Research Article
Simple Adaptive Neural Network Controller Design for Modern Agricultural Mechanical Systems

[1]Hui HU, [2]Wang Yingjun, [3]Xilong Qu and [4]Zhongxiao Hao
[1]Depertment of Electrical and Information Engineering, Hunan Institute of Engineering,
Hunan Xiangtan, China
[2]School of Information and Engineering, Henan Institute of Science and Technology, Xinxian, China
[3]Department of Computer Science, Hunan Institute of Engineering, Hunan Xiangtan, China
[4]School of Information Science and Electrical Engineering, Hebei University of Engineering,
Handan, China

Abstract: The study proposes a new simple output feedback adaptive tracking control scheme using neural network for a class of complicated modern agricultural mechanical systems that only the system output variables can be measured. The scheme avoids design state observer and Lipschiz assumption, SPR conditions are not required and few parameters in control laws and weights update laws need to be tuned. Only one RBF neural network is employed to approximate the lumped uncertain nonlinear function. The stability analysis of the closed-loop system is performing using a Lyapunov approach which shows that the output tracking error and all states in the closed-loop system are boundedness. The effectiveness of the proposed adaptive control scheme is demonstrated through the simulations.

Keywords: Adaptive, agricultural mechanical systems, neural network, output feedback

INTRODUCTION

It is harder to establish the mathematical model for modern agricultural mechanical systems which are to be controlled become more and more complicated. In recent years, fuzzy logic control (Imaduddin *et al.*, 2011; Sarkar *et al.*, 2012) and adaptive neural network that model the functional mechanism of the human brain that can cooperate with human expert knowledge have been successfully applied to many control problems because they need no accurate mathematical models of the system under control. Likewise, for a class of nonlinear continuous-time systems, adaptive direct and indirect control using fuzzy logic have been proposed by Liu and Wan (2002a) by using "dominate inputs" concept. Controllers proposed by Liu and Wan (2002b) using a state feedback approach is valid if all of the system states are available for measurement. In practice, however, the state feedback control does not always hold because system states are not always available. Based on controllers proposed by Liu and Wan (2002a, b) and Tong and Qu (2005) present adaptive output control algorithms based on state observer and error observer. Most of them deal with the control problem of the affine nonlinear systems. However, in practice, the control methods of affine nonlinear systems do not always hold and the control

methods of the non-affine nonlinear systems are necessary and in fact many mechanical systems are non-affine nonlinear systems. And few results are available for non-affine nonlinear systems in which the control input appears in a nonlinear fashion. Boukezzoula *et al.* (2003) addressed the indirect adaptive fuzzy control problem of SISO non-affine nonlinear systems. The approach is based on the approximation of the nonlinear plant dynamics by a fuzzy system and then the control action is computed based on local inversion of the fuzzy model. Wang *et al.* (2000) proposed an indirect adaptive fuzzy controller, within this approach, the SISO non-affine nonlinear system is firstly transformed into an affine form by considering a Taylor series expansion around an operating trajectory. However, the indirect adaptive approach has the drawback of the controller singularity problem, i.e., division by zero may occur in the control law. An observer-based direct adaptive fuzzy-neural control scheme is presented for non-affine nonlinear systems (Leu *et al.*, 2005). By using implicit function theorem and Taylor series expansion and SPR Lyapunov theory, the stability of the close-loop system is verified. Recently, an output feedback-based adaptive neural controller has been presented for a class of uncertain non-affine nonlinear systems with unmodelled dynamics which reduce the complexity of

Corresponding Author: Hui HU, Department of Electrical and Information Engineering, Hunan Institute of Engineering, Hunan Xiangtan, China

control design (Du *et al.*, 2010). But in the scheme, a low-pass filter is designed to make the estimation error dynamics satisfy the Strictly Positive-Real (SPR) condition so that they can use Meyer-Kalmon-Yakubovitz (MKY) lemma, which makes the stability analysis of the closed-loop system and real implementation very complicated. And the parameters of filter are hard to be chosen. Output feedback tracking control scheme is investigated for a class of uncertain nonlinear systems (Hu and Guo, 2012). But the observer must be employed. In order to simplify the design of controller, an output feedback-based adaptive neural controller has been proposed for a class of uncertain nonlinear systems (Hu *et al.*, 2012). No state observer was employed in the algorithm and only the output error was used in control laws and weights update laws.

Based on the above observation, a novel systematic design procedure is developed for non-affine nonlinear systems which only the output variables can be measured without state observer to simplify the design of control system. First, a low-pass filter is employed to transform the normal form non-affine nonlinear system into affine in the pseudo-input dynamics. No state observer is employed and the neural weights update laws is tuned according to only the output tracking error. The stability analysis depends heavily on the universal function approximation property, only one RBFN is employed to approximate the lumped uncertain nonlinear function. There are no restrictive conditions on the design constants. The proposed scheme has few adapting parameters to be tuned and Lipschiz assumption, SPR condition are not required.

PROBLEM FORMULATION

The following notations and definitions will be used extensively throughout this study. Let R be the real number and R^n represent the real n-vectors. |k| denotes the usual Euclidean norm of a vector k. In case where k is a scalar, |k| denotes its absolute value.

We consider the following non-affine nonlinear system:

$$\begin{cases} \dot{x}_i = x_{i+1} & i = 1, \cdots, n-1 \\ \dot{x}_n = f(\underline{x}, u) \\ y = x_1 \end{cases} \qquad (1)$$

where, $y \in R$, $u \in R$ are the output and input of the system and $\underline{x} = [x_1, \cdots, x_n]^T \in R^n$ is the system state vector. The smooth function f() is unknown. The states are not measurable, only y is available for control design.

In this study, we will make the following assumptions regarding the system (1) and the desired trajectory $y_d(t)$.

Assumption 1: The value of $\frac{\partial f}{\partial u}$ is nonzero. Without loss of generality, we assume that for all $\underline{x} \in R^n$, $\frac{\partial f}{\partial u} \geq f_u > 0$.

Assumption 2: The desired trajectory y_d and its time derivative $y^i_d(t)$, $i = 1, \ldots, n$ are smooth and bounded.

The control objective is to design an adaptive neural network controller for a class of non-affine nonlinear systems (1) such that the system output y follows a desired trajectory y_d, while all signals in the closed-loop system are bounded.

In the followings, we will adopt low-pass filter to transform (1) into affine in the pseudo-input dynamics (Park *et al.*, 1995). The overall scheme is illustrated in Fig. 1.

The transfer function of the low-pass filter is:

$$L(s) = \frac{\kappa}{s + \kappa} \qquad (2)$$

where, κ is a positive design constant. Then, although the pseudo-control u_p shows a chattering phenomenon due to a switching function, the actual control input u applied to the real plant is smooth because u is made by low pass filtering of u_p:

$$\dot{u} = -\kappa u + \kappa u_p \qquad (3)$$

We define the augmented state variable as $\underline{\varsigma} = [x_1, x_2, \cdots, x_n, x_{n+1}]^T = [y, \dot{y}, \cdots, y^{(n-1)}, y^{(n)}]^T \in R^m$ and $\underline{\eta} = [\underline{x}, u]^T \in R^m$ with $m = n+1$. Then:

$$\dot{x}_i = x_{i+1} \quad i = 1, 2, \cdots, n-1$$
$$\dot{x}_n = f(\underline{x}, u) =: x_{n+1}$$
$$\dot{x}_{n+1} = \frac{\partial}{\partial \underline{\eta}} f(\underline{x}, u) \dot{\underline{\eta}}$$
$$= \sum_{i=1}^{n} \frac{\partial f}{\partial x_i} \dot{x}_i + \frac{\partial f}{\partial u} \dot{u}$$
$$= \left(\sum_{i=1}^{n} \frac{\partial f}{\partial x_i} x_{i+1} - \kappa \frac{\partial f}{\partial u} u \right) + \kappa \frac{\partial f}{\partial u} u_p \qquad (4)$$

The functions $a(\underline{\eta})$ and $b(\underline{\eta})$ are be defined as:

$$a(\underline{\eta}) = \left(\sum_{i=1}^{n} \frac{\partial f}{\partial x_i} x_{i+1} - \kappa \frac{\partial f}{\partial u} u \right)$$
$$b(\underline{\eta}) = \kappa \frac{\partial f}{\partial u} \qquad (5)$$

where, $b(\underline{\eta})$ is nonzero and positive according to Assumption 1. For all $\underline{\eta} \in R^m$ there exist positive constant b_0 such that $b(\underline{\eta}) \geq b_0$. By this way the original n^{th}-order non-affine nonlinear system becomes
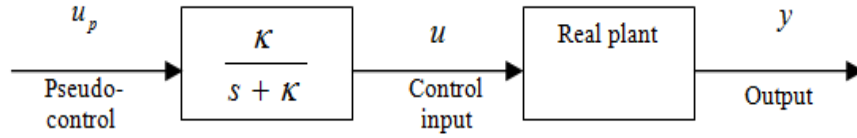
Fig. 1: Basic idea for smoothing control

the mth-order affine in the pseudo-input nonlinear system:

$$\dot{x}_i = x_{i+1} \quad i = 1, 2, \cdots, n$$
$$\dot{x}_m = a(\underline{\eta}) + b(\underline{\eta}) u_p \tag{6}$$

ADAPTIVE NEURAL NETWORK CONTROLLER DESIGN

Define the reference vector $\underline{y}_d = [y_d \ \dot{y}_d \ \cdots \ y_d^{(n)}]^T \in R^m$. The tracking error is defined as $e = y_d - y$ and the tracking error vector as $\underline{e} = \underline{y}_d - \underline{\varsigma} = [e, \dot{e}, \ \cdots \ e^{(n)}]^T \in R^m$. We define a filtered tracking error as:

$$s = \left(\frac{d}{dt} + \lambda\right)^{m-1} e = \left[\tau^T \ 1\right] \underline{e} = \Lambda \underline{e} \tag{7}$$

where, $\tau = \left[\lambda^{m-1}, (m-1)\lambda^{m-2}, \cdots, (m-1)\lambda\right]^T$, $\Lambda = \left[\tau^T \ 1\right]$ and $\lambda > 0$ is a design constant. The time derivative of s is derived as:

$$\begin{aligned}
\dot{s} &= \Lambda_1^T \underline{e} + y_d^{(m)} - y^{(m)} \\
&= \Lambda_1^T \underline{y}_d - \Lambda_1^T \underline{\varsigma} + y_d^{(m)} - a(\underline{\eta}) - b(\underline{\eta}) u_p \\
&= -a(\underline{\eta}) - \Lambda_1^T \underline{\varsigma} - b(\underline{\eta}) u_p + v_1
\end{aligned} \tag{8}$$

where, $\Lambda_1 = \left[0 \ \tau^T\right]^T$, $v_1 = y_d^{(m)} + \Lambda_1^T \underline{y}_d$. For the system (1) if the control input is determined as:

$$u_p^* = k(t)\lambda^{m-1} e + \frac{a(\underline{\eta}) + v}{b(\underline{\eta})} \tag{9}$$

where, k (t) $> \frac{1}{2}$ is a design parameter, $\underline{a}(\underline{\eta}) = -a(\underline{\eta}) - \Lambda_1^T \underline{\varsigma} - b(\underline{\eta}) k \tau_2^T \underline{\varsigma}$, $v(\underline{\eta}, v_1, v_2) = v_1 + b(\underline{\eta}) v_2$, $v_2 = k \tau_2^T \underline{y}_d$, $\tau_2 = \left[0, (m-1)\lambda^{m-2}, \cdots (m-1)\lambda, 1\right]^T$, Then, s converges to zero.

Proof: Let us choose the following Lyapunov-like function $V_s = \frac{1}{2} s^2$. Differentiating V_s with respect to time and using (8), we obtain:

$$\begin{aligned}
\dot{V}_s &= s\dot{s} = s\left(-a(\underline{\eta}) - \Lambda_1^T \underline{\varsigma} - b(\underline{\eta}) u_p + v_1\right) \\
&= s\left[-a(\underline{\eta}) - \Lambda_1^T \underline{\varsigma} - b(\underline{\eta})\left(k(t)\lambda^{n-1} e + \frac{a(\underline{\eta}) + v}{b(\underline{\eta})}\right) + v_1\right] \\
&= s\left[-b(\underline{\eta}) k(t)\lambda^{m-1} e + b(\underline{\eta}) k \tau_2^T \underline{\varsigma} - b(\underline{\eta}) k \tau_2^T \underline{y}_d\right] \\
&= -b(\underline{\eta}) k(t) s^2
\end{aligned} \tag{10}$$

Equation (10) implies that $\lim\limits_{t \to \infty} s = 0$. We rewrite the ideal controller (9) as:

$$u^* = k(t)\lambda^{m-1} e + u_{ad}^* \tag{11}$$

where, $u_{ad}^* = \frac{a(\underline{\eta}) + v}{b(\underline{\eta})}$ is an unknown function because $\underline{a}(\underline{\eta})$ $b(\underline{\eta})$ are unknown in ideal controller (9) and the state vector $\underline{\varsigma}$ cannot be measured. So the ideal controller is not available.

In this study, a Radial Basis Function (RBF) Neural Network (NN) is used to capture the unknown nonlinearity u_{ad}^* in (11). In general, the output of the multiple-input-single-output RBFNN is described by:

$$h(\xi) = W^T \phi(\xi) \tag{12}$$

where, $h(\xi) \in R$ is the RBFN output, $W \in R^L$ is the adjustable parameter vector, $\phi(\ ) : R^{n+1} \to R^L$ is a nonlinear vector function of the inputs with L being the number of RBFs. The ith element of W, $\omega_i, i = 1, \cdots, L$, is the synaptic weight between the ith neuron in the hidden layer and output neuron and $\phi_i(\xi)$ is a Gaussian function in the form of:

$$\phi_i(\xi) = \exp\left(-\frac{|\xi - v_i|}{2\delta_i^2}\right) \tag{13}$$

where, v_i is a m-dimensional vector representing the center of the ith basis function and δ_i is the variance representing the spread of the basis function.

The key advantage of RBFN is that it has the capability to approximate nonlinear mappings to any degree of accuracy. So:

$$u_{ad}^* = \frac{a(\underline{\eta}) + v}{b(\underline{\eta})} = W^{*T}\phi(\xi) + \varepsilon \qquad (14)$$

where, approximation error ε satisfy $|\varepsilon| \le \varepsilon_0$, $\xi = [y(t), y(t-d_1), \cdots, y(t-(m-1)d_1), v_1(t), v_2(t)]^T$ is the input vector to the RBFNN and $d_1 > 0$ is a positive time delay. W* is an ideal parameter vector which minimizes the function $|\varepsilon|$ and be defined as:

$$W^* = \arg\min_{W \in \Omega_\omega} \left\{ \sup |W^T\phi(\xi) - u_{ad}^*| \right\} \qquad (15)$$

where, $\Omega_\omega = \{W \mid \|W\| \le \varepsilon_\omega\}$, $\varepsilon_\omega > 0$ is the design constant. So the neural network output feedback controller can be described as:

$$u_p = k\lambda^{m-1}e + \hat{u}_{ad}(\xi) \qquad (16)$$

where, $\hat{u}_{ad}(\xi) = \hat{W}^T\phi(\xi)$ is the output of RBFNN, $\hat{W}$ is the estimated value of the optimal weight W*.

Let the corresponding neural network weights updating algorithms be given by:

$$\dot{\hat{W}} = \gamma(e\phi - \sigma|e|\hat{W}) \qquad (17)$$

where, adaptive gain γ, $\sigma > 0$ and to improve the robustness of adaptive law in the presence of the approximation error, we introduce the *e*-modification term. The parameter vector $\hat{W}$ is bounded and converges to the residual set:

$$\Theta_\omega = \left\{ \hat{W} \mid \|\hat{W}\| \le \frac{\phi_m}{\sigma} \right\} \qquad (18)$$

where $\|\phi(\xi)\| \le \phi_m$, ϕ_m is a constant. If $\hat{W}(0) \in \Theta_\omega$, then $\hat{W}(t) \in \Theta_\omega, \forall t \ge 0$.

Proof: Let us consider the following positive function:

$$V_\omega = \frac{1}{2\gamma}\hat{W}^T\hat{W}$$

The time derivative of the function V_ω along (17) is derived as:

$$\begin{aligned} \dot{V}_\omega &= \frac{1}{\gamma}\hat{W}^T\dot{\hat{W}} = \hat{W}^T(e\phi - \sigma|e|\hat{W}) \\ &= \hat{W}^T e\phi - \sigma|e|\|\hat{W}\|^2 \\ &\le \|\hat{W}\|\|\phi\||e| - \sigma|e|\|\hat{W}\|^2 \\ &\le -|e|\|\hat{W}\|(\sigma\|\hat{W}\| - \phi_m) \end{aligned} \qquad (19)$$

Equation (19) implies that for $\|\hat{W}\| > \frac{\phi_m}{\sigma}$ then $\dot{V}_\omega \le 0$ and, therefore, $\hat{W}(t) \in \Theta_\omega, \forall t \ge 0$.

From (8), the time derivative of the filtered tracking error can be derived as:

$$\begin{aligned} \dot{s}_i &= -a(\underline{\eta}) - \Lambda_1^T\underline{\varsigma} - b(\underline{\eta})u_p + v_1 \\ &= -a(\underline{\eta}) - \Lambda_1^T\underline{\varsigma} - b(\underline{\eta})u_p - b(\underline{\eta})u_{ad}^* + b(\underline{\eta})u_{ad}^* + v_1 \\ &= -a(\underline{\eta}) - \Lambda_1^T\underline{\varsigma} - b(\underline{\eta})u_p - b(\underline{\eta})\frac{a(\eta)+v}{b(\underline{\eta})} + b(\underline{\eta})u_{ad}^* + v_1 \\ &= b(\underline{\eta})(-k\lambda^{m-1}e - \hat{W}^T\phi + W^{*T}\phi + \varepsilon - k\tau_2^T\underline{e}) \\ &= b(\underline{\eta})(-ks - \tilde{W}^T\phi + \varepsilon) \end{aligned} \qquad 20)$$

where, $\tilde{W} = \hat{W} - W^*$.

STABILITY ANALYSIS

Now we can prove the following theorem, which shows the boundedness of all the signals in the closed-loop system.

Theorem 1: If Assumption 1 is satisfied and approximation error ε is bounded then, for the non-affine nonlinear system (1), the controller input (16) and adaptive law (17) guarantees that all the signals in the closed-loop system are bounded and the state vector $\underline{x}$ remains in:

$$\Omega_x = \left\{ \underline{x}(t) \mid |e_i(t)| \le 2^i\lambda^{i-m}\frac{b_\omega\phi_m + \varepsilon_0}{\sqrt{k-0.5}}, i = 1,2,\cdots,m \right\},$$
$$\forall t \ge T$$

where, $b_\omega = \frac{\phi_m}{\sigma} + \|W^*\|$.

Proof: Consider the Lyapunov function candidate $V_s = \frac{1}{2}s^2$. Differentiating V_s along (20), we obtain:

$$\begin{aligned} \dot{V}_s &= s\dot{s} = b(\underline{\eta})(-ks - \tilde{W}^T\phi + \varepsilon)s \\ &\le -b(\underline{\eta})ks^2 + b(\underline{\eta})\|\tilde{W}\|\|\phi\||s| + b(\underline{\eta})|\varepsilon||s| \\ &\le -b(\underline{\eta})ks^2 + b(\underline{\eta})\|\tilde{W}\|\|\phi\||s| + b(\underline{\eta})\varepsilon_0|s| \\ &\le -b(\underline{\eta})ks^2 + b(\underline{\eta})|s|(\|\tilde{W}\|\|\phi\| + \varepsilon_0) \end{aligned} \qquad (21)$$

According to (18), we know that $\|\tilde{W}\| \le b_\omega$, $b_\omega + \frac{\phi_m}{\sigma} + \|W^*\|$, then:

$$\dot{V}_s \le -b(\underline{\eta})ks^2 + b(\underline{\eta})|s|(b_\omega\phi_m + \varepsilon_0) \qquad (22)$$

From the inequality $|\alpha||\beta| \leq (\alpha^2 + \beta^2)/2$, we have the following inequality:

$$\dot{V}_s \leq -b(\underline{\eta})ks^2 + 0.5b(\underline{\eta})\left((b_\omega \phi_m + \varepsilon_0)^2 + s^2\right)$$

$$= -b(\underline{\eta})\left[(k-0.5)s^2 - \frac{(b_\omega \phi_m + \varepsilon_0)^2}{2}\right]$$

$$= -2b(\underline{\eta})(k-0.5)\left[V_s - \frac{(b_\omega \phi_m + \varepsilon_0)^2}{4(k-0.5)}\right] \tag{23}$$

Using the comparison principle, we obtain:

$$\bar{V}_s \leq \bar{V}_s(0)e^{-2(k-0.5)\int_0^t b(\underline{\eta}(\tau))d\tau} \tag{24}$$

where $\bar{V}_s = V_s - \dfrac{(b_\omega \phi_m + \varepsilon_0)^2}{4(k-0.5)}$ and we know $\dfrac{(b_\omega \phi_m + \varepsilon_0)^2}{4(k-0.5)}$ is constant.

Therefore,

$$V_s - \frac{(b_\omega \phi_m + \varepsilon_0)^2}{4(k-0.5)} \leq \left[V_s(0) - \frac{(b_\omega \phi_m + \varepsilon_0)^2}{4(k-0.5)}\right]e^{-2(k-0.5)\int_0^t b(\underline{\eta}(\tau))d\tau} \tag{25}$$

Since $b(\underline{\eta}) \geq b_0 > 0$ and $-\dfrac{(b_\omega \phi_m + \varepsilon_0)^2}{4(k-0.5)}e^{-2(k-0.5)b_0 t} \leq 0$, it follows that:

$$V_s \leq \bar{V}_s(0)e^{-2(k-0.5)b_0 t} + \frac{(b_\omega \phi_m + \varepsilon_0)^2}{4(k-0.5)} \tag{26}$$

Therefore,

$$s^2 \leq s^2(0)e^{-2(k-0.5)b_0 t} + \frac{(b_\omega \phi_m + \varepsilon_0)^2}{2(k-0.5)} \tag{27}$$

We can conclude for the above equation that s and $\underline{x}$ are bounded, respectively. The state vector $\underline{x}$ will remain in Ω_x for all $t \geq T$ based on the method (Ioannou and Sun, 1996). This completes the proof.

SIMULATION STUDY

Consider the following non-affine nonlinear system:

$$\dot{x}_1 = x_2$$
$$\dot{x}_2 = x_1^2 + 0.15u^3 + 0.1(1 + x_2^2)u + \sin(0.1u) \tag{28}$$
$$y = x_1$$

The tracking objective is to make the system output y follow the desired trajectory $y_d = 0.5 \sin(\pi(t-0.5))$.
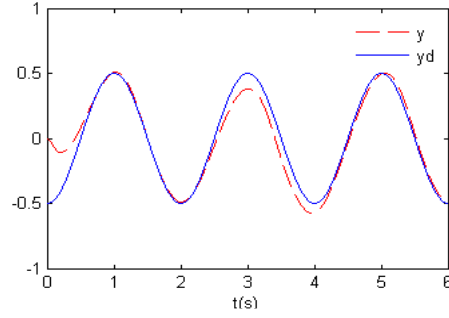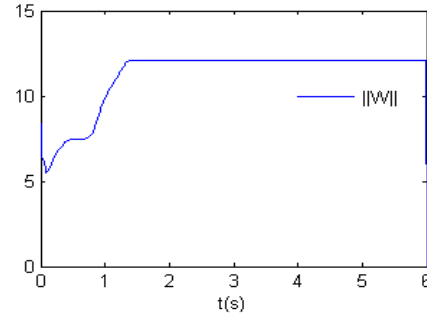

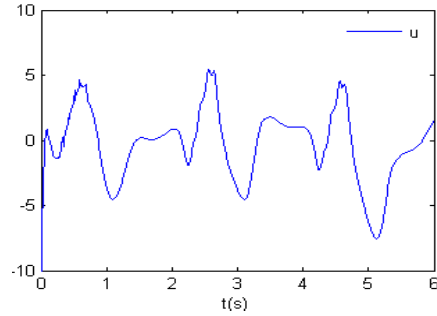Fig. 2: Plots of output tracking of system

Fig. 3: Plots of the weights norm
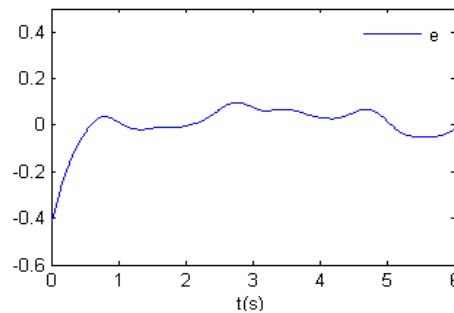

Fig. 4: Plots of control input

Fig. 5: Plots of output error

From (28), we know $\dfrac{\partial f}{\partial u} > 0$ which satisfy the assumption. The adaptive gain $\gamma = 95.0$, $\sigma = 0.02$. The simulation parameters are selected as follows: $\kappa = 20.0$, $\lambda = 2.0$, $k = 22.0$. According to the design process, we can get controller and weights update law as follows:

$$\dot{u} = -20 \times u + 20 \times u_p$$

$$u_p = 22 \times 2^2 \times e + \hat{W} \times \phi(\xi)$$

$$\dot{\hat{W}} = 95 \times (e\phi - 0.02 \times |e|\hat{W})$$

The system initial conditions are $x_1(0) = 0$, $x_2(0) = 0$. The simulation result using MATLAB is shown in Fig. 2 to 5.

Figure 2 and 5 shows the results of output tracking. It can be seen that the actual trajectory converges rapidly to the desired one. The weights norm is shown in Fig. 3 and the bounded control input is indicated in Fig. 4. These simulation results demonstrate the tracking capability of the proposed controlled and its effectiveness for control tracking of uncertain non-affine nonlinear systems.

CONCLUSION

This study proposes a new output feedback adaptive neural network adaptive controller for modern agricultural mechanical systems. The distinguished aspect of the proposed control algorithm is that no state observer is employed. Only the output error is used to generate control input and update laws. The stability analysis depends heavily on the universal function approximation property, only one RBFN is employed to approximate the lumped uncertain nonlinear function (16). There are no restrictive conditions on the design constants. So the system construct is very simple. Output tracking error and all states in the closed-loop system are guaranteed to be bounded by Lyapunov approach. Simulation results have verified the effectiveness of the proposed approach.

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