^n, \tag{2}$$

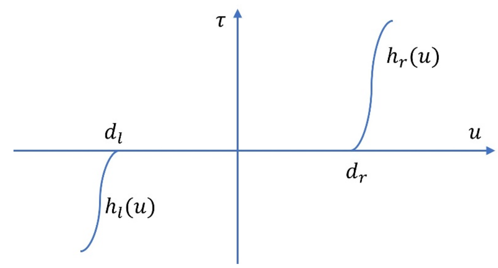

Fig. 1. Dead zone model.

where m_1 and m_2 are known positive constants.

Property 2: $\dot{M}_R(q)-2C_R(q,\dot{q})$ is skew symmetry matrix, in which

$$x^T[\dot{M}_R(q)-2C_R(q,\dot{q})]x=0. \tag{3}$$

Property 3: $C_R(q,\dot{q})\dot{q}$, $G_R(q)$ and $F_R(q)$ are satisfied:

$$\begin{aligned}&\|C_R(q,\dot{q})\dot{q}\|\le C_k\|\dot{q}\|^2,\\&\|G_R(q)\|\le G_k,\\&\|F_R(\dot{q})\|\le F_k\|\dot{q}\|+F_0,\end{aligned} \tag{4}$$

where C_k, G_k, F_k, F_0 are positive constants.

Property 4: $\tau_0\in R^n$ is the unknown disturbance and τ_0 is bounded as follows:

$$\|\tau_0\|\le\tau_k,\ \ \tau_k>0. \tag{5}$$

According to assumptions were given in [2], the dead zone function that is shown in Fig. 1, is expressed as follows:

$$\begin{aligned}\tau=&D(u)\\=&\begin{cases}h_r(u-d_r) & \text{for } u>d_r,\\ 0 & \text{for } d_l\le u\le d_r,\\ h_l(u+d_l) & \text{for } u<d_l.\end{cases}\end{aligned} \tag{6}$$

Here, $d_r>0$, $d_l<0$ are unknown constant parameters of dead zone. $h_l(u)$, $h_r(u)$ are the unknown smooth functions, where u is control input before entering the dead zone. τ is control input after entering the dead zone.
Therefore (6) can be rewritten as

$$\tau=D(u)=u-sat_D(u), \tag{7}$$

where the asymmetric saturation function is defined as

$$sat_D(u)=\begin{cases}dr & \text{for } u>d_r,\\ u & \text{for } dl\le u\le dr,\\ dl & \text{for } u<d_l.\end{cases} \tag{8}$$

2.2. Structure of RBFNNs

RBFNNs are a local mapping networks, which have a few neurons respond to local area of the input space and

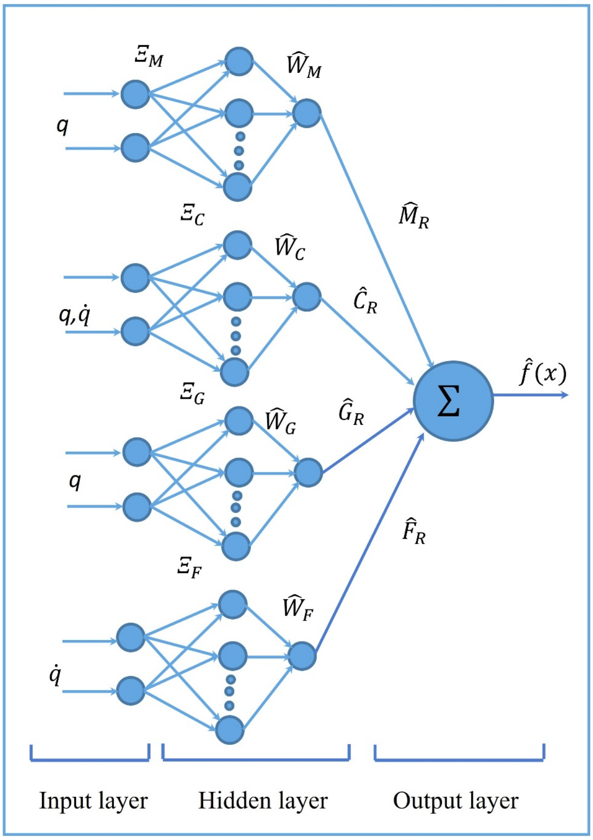

Fig. 2. Structure of RBF neural networks.

determine the output of RBF networks. RBF networks can approximate any single value continuous function with arbitrary precision by the enough number of neurons in hidden layer. The configuration of RBFNNs are described in Fig. 2.

Assume the output values of ideal RBFNNs are $M_R(q)$, $C_R(q,\dot{q})$, $G_R(q)$, $F_R(\dot{q})$ and calculated as

$$\begin{aligned} M(q) &= M_R(q)+\Gamma_M \\ &= W_M^T * \Xi_M(q)+\Gamma_M, \end{aligned} \tag{9}$$

$$\begin{aligned} C(q,\cdot q) &= C_R(q,\dot{q})+\Gamma_C \\ &= W_C^T * \Xi_C(q,q)+\Gamma_C, \end{aligned} \tag{10}$$

$$\begin{aligned} G(q) &= G_R(q)+\Gamma_G \\ &= W_G^T * \Xi_G(q)+\Gamma_G, \end{aligned} \tag{11}$$

$$\begin{aligned} F(\dot{q}) &= M_F(q)+\Gamma_F \\ &= W_F^T * \Xi_F(\dot{q})+\Gamma_F, \end{aligned} \tag{12}$$

where W_M, $W(C)$, and W_G, W_F are ideal optimum weight value of RBF; Ξ_M, Ξ_C, Ξ_G, Ξ_F are outputs of hiden layer, Γ_M, Γ_C, Γ_G and Γ_F are modeling error of $M(q)$, $C(q,\cdot q)$, $G(q)$, and $F(\cdot q)$, respectively, and n is the number of hidden notes.

The estimated values of $M_R(q)$, $C_R(q,\dot{q})$, $G_R(q)$ and $F_R(\dot{q})$ can be expressed by RBF as follows:

$$\hat{M}_R(q) = \hat{W}_M^T * \Xi_M(q), \tag{13}$$

$$\hat{C}_R(q,\dot{q}) = \hat{W}_C^T * \Xi_C(q,\dot{q}), \tag{14}$$

$$\hat{G}_R(q) = \hat{W}_G^T * \Xi_G(q), \tag{15}$$

$$\hat{F}_R(\dot{q}) = \hat{W}_F^T * \Xi_F(\dot{q}), \tag{16}$$

where $\hat{W}_M$, $\hat{W}_C$, $\hat{W}_G$, and $\hat{W}_F$ are estimates of W_M, W_C, W_G and W_F, respectively.

3. CONTROL DESIGN AND STABILITY ANALYSIS

3.1. Control design

We recommend the RBFNNs to find an adaptive law of the suitable adaptive RBFNNs model that makes control system able to achieve the required approximation errors accuracy. Architecture of the dead zone compensator is shown in Fig. 3.

To compensate the effects of dead zone, the control input after passing the dead zone can be described in the following form:

$$u = \tau_d + \eta \hat{d}_r + (I-\eta)\hat{d}_l, \tag{17}$$

where $\eta = I$ if $\tau_d \le 0$, $\eta = 0$ if $\tau_d < 0$. The Direct control input for robot manipulator can be expressed as follows:

$$\begin{aligned} \tau &= \tau - d + \eta\hat{d}_r + (I-\eta)\hat{d}_l - E_D(\tau_d + \eta\hat{d}_r + (I-\eta)\hat{d}_l) \\ &= \tau_d - \tilde{D}^T \text{Ю} + \tilde{D}^T\delta, \end{aligned} \tag{18}$$

where $\tilde{D} = D - \hat{D}$, $\tilde{D} = diag\{\tilde{d}_1,\ \tilde{d}_2,\ ...,\ \tilde{d}_n\}$ and $\text{Ю} = [\eta\ \ I-\eta]^T$ and the modelling mismatch δ satisfies the bound.

$$\|\delta\| \le \sqrt{n}. \tag{19}$$

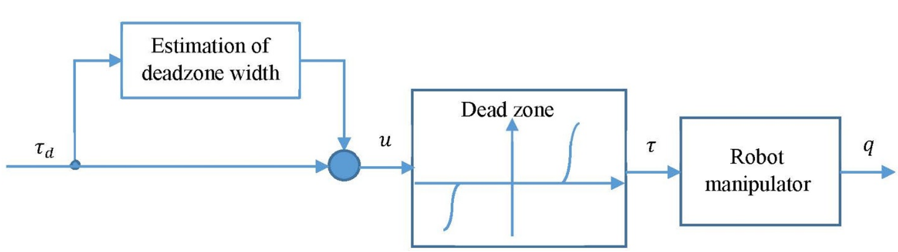

Fig. 3. Addative dead zone.

Define a tracking error vector $e(t)$ and the sliding mode function $s(t)$ as the following equations:

$$e(t) = q_d - q \text{ and } \dot{e}(t) = \dot{q}_d - \dot{q}, \tag{20}$$

$$s(t) = \dot{e} + \lambda e, \tag{21}$$

where $\lambda = diag(\lambda_1, \lambda_2, ..., \lambda_n)$ is the constant gain matrix. Substituting (5-8) into (1), it can be rewritten as follows:

$$M\dot{s} + Cs = M(q)(\ddot{q}_d + \lambda \dot{e}) + C(q,\dot{q})(\dot{q}_d + \lambda e) + G(q) + F(\dot{q}) + \tau_d - \tau,$$

$$M\dot{s} + Cs = f(x) + \Gamma - \tau, \tag{22}$$

where $f(x)$ is defined as $f(x) = W_M^T * \Xi_M(q)(\ddot{q}_d + \lambda\dot{e}) + W_C^T * \Xi_C(q,\cdot q)(\dot{q}_d + \lambda e) + W_G^T * \Xi_G(q) + W_F^T * \Xi_F(\dot{q})$ and $\Gamma = \Gamma_M(\ddot{q}_d + \lambda\dot{e}) + \Gamma_C(\dot{q}_d + \lambda e) + \Gamma_G + \Gamma_F + \tau_d$.

Architecture of the adaptive RBFNNs with the unknown dead zone is shown in Fig. 4.

From Fig. 4, the adaptive control law is characterized as presented below:

$$\tau = \hat{f}(x) + \tau_s + K_s s - \tilde{D}^T \text{Ю} + \tilde{D}^T \delta, \tag{23}$$

where K_s is the positive definite matrix and $K_s = diag\{k_{s1}, k_{s2}, ..., k_{sn}\}$, τ_s is a SMC robust term that is used to suppress the effects of uncertainties and approximation errors, and $\hat{f}(x)$ is the approximation of the adaptive function $f(x)$ and is defined as

$$\hat{f}(x) = \hat{W}_M^T * \Xi_M(q)(\ddot{q}_d + \lambda\dot{e}) + W_C^T * \Xi_C(q,\dot{q})(\dot{q}_d + \lambda e) + \hat{W}_G^T * \Xi_G(q) + \hat{W}_F^T * \Xi_F(\dot{q}).$$

The robust term is proposed as follows:

$$\tau_s = \frac{s}{\|s\|}\left(\frac{k_M W_M^2}{4} + \frac{k_C W_C^2}{4} + \frac{k_G W_G^2}{4} + \frac{k_F W_F^2}{4}\right) + K_P sgn(s) = \frac{s}{\|s\|}\Omega + K_p sgn(s), \tag{24}$$

where $\Omega = \frac{k_M W_M^2}{4} + \frac{k_C W_C^2}{4} + \frac{k_G W_G^2}{4} + \frac{k_F W_F^2}{4}$; $K_P \geq \|\Gamma\|$.

Substituting (23) into (22), we have

$$M(q)s + C(q,\dot{q})s = \tilde{f}(x) - K_s s - \tau_s + \tilde{D}^T \text{Ю} - \tilde{D}^T \delta + \Gamma, \tag{25}$$

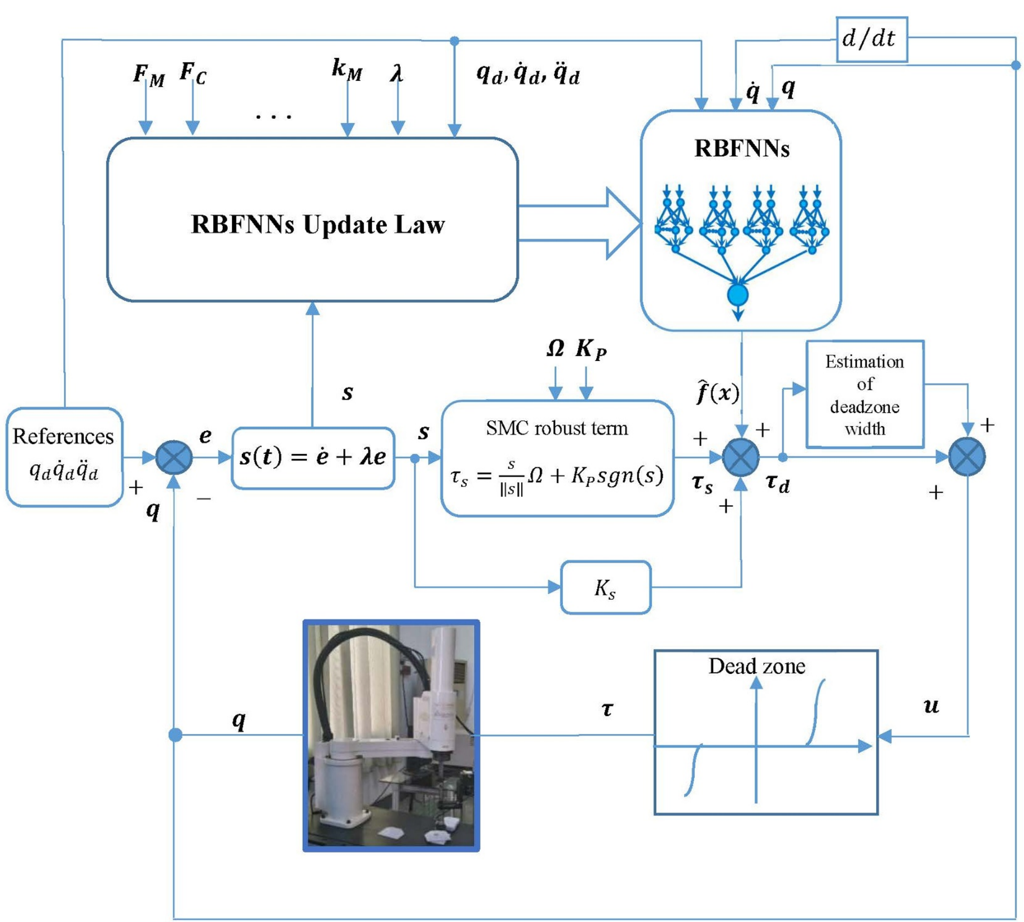

Fig. 4. The block diagram of the adaptive robust RBF neural network control system.

where

$$\begin{aligned}\tilde{f}(x) =& f(x) - \tilde{f}(x)\\ =& [\tilde{W}_M^T * \Xi_M(q)](\ddot{q}_d + \lambda\dot{e})\\ &+ [\tilde{W}_C^T * \Xi_C(q,\dot{q})](\dot{q}_d + \lambda e) + \tilde{W}_G^T * \Xi_G(q)\\ &+ \tilde{W}_F^T * \Xi_F(\dot{q}),\end{aligned} \tag{26}$$

and $\tilde{W}_M = W_M - \hat{W}_M$; $\tilde{W}_C = W_C - \hat{W}_C$; $\tilde{W}_G = W_G - \hat{W}_G$. By applying the adaptive control law (23) to the dynamic (1), and using the sliding mode control robust term function (24), the online RBFNNs adaptive update laws are designed as

$$\begin{cases}\dot{\hat{W}}_M = F_M \Xi_M(\ddot{q}_d + \lambda\dot{e})s^T - k_M F_M\|s\|\hat{W}_M,\\ \dot{\hat{W}}_C = F_C \Xi_C(\dot{q}_d + \lambda e)s^T - k_C F_C\|s\|\hat{W}_C,\\ \dot{\hat{W}}_G = F_G \Xi_G s^T - k_G F_G\|s\|\hat{W}_G,\\ \dot{\hat{W}}_F = F_F \Xi_F s^T - k_F F_F\|s\|\hat{W}_F,\\ \dot{\hat{D}} = F_D \text{Ю} s^T - F_D k_D \hat{D}\|s\|,\end{cases} \tag{27}$$

where F_M, F_C, F_G, F_F, F_D, k_M, k_C, k_G, k_F, k_D are the positive and diagonal constant matrices.

3.2. Stability analysis

Theorem 1: Consider an n-link robot manipulator represented by (1). If the RBFNNs adaptive update laws are designed as (23), and the SMC robust term τ_s is given by (24), then the tracking error and the convergence of all the system parameters can be assured and approached to zero.

Therefore, to guarantee the stability of the total control system, consider the Lyapunov function candidate as follows:

$$\begin{aligned}V(t) =& \frac{1}{2}\big[s^T M s + tr(\tilde{W}_M^T F_M^{-1}\tilde{W}_M) + tr(\tilde{W}_C^T F_C^{-1}\tilde{W}_C)\\ &+ tr(\tilde{W}_G^T F_G^{(}-1)\tilde{W}_G) + tr(\tilde{W}_F^T F_F^{-1}\tilde{W}_F)\\ &+ tr(\tilde{D}^T F_D^{-1}\tilde{D})\big].\end{aligned} \tag{28}$$

The derivative of $V(t)$ along to time, the following equation can be obtained as

$$\begin{aligned}\dot{V}(t) =& s^T\left(M\dot{s} + \frac{1}{2}\dot{M}s\right) + tr(\tilde{W}_M^T F_M^{-1}\dot{\tilde{W}}_M)\\ &+ tr(\tilde{W}_C^T F_C^{-1}\dot{\tilde{W}}_C) + tr(\tilde{W}_G^T F_G^{-1}\dot{\tilde{W}}_G)\\ &+ tr(\tilde{W}_F^T F_F^{-1}\dot{\tilde{W}}_F) + tr(\tilde{D}^T F_D^{-1}\dot{\tilde{D}}).\end{aligned} \tag{29}$$

According Property 2, (29) becomes

$$\begin{aligned}\dot{V}(t) =& s^T(M\dot{s} + Cs) + tr(\tilde{W}_M^T F_M^{-1}\dot{\tilde{W}}_M)\\ &+ tr(\tilde{W}_C^T F_C^{-1}\dot{\tilde{W}}_C) + tr(\tilde{W}_G^T F_G^{-1}\dot{\tilde{W}}_G)\\ &+ tr(\tilde{W}_F^T F_F^{-1}\dot{\tilde{W}}_F) + tr(\tilde{D}^T F_D^{-1}\dot{\tilde{D}}).\end{aligned} \tag{30}$$

Submitting (25) and (26) into (30), yields

$$\begin{aligned}\dot{V}(t) =& -s^T K_s s + s^T[\tilde{W}_M^T * \Xi_M(q)](\ddot{q}_d + \lambda\dot{e})\\ &+ s^T[\tilde{W}_C^T * \Xi_C(q,\dot{q})](\dot{q}_d + \lambda e)\\ &+ s^T[\tilde{W}_G^T * \Xi_G(q)]\\ &+ s^T[\tilde{W}_F^T * \Xi_F(\dot{q})] - s^T\tau_s\\ &+ s^T(\tilde{D}^T \text{Ю} - \tilde{D}^T\delta) + s^T\Gamma\\ &+ tr(\tilde{W}_M^T F_M^{-1}\dot{\tilde{W}}_M) + tr(\tilde{W}_C^T F_C^{-1}\dot{\tilde{W}}_C)\\ &+ tr(\tilde{W}_G^T F_G^{-1}\dot{\tilde{W}}_G) + tr(\tilde{W}_F^T F_F^{-1}\dot{\tilde{W}}_F)\\ &+ tr(\tilde{D}^T F_D^{-1}\dot{\tilde{D}})\\ =& -s^T K_s s - s^T\tau_s + s^T\Gamma\\ &+ s^T(\tilde{D}^T \text{Ю} - \tilde{D}^T\delta)\\ &+ tr\tilde{W}_M^T[F_M^{-1}\dot{\tilde{W}}_M + s^T\Xi_M(q)(\ddot{q}_d + \lambda\dot{e})]\\ &+ tr\tilde{W}_C^T[F_C^{-1}\dot{\tilde{W}}_C + s^T\Xi_C(q,\dot{q})(\dot{q}_d + \lambda e)]\\ &+ tr\tilde{W}_G^T[F_G^{-1}\dot{\tilde{W}}_G + s^T\Xi_G(q)]\\ &+ tr\tilde{W}_F^T[F_F^{-1}\dot{\tilde{W}}_F + s^T\Xi_F(\dot{q})]\\ &+ tr(\tilde{D}^T F_D^{-1}\dot{\tilde{D}}).\end{aligned} \tag{31}$$

Substituting (27) into (31), we have

$$\begin{aligned}\dot{V}(t) =& -s^T K_s s - s^T\tau_s + s^T\Gamma\\ &+ k_M\|s\|tr\tilde{W}_M^T(W_M - \tilde{W}_M)\\ &+ k_C\|s\|tr\tilde{W}_C^T(W_C - \tilde{W}_C)\\ &+ k_G\|s\|tr\tilde{W}_G^T(W_G - \tilde{W}_G)\\ &+ k_F\|s\|tr\tilde{W}_F^T(W_F - \tilde{W}_F)\\ &+ tr(\tilde{D}^T s^T(\text{Ю} - \delta)) - tr(\tilde{D}^T(\text{Ю}s^T - k_D\hat{D}\|s\|)),\end{aligned}$$

$$\begin{aligned}\dot{V}(t) =& -s^T K_s s - s^T\tau_s + s^T\Gamma\\ &+ k_M\|s\|tr\tilde{W}_M^T(W_M - \tilde{W}_M)\\ &+ k_C\|s\|tr\tilde{W}_C^T(W_C - \tilde{W}_C)\\ &+ k_G\|s\|tr\tilde{W}_G^T(W_G - \tilde{W}_G)\\ &+ k_F\|s\|tr\tilde{W}_F^T(W_F - \tilde{W}_F)\\ &+ tr(\tilde{D}^T s^T(k_D(D - \tilde{D}) - \delta)).\end{aligned}$$

By using $tr\tilde{W}^T(W - \tilde{W}) = (\tilde{W}W) - \|\tilde{W}\|^2 \le \|\tilde{W}\|\|W\| - \|\tilde{W}\|^2$, we have

$$\begin{aligned}\dot{V}(t) \le& -s^T K_s s - s^T\tau_s + s^T\Gamma\\ &+ k_M\|s\|(\|\tilde{W}_M\|\|W_M\| - \|\tilde{W}_M\|^2)\\ &+ k_C\|s\|(\|\tilde{W}_C\|\|W_C\| - \|\tilde{W}_C\|^2)\\ &+ k_G\|s\|(\|\tilde{W}_G\|\|W_G\| - \|\tilde{W}_G\|^2)\\ &+ k_F\|s\|(\|\tilde{W}_F\|\|W_F\| - \|\tilde{W}_F\|^2)\\ &+ \sqrt{n}\|s\|\|\tilde{D}\| + k_D D_M\|s\|\|\tilde{D}\| - k_D\|s\|\|\tilde{D}\|^2.\end{aligned} \tag{32}$$

Substitute (24) into (32), we have

$$\begin{aligned}\dot{V}(t) \le& -s^T K_s s\\ &- s^T\left(\frac{k_M W_M^2}{4} + \frac{k_C W_C^2}{4} + \frac{k_G W_G^2}{4} + \frac{k_F W_F^2}{4}\right)\end{aligned}$$

$$
\begin{aligned}
&+k_M\|s\|(\|\tilde{W}_M\|\|W_M\|-\|\tilde{W}_M\|^2)\\
&+k_C\|s\|(\|\tilde{W}_C\|\|W_C\|-\|\tilde{W}_C\|^2)\\
&+k_G\|s\|(\|\tilde{W}_G\|\|W_G\|-\|\tilde{W}_G\|^2)\\
&+k_F\|s\|(\|\tilde{W}_F\|\|W_F\|-\|\tilde{W}_F\|^2)\\
&+\sqrt{n}\|s\|\|\tilde{D}\|+k_DD_M\|s\|\|\tilde{D}\|\\
&-k_D\|s\|\|\tilde{D}\|^2,
\end{aligned}
$$

$$
\begin{aligned}
\dot{V}(t)\le{}& -s^TK_ss-k_M\|s\|\left(\frac{W_M}{2}-\|\tilde{W}_M\|\right)^2\\
&-k_C\|s\|\left(\frac{W_C}{2}-\|\tilde{W}_C\|\right)^2\\
&-k_G\|s\|\left(\frac{W_G}{2}-\|\tilde{W}_G\|\right)^2\\
&-k_F\|s\|\left(\frac{W_F}{2}-\|\tilde{W}_F\|\right)^2+\sqrt{n}\|s\|\|\tilde{D}\|\\
&+k_DD_M\|s\|\|\tilde{D}\|-k_D\|s\|\|\tilde{D}\|^2,\\
\dot{V}(t)\le{}& -s^TK_ss+\sqrt{n}\|s\|\|\tilde{D}\|\\
&+k_DD_M\|s\|\|\tilde{D}\|-k_D\|s\|\|\tilde{D}\|^2,\\
\dot{V}(t)\le{}& -s^TK_ss+c_0\|s\|\|\tilde{D}\|-k_D\|s\|\|\tilde{D}\|^2,
\end{aligned}
$$

with $c_0=\sqrt{n}+k_DD_M$. We see that to make sure $V(t)\le 0$,

$$-c_0\|s\|\|\tilde{D}\|+k_D\|s\|\|\tilde{D}\|^2>0. \tag{33}$$

So, if we choose suitable constant vectors k_D, D_M which satisfy (34), $\dot{V}(t)\le 0$, $\dot{V}(t)$ is a negative semidefinite function. Hence, all parameters of the adaptive control system are bounded with $t>0$, and all initial conditions are bounded at $t=0$, $0\le V(0)\le\infty$ is ensured. Furthermore, integrating $\dot{V}(t)$ with respect to time as follows:

$$\int_0^i nfty\dot{V}(t)dt\le-\int_0^\infty s^TK_ssdt. \tag{34}$$

Equation (35) can be rewritten as

$$\int_0^\infty s^TK_ssdt\le-\int_0^\infty V(t)dt=V(0)-V(\infty). \tag{35}$$

Because $V(0)$ is a bounded function, and $V(t)$ is non-increasing and bounded, we have

$$\lim_{n\to\infty}\int_0^t s^TK_ssdt<\infty. \tag{36}$$

According to Barbalat's Lemma, it can be shown that $\lim_{t\to\infty}\int_0^t s^TK_ssdt=0$. Therefore, both the global stability of the system and the tracking errors are guaranteed and converged to zero when $t\to\infty$ by the adapting control law (27).

Remark 1: In accordance with the above analysis and the designing of the proposed controllers, the assumptions for the parameters bounds are used to analyze the stability of the controlled system. Furthermore, the knowledge of the bounds actually disappears in our designed controllers. It is easy to show that our control system, with adaptive online update laws, is strictly stated passive. This advantageous feature can be used to conclude some internal boundedness properties of the controlled system without the assumption of observability and stability.

4. SIMULATION AND EXPERIMENTAL RESULTS

4.1. Simulation results

In this section, for illustrative purposes, a three-link Industrial robot manipulator is employed to verify the effectiveness of the proposed control scheme. We consider, the dynamic equation of the three-link IRMs in electric power substation model that is shown in Fig. 5, can be described by using Lagrange method.

$$
M=\begin{bmatrix}M_{11}&M_{12}&M_{13}\\M_{21}&M_{22}&M_{23}\\M_{31}&M_{32}&M_{33}\end{bmatrix};\ C=\begin{bmatrix}C_{11}&C_{12}&C_{13}\\C_{21}&C_{22}&C_{23}\\C_{31}&C_{32}&C_{33}\end{bmatrix};
$$

$$
G=\begin{bmatrix}g_1\\g_2\\g_3\end{bmatrix};
$$

$$
\begin{aligned}
M_{11}={}&l_1^2\left(\frac{p_1}{3}+p_2+p_3\right)+l_1l_2(p_2+2p_3)\cos(\theta_2)\\
&+l_2^2\left(\frac{p_2}{3}+p_3\right),\\
M_{12}={}&-l_1l_2\left(\frac{p_2}{3}+p_3\right)\cos(\theta_2)-l_2^2\left(\frac{p_2}{3}+p_3\right);\\
M_{13}={}&M_{23}=M_{31}=M_{32}=0;\ M_{21}=M_{12},\\
M_{22}={}&l_2^2\left(\frac{p_2}{3}+p_3\right);\ M_{33}=p_3,\\
C_{11}={}&-\dot{q}_2(p_2+2p_3);\ C_{12}=C_{21};\\
C_{13}={}&C_{22}=C_{23}=C_{31}=C_{32}=C_{33}=0,\\
g_1={}&g_2=g_3=-p_3g,
\end{aligned}
$$

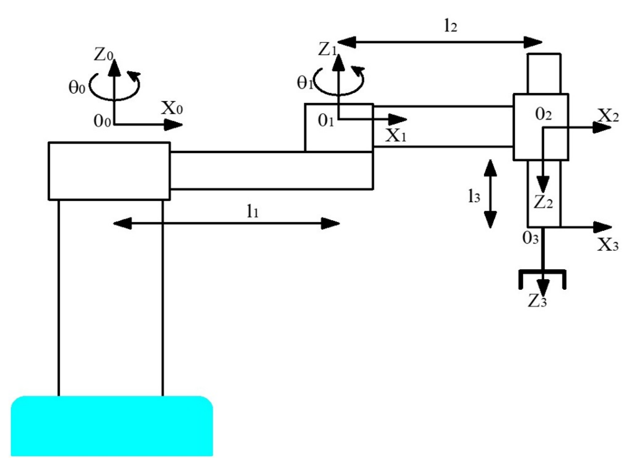

Fig. 5. The model of three-joint IRMs.

where p_1, p_2, p_3 are links masses; l_1, l_2, l_3 are links lengths; $g = 10$ (m/s^2) is acceleration of gravity.

The parameters of three link industrial robot manipulator are given as follows:

$$p_1 = 4 \text{ (kg)}, \; p_2 = 3 \text{ (kg)}, \; p_3 = 1.5 \text{ (kg)};$$
$$l_1 = 0.4 \text{ (m)}, \; l_2 = 0.3 \text{ (m)}, \; l_3 = 0.2 \text{ (m)}.$$

The object is to design control input in order to force joint variables $\theta = [\theta_1 \;\; \theta_2 \;\; \theta_3]^T$ to track desired trajectories as time goes to infinity. The desired position trajectories of the three link IRMs are chosen by

$$\theta_d = \left[\theta_{d1} \;\; \theta_{d2} \;\; \theta_{d3}\right]^T = \left[0.5\sin(2\pi t) \;\; 0.5\sin(2\pi t) \;\; 0.5\sin(2\pi t)\right]^T.$$

In addition, external disturbances and friction force in this simulation are selected as follows:

$$\tau_0 = \begin{bmatrix} 2\sin(\pi t) \\ 2\sin(\pi t) \\ 2\sin(\pi t) \end{bmatrix}; \; F_R(\theta) = \begin{bmatrix} 5\dot{\theta}_1 + 0.2sign(\dot{\theta}_1) \\ 5\dot{\theta}_2 + 0.2sign(\dot{\theta}_2) \\ 5\dot{\theta}_3 + 0.2sign(\dot{\theta}_3) \end{bmatrix}.$$

The parameter values used in the adaptive control system are chosen for the convenience of simulations as follows:

$$\lambda = diag(5,5,5); \; K_s = diag(100,100,100).$$

In the following passage, this proposed intelligent control scheme is applied to the IRMs in comparison with the PID controller and NNs [26]. Fig. 6 shows the simulation results of the PID, NNs and the proposed intelligent controllers. From the simulated results, the PID, NNs and the proposed intelligent controller can make the tracking errors decrease during the learning process since both controllers have learning ability. However, the proposed intelligent control system has faster reduction rate in tracking errors than the PID and NNs systems. It means that with all parameters being updated in the dynamic structure RBFNNs and the number of rule nodes being dynamically adjusted, the approximation ability of the dynamics structure RBFNNs is better than the PID and NNs systems. Moreover, from Fig. 6 can observe that when the tracking errors reach the big value, the control force of the proposed intelligent controller is smoother and has smaller oscillation than the PID and NNs to achieve the requested level of performance.

4.2. Experimental results

In this section, a three link robot manipulators in our Lab for intelligent automation technology is applied to verify the effectiveness of the proposed control scheme. The experimental control system model is presented in Fig. 7. It consists of an IBM PC with Pentium microprocessor, an encoder board to acquire the angles of the joint 1, joint 2, joint 3, and an A/D module to send commend signals to the servo amplifier. The proposed control algorithm is implemented using MatLab Simulink.

In this Experimental, two different experimental cases are adopted to investigate the applicability and the performance of the proposed technique under various environments as the parameter variation and the change of the external disturbance.

The first case: Assumes that 1-kg payload is added in the masses of three links IRMs, the desired input trajectories and the others parameters are the same as in the simulation case. The experimental results for the first experimental case of joint trajectory, tracking errors and control torques are shown in Fig. 8. From Fig. 8, it is easy to see that the responses and the tracking error norm of this proposed intelligent control scheme are quite better than both the PID and NNs methods. Moreover, Fig. 8 implies that the proposed intelligent controller torques are less and smooth than PID and NNs in [26] which still exist the chattering phenomena when the load of manipulators changed. Therefore, the robust tracking performance of the proposed control scheme is better than the PID and NNs under parameter variation. It means that due to the dynamic structure, the proposed intelligent controller is less sensitive to the parameter variation than the PID and NNs.

The second case: In this case, we assume that the robot is tracking a trajectory and suddenly the external disturbance is injected into control system. This happened after the first 0,6s of the experimental time, and all other parameters are chosen as in the simulation case. The shapes of the external disturbance are expressed as follows:

$$d(t) = [50\sin(20t) \;\; 50\sin(20t)]^T.$$

The experimental responses of joint position, tracking error and control torque, respectively, are shown in Fig. 9. From this experimental, we can find that, the control performance and robustness of the proposed controller under external disturbance are better than PID and NNs controller in [26]. The performance of our proposed approach is slightly affected more than NNs and PID approach when the external disturbance is suddenly injected more into control system. This means that the desired trajectory is not exciting persistently, which happens often in real application.

5. CONCLUSIONS

In this paper, a novel adaptive tracking neural network with deadzone robust compensator is designed to tackle the deadzone problem faced to achieve the high precision position tracking under various environments for Industrial Robot Manipulators. The performance of the proposed control is demonstrated in the illustrated simulation and experiment of three link Industrial Robot Manipulators under various environments such as the mass variation, the external disturbances and modeling uncertainties. The simulation and experiment results have shown that the proposed control scheme is not only reduce the chattering phenomenon, but also can achieve the high precision position tracking and good robustness in the trajectory tracking control. Besides that, with the proposed control, the random disturbance and unknown nonlinear deadzone have limited effects on the robot system.

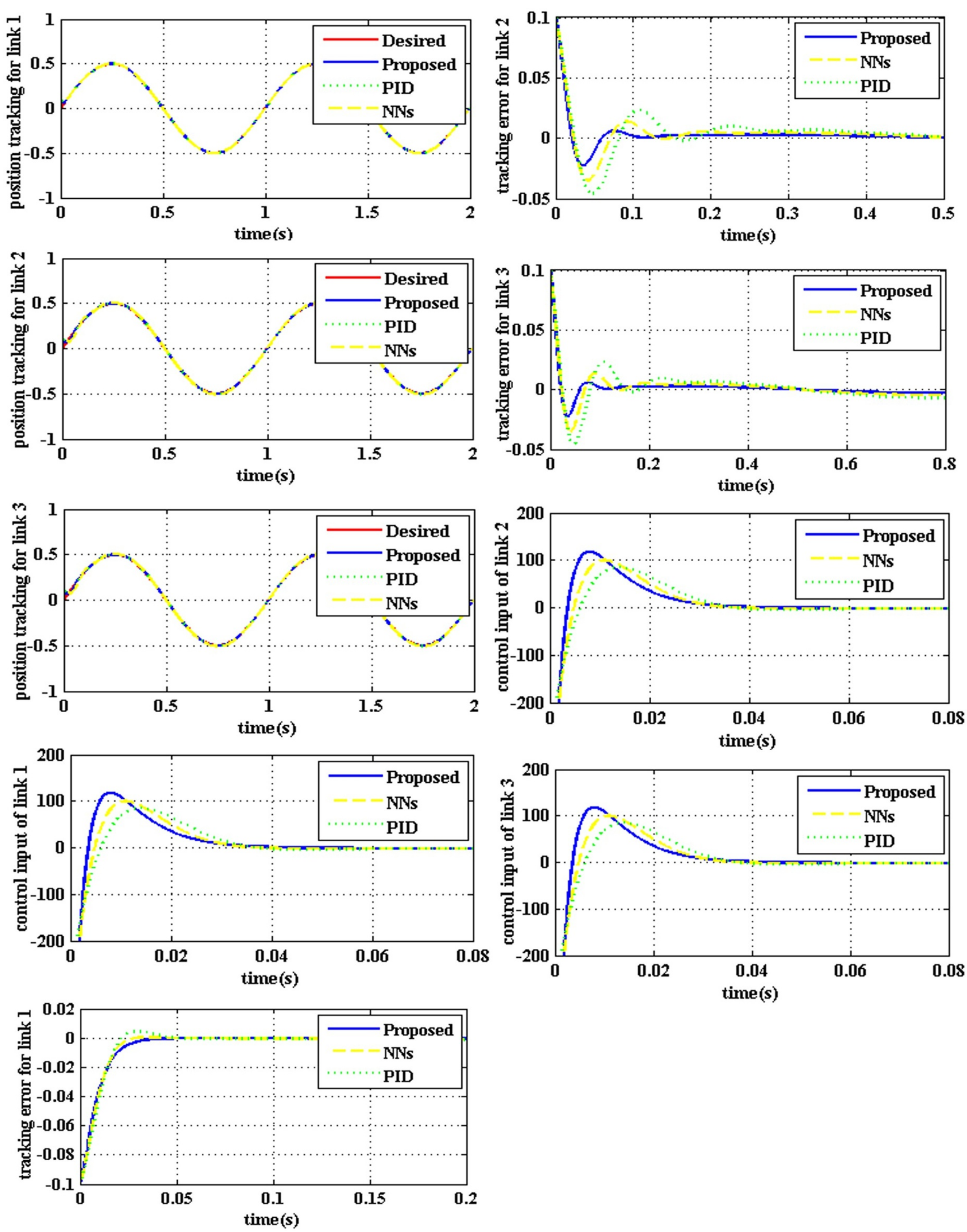

Fig. 6. Simulated position responses, tracking errors, and control efforts of the proposed system, NNs and PID.

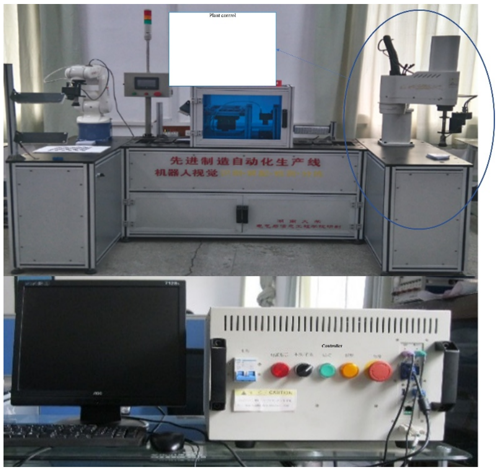

Fig. 7. Experimental control system.

REFERENCES

[1] Y. Yang, G. Feng, and J. Ren, "A combined backstepping and small - Gan approach to robust adaptive fuzzy control for strict - feedback nonlinear systems," *IEEE Transactions on Systems*, vol. 34, no. 3, pp. 406-420, May 2004.

[2] R. J. Wai and Z. W. Yang, "Adaptive fuzzy neural network control design via a T-S fuzzy model for a robot manipulator including actuator dynamics," *IEEE Transactions on Systems, man, and Cybernetics*, vol. 38, no. 5, pp. 1326-1346, 2008.

[3] S. Islam and P. X. Liu, "Robust adaptive fuzzy output feedback control system for robot manipulators," *IEEE/ASME Transactions on Mechatronics*, vol. 16, no. 2, pp. 288-296, April 2011.

[4] C. B. Regaya, F. Farhani, A. Zaafouri, and A. Chaari, "A novel adaptive control method for induction motor based on backstepping approach using dSpace DS 1104 control board," *Mechanical Systems and Signal Processing*, vol. 100, pp. 466-481, 2018.

[5] W. He, D. O. Amoateng, C. Yang, and D. Gong, "Adaptive neural network control of a robotic manipulator with unknown backlash - like hysteresis," *IET Control Theory & Applications*, vol. 11, no. 4, pp. 567-575, March 2017.

[6] P. V. Cuong and W. Y. Nan, "Robust adaptive trajectory tracking sliding mode control based on neural networks for cleaning and detecting robot manipulators," *Journal of Intelligent & Robotic Systems*, vol. 79, no. 1, pp: 101-114, December 2015.

[7] A. Zaafouri, C. B. Regaya, H. B. Azza, and A. Chaâari, "DSP-based adaptive backstepping using the tracking errors for high-performance sensorless speed control of induction motor drive," *ISA Transactions*, vol. 60, pp. 333-347, 2016.

[8] C. Sun, W. He, and J. Hong, "Neural network control of a flexible robotic manipulator using the lumped spring - mass model," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 47, no. 8, pp. 1863-1874, August 2017.

[9] C. B. Regaya, F. Farhani, A. Zaafouri, and A. Chaari, "High-performance control of IM using MRAS-fuzzy logic observer," *International Journal of Tomography & Simulation*, vol. 30, no. 2, pp. 40-52, 2017.

[10] C. Yang, Z. Li, and J. Li, "Trajectory planning and optimized adaptive control for a class of wheeled inverted pendulum vehicle models," *IEEE Trans. Cybern.*, vol. 43, no. 1, pp. 24-36, February 2013.

[11] W. He, Y. Dong, and C. Sun, "Adaptive neural impedance control of a robotic manipulator with input saturation," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 46, no. 3, pp. 334-344, March 2016.

[12] Y.-J. Liu and S.-C. Tong, "Barrier Lyapunov functions-based adaptive control for a class of nonlinear pure-feedback systems with full state constraints," *Automatica*, vol. 64, no. 2, pp. 70-75, 2016.

[13] Y.-J. Liu and S.-C. Tong, "Barrier Lyapunov functions for Nussbaum gain adaptive control of full state constrained nonlinear systems," *Automatica*, vol. 76, no. 2, pp. 143-152, 2017.

[14] Y. H. Kim and F. L. Lewis, "Neural network output feedback control of robot manipulators," *IEEE Trans. Robot. Autom.*, vol. 15, no. 2, pp. 301-309, Apr. 1999.

[15] H. Hamdi, C. B. Regaya, and A. Zaafouri, "Real-time study of a photovoltaic system with boost converter using the PSO-RBF neural network algorithms in a MyRio controller," *Solar Energy*, vol. 183, pp: 1-16, 2019.

[16] W. He, W. Ge, Y. Li, Y.-J. Liu, C. Yang, and C. Sun, "Model identification and control design for a humanoid robot," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 47, no. 1, pp. 45-57, Jan. 2017.

[17] C. Wang and D. J. Hill, *Deterministic Learning Theory for Identification, Recognition, and Control*, CRC Press, Boca Raton, FL, USA, 2009.

[18] X. Xie, D. Yang, and H. Ma, "Observer design of discrete-time T-S fuzzy systems via multi-instant homogenous matrix polynomials," *IEEE Trans. Fuzzy Syst.*, vol. 22, no. 6, pp. 1714-1719, Dec. 2014.

[19] V. T. Yen, W. Y. Nan, and P. V. Cuong, "Robust adaptive sliding mode neural networks control for Industrial robot manipulators," *International Journal of Control, Automation and Systems*, vol. 17, no. 03, pp. 783-792, 2019.

[20] W. Yu and X. Li, "Fuzzy identification using fuzzy neural networks with stable learning algorithms," *IEEE Trans. Fuzzy Syst.*, vol. 12, no. 3, pp. 411-420, Jun. 2004.

[21] W. Yu and J. de J. Rubio, "Recurrent neural networks training with stable bounding ellipsoid algorithm," *IEEE Trans. Neural Netw.*, vol. 20, no. 6, pp. 983-991, Jun. 2009.

[22] S.-L. Dai, C. Wang, and M. Wang, "Dynamic learning from adaptive neural network control of a class of nonaffine nonlinear systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 25, no. 1, pp. 111-123, Jan. 2014.

[23] M. Chen, S. S. Ge, and B. Ren, "Adaptive tracking control of uncertain MIMO nonlinear systems with input constraints," *Automatica*, vol. 47, no. 3, pp. 452-465, 2011.

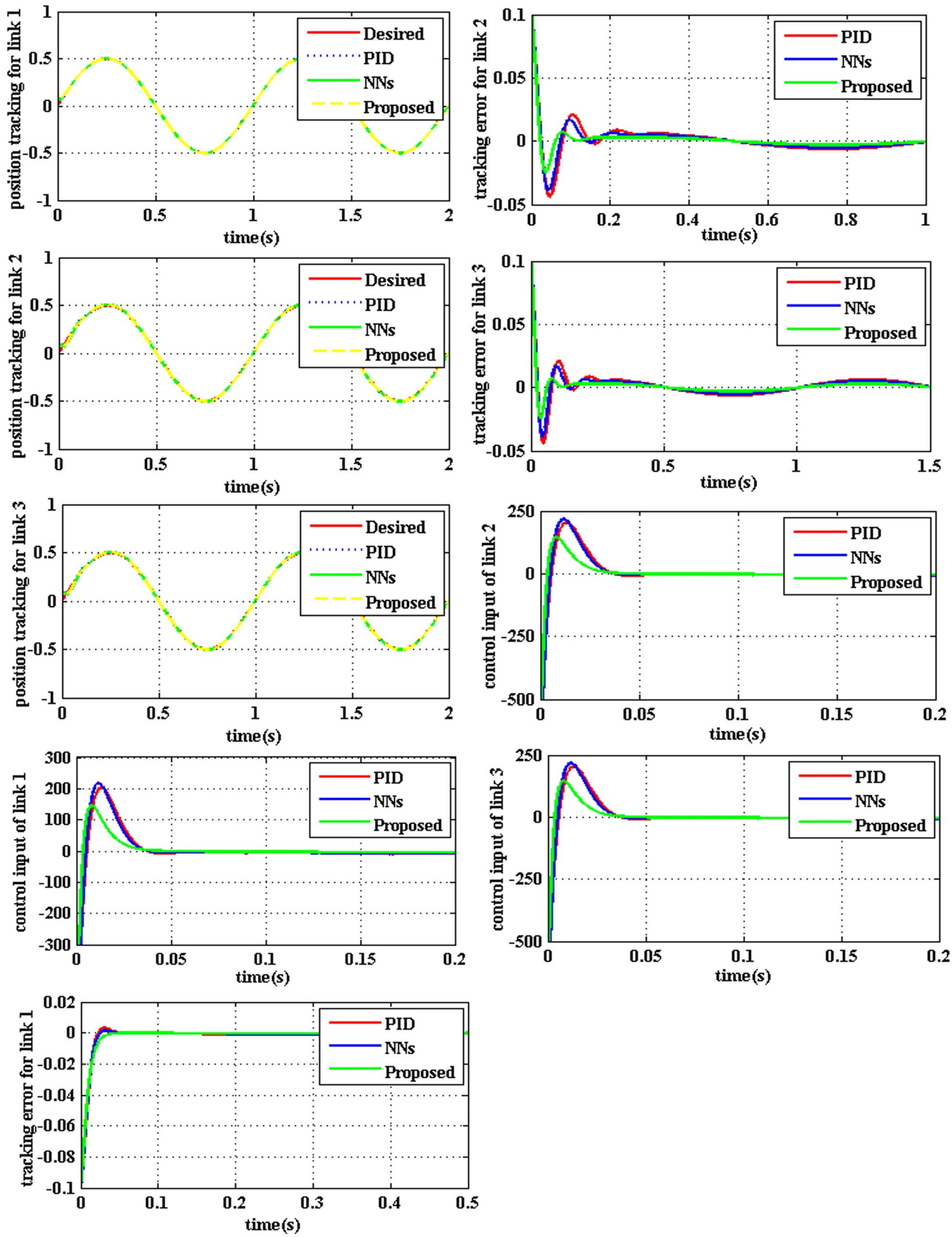

Fig. 8. The experimental results of position responses, tracking errors and control efforts, for the first case.

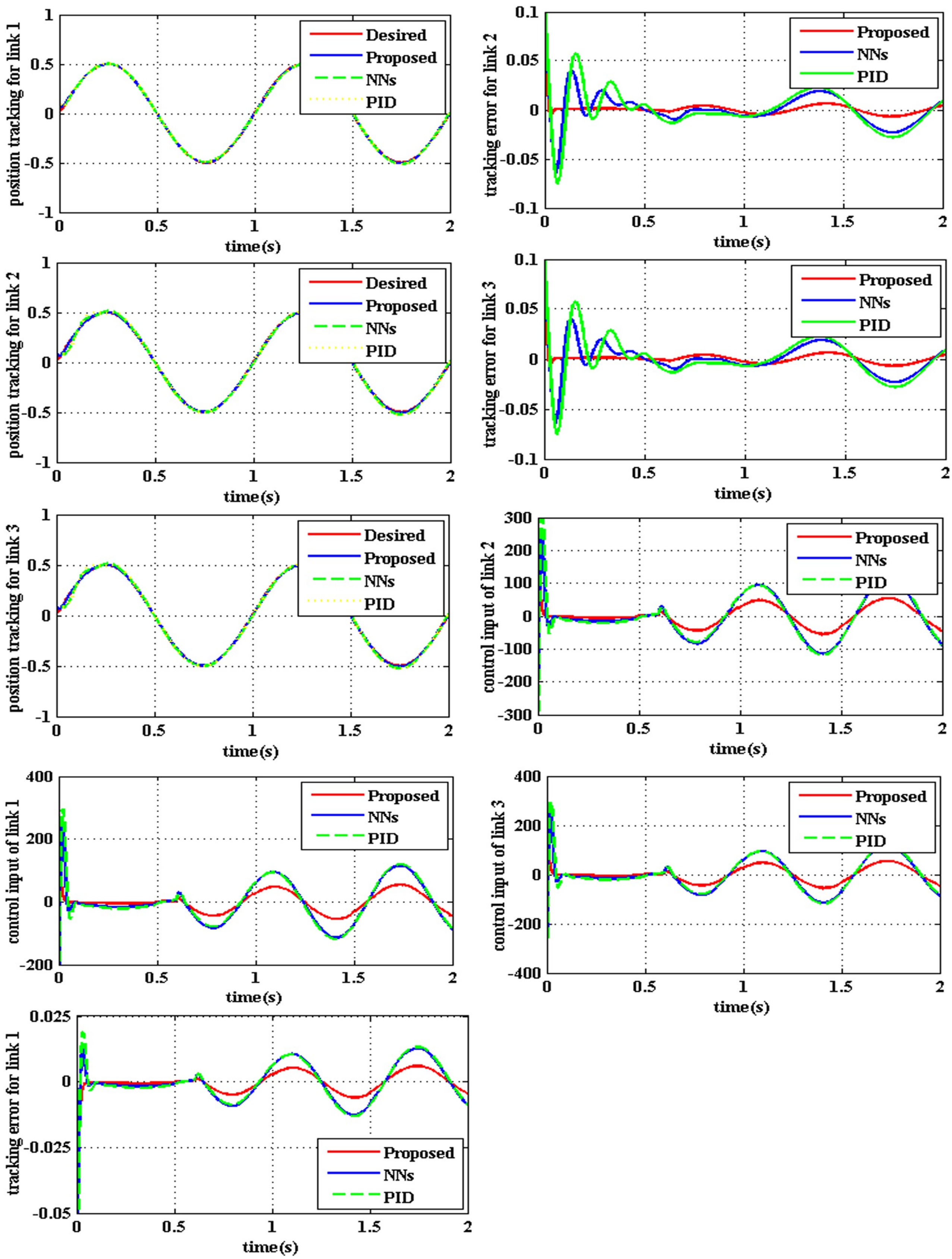

Fig. 9. The experimental results of position responses, tracking errors and control efforts for the second case.

[24] S.-C. Huang and B.-H. Do, "Radial basis function based neural network for motion detection in dynamic scenes," *IEEE Trans. Cybern.*, vol. 44, no. 1, pp. 114-125, Jan. 2014.

[25] C. Yang, Y. Jiang, Z. Li, W. He, and C.-Y. Su, "Neural control of bimanual robots with guaranteed global stability and motion precision," *IEEE Trans. Ind. Informat.*, vol. 13, no. 3, pp. 1162-1171, Jun. 2017.

[26] S. Jung, "Improvement of tracking control of a sliding mode controller for robot manipulators by a neural network," *International Journal of Control, Automation and Systems*, vol. 16, no. 02, pp. 9373-943, 2018.

[27] R. R. Selmic and F. L. Lewis, "Deadzone compensation in motion control systems using neural networks," *IEEE Trans. Autom. Control*, vol. 45, no. 4, pp. 602-613, Apr. 2000.

[28] Y.-J. Liu and S. Tong, "Adaptive NN tracking control of uncertain nonlinear discrete-time systems with nonaffine dead-zone input," *IEEE Trans. Cybern.*, vol. 45, no. 3, pp. 497-505, Mar. 2015.

[29] C. H. Tsai and H. T. Chuang, "Deadzone compensation based on constrained RBF neural network," *Journal of the Franklin Institute*, vol. 341, no. 4, pp. 361-374, July 2004.

[30] F. L. Lewis, K. Tim, L. Z. Wang, and Z. X. Li, "Deadzone compensation in motion control systems using adaptive fuzzy control system," *IEEE Trans. Control. Syst. Techno.*, vol. 7, no. 6, pp. 731-742, December 1999.

[31] X.-S. Wang, C.-Y. Su, and H. Hong, "Robust adaptive control of a class of nonlinear systems with unknown deadzone," *Automatica*, vol. 40, no. 3, pp. 407-413, 2004.

[32] T. P. Zhang and S. S. Ge, "Adaptive dynamic surface control of nonlinear systems with unknown dead zone in pure feedback form," *Automatica*, vol. 44, no. 7, pp. 1895-1903, 2008.

La Van Truong received his Bachelor's degree in Automation Engineering from the Thai Nguyen University and Master's degree from Department of Automatic Control from Military Technical Academy, Vietnam, in 2007 and 2010, respectively. His research interests include robot control, neural network, adaptive control and optimal control. He with the Faculty of Electrical & Electronics Engineering, Nam Dinh University of technology education, Nam Dinh, Vietnam.

Shou Dao Huang was born in Hunan, China, in 1962. He received his B.S. and Ph.D. degrees from the College of Electrical and Information Engineering, Hunan University, Changsha, China, in 1983 and 2005, respectively. He is currently a Full Professor with the College of Electrical and Information Engineering, Hunan University. His current research interests include motor design and control, power electronic system and control, and wind energy conversion system.

Vu Thi Yen received her B.S. and M.S. degrees in Automation Engineering from the Thai Nguyen University, College of Engineering, Vietnam, in 2008 and 2011, respectively, and a Ph.D. degree in Control Science and Engineering from Hunan University, Changsha, China, in 2019. She joined the Faculty of Electrical Engineering as a Lecturer in Hanoi University of Industry, Hanoi, Viet Nam since 2020. Her research interests include Robot control, Fuzzy neural network, and robust control.

Pham Van Cuong received his Bachelor's and Master's degrees from Department of Automatic Control, Military Technical Academy, Vietnam, in 2007 and 2010, respectively, and his Ph.D. degree in Control Science and Engineering from Hunan University, Changsha, China, in 2015. He joined the Faculty of Electrical Engineering Technology as a Lecturer in Hanoi University of Industry, Hanoi, Viet Nam since 2003. His research interests include intelligent control theory, adaptive control, robust control, applications and robot manipulators.