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OBSERVER-BASED HYBRID ADAPTIVE NN DECENTRALIZED CONTROL FOR NONLINEAR INTERCONNECTED SYSTEMS

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Abstract. *A hybrid adaptive neural network (NN) output-feedback control approach is proposed for a class of interconnected nonlinear systems with unmeasured states. In the design, NNs are utilized to approximate the unknown nonlinear functions, and NN state observers are designed to estimate the unmeasured states. By utilizing the designed state observers, a serial-parallel estimation model is established. Based on dynamic surface control technique and the prediction error between the system states observer model and the serial-parallel estimation model, the adaptive NN decentralized controllers are developed. It is proved that all the signals of the closed-loop system are bounded. Simulation studies illustrate the effectiveness of the proposed approach.*
Keywords: Hybrid adaptive NN control, Dynamic surface control, Decentralized output-feedback control, Serial-parallel estimation model

1. **Introduction.** In the past decades, adaptive neural network (NN) or fuzzy backstepping control has received much attention, and many significant developments have been achieved. However, due to the employment of the backstepping technique, these methods inevitably suffer from another problem of "explosion of complexity", which is caused by repeated differentiations of some nonlinear functions, i.e., the virtual controllers designed at each step within the conventional backstepping technique. As a result, the complexity of a controller drastically grows as the order of the system increases. To overcome the problem of the "explosion of complexity", an adaptive NN backstepping control approach was first proposed by [1] for a class of single-input and single-output uncertain nonlinear systems based on the so called dynamic surface control (DSC) technique. Since then, several adaptive NN and fuzzy backstepping DSC control schemes have been developed [2-4].

Though the adaptive fuzzy or NN control design gained much progress, the original intention employing fuzzy system/NN for approximating the system uncertainty is missing. Intuitively, the more precise approximation of the nonlinear function is achieved, the better performance is expected. However, most efforts have been directed towards achieving the stability and tracking performance. Little attention has been paid to the accuracy of the identified intelligent models and to the transparency and interpretability. By designing a serial-parallel estimation model and by using the modeling error, the hybrid adaptive fuzzy identification and control was proposed in [5]. The method achieves faster and improved tracking performance. However, the nth derivative of the plant output is required to be known in [5], which is quite impractical. Recently, the authors in [6] proposed a novel composite neural dynamic surface control of a class of uncertain nonlinear strict-feedback systems without satisfying the matching conditions. The proposed control method used the prediction error between system states and serial-parallel estimation model to construct the composite laws for NN weights updating, and achieved better tracking performance than the previous methods [1]. However, the result in [6] requires that the states of the controlled system are measured directly. [7] proposed a composite adaptive fuzzy output feedback backstepping control method for a class of single-input and single-output nonlinear systems. To the author's best knowledge, by far, no composite adaptive NN decentralized control results are available for uncertain interconnected nonlinear systems without satisfying the matching conditions, and the direct measurement of the states. Compared with the existing literature, the main advantage of the proposed control scheme is that this paper first investigated composite adaptive NN decentralized control approach proposed for uncertain interconnected nonlinear systems without satisfying the matching conditions. And the designed controller ensures that all the variables involved in the closed-loop system are bounded.

2. **Problem Formulations and Preliminaries.**

Consider a class of large-scale nonlinear systems in the following form:

$$\begin{cases} \dot{x}_{i,1} = x_{i,2} + f_{i,1}(y_i) + \Delta_{i,1}(y_1, \ldots, y_N) \\ \dot{x}_{i,2} = x_{i,3} + f_{i,2}(y_i) + \Delta_{i,2}(y_1, \ldots, y_N) \\ \quad \vdots \\ \dot{x}_{i,n_i-1} = x_{i,n_i} + f_{i,n_i-1}(y_i) + \Delta_{i,n_i-1}(y_1, \ldots, y_N) \\ \dot{x}_{i,n_i} = u_i + f_{i,n_i}(y_i) + \Delta_{i,n_i}(y_1, \ldots, y_N) \\ y_i = x_{i,1} \end{cases} \tag{1}$$

where $x_i = [x_{i,1}, \cdots, x_{i,n_i}]^T \in R^{n_i}$ is the system state vector; $u_i \in R$ and $y_i \in R$ are the control input and the output of the ith subsystem, respectively. $f_{i,j}(\cdot)$ and $\Delta_{i,j}(\cdot)$ $(1 \le i \le N,\ 1 \le j \le n_i)$ are unknown nonlinear smooth functions, representing the nonlinearities in the ith subsystem and the interconnection effects between the ith subsystem and other subsystems. Throughout this paper, it is assumed that the only output y_i is available for measurement.

Assumption 2.1. *$\Delta_{i,j}(\cdot)$ satisfies $|\Delta_{i,j}(y_1, \ldots, y_N)|^2 \le y_1^2 + \cdots + y_N^2$, $(1 \le i \le N$, $1 \le j \le n_i)$.*

Control objective: For a given reference signal $y_{i,r}(t)$ $(1 \le i \le N)$, $t \ge 0$, which is a smooth function of t with its time derivative $\dot{y}_{i,r}$ bounded for $t \ge 0$, the control objective is to design an adaptive NN output feedback control scheme such that all the variables involved in the closed-loop system are bounded.

The control design presented in this paper employs RBF NNs to approximate the nonlinear function $f_{i,j}(\cdot)$ in system (1), and assume that

$$f_{i,j}(y_i) = W_{i,j}^{*T} \varphi_{i,j}(y_i) + \varepsilon_{i,j}(y_i) \tag{2}$$

where $W_{i,j}^*$ is the ideal constant weight, and $\varepsilon_{i,j}(\cdot)$ is the approximation error, and it is usually assumed that $|\varepsilon_{i,j}(\cdot)| \le \varepsilon_{i,j}^*$, where $\varepsilon_{i,j}^*$ is a known constant.

By substituting (2) into (1), system (1) can be presented in the following form

$$\begin{cases} \dot{x}_i = A_i x_i + K_i y_i + \sum_{j=1}^{n_i} B_{i,j} W_{i,j}^{*T} \varphi_{i,j}(y_i) + B_{i,n_i} u_i + \Delta_i + \varepsilon_i \\ y_i = C_i^T x_i \end{cases} \tag{3}$$

where $A_i = \begin{bmatrix} -k_{i,1} & & & \\ \vdots & & I_{n_i-1} & \\ -k_{i,n_i} & 0 & \dots & 0 \end{bmatrix}$, $K_i = [k_{i,1}, \dots, k_{i,n_i}]^T$, $\Delta_i = [\Delta_{i,1}, \dots, \Delta_{i,n_i}]^T$, $\varepsilon_i = [\varepsilon_{i,1}, \dots, \varepsilon_{i,n_i}]^T$, $B_{i,j} = [\underbrace{0 \ \dots \ 1}_{j} \ \ \dots \ 0 \,]^T$ and $C_i^T = [\, 1 \ \cdots \ 0 \ \cdots \ 0 \,]$, and vector K_i is chosen such that A_i is a strict Hurwitz matrix. Thus, given a $Q_i = Q_i^T > 0$, there exists a $P_i = P_i^T > 0$ such that

$$A_i^T P_i + P_i A_i = -2Q_i \tag{4}$$

Since the state variables are not available, a locally state observer for the ith subsystem is designed as:

$$\begin{cases} \dot{\hat{x}}_i = A_i \hat{x}_i + K_i y_i + \sum\limits_{j=1}^{n_i} B_{i,j} W_{i,j}^T \varphi_{i,j}(y_i) + B_{i,n_i} u_i \\ \hat{y}_i = C_i^T \hat{x}_i \end{cases} \tag{5}$$

Let $e_i = x_i - \hat{x}_i$ be observer error, and then from (3) and (5), one can obtain the observer error equation

$$\dot{e}_i = A_i e_i + \sum_{j=1}^{n_i} B_{i,j} \left(W_{i,j}^{*T} \varphi_{i,j}(y_i) - W_{i,j}^T \varphi_{i,j}^T(y_i) \right) + \Delta_i + \varepsilon_i \tag{6}$$

Based on (5), a serial-parallel estimation model is designed as

$$\begin{cases} \dot{\hat{\hat{x}}}_{i,1} = \hat{x}_{i,2} + W_{i,1}^T \varphi_{i,1}(y_i) + \lambda_{i,1} \left(\hat{x}_{i,1} - \hat{\hat{x}}_{i,1} \right) \\ \dot{\hat{\hat{x}}}_{i,2} = \hat{x}_{i,3} + W_{i,2}^T \varphi_{i,2}(y_i) + \lambda_{i,2} \left(\hat{x}_{i,2} - \hat{\hat{x}}_{i,2} \right) \\ \qquad \vdots \\ \dot{\hat{\hat{x}}}_{i,n_i-1} = \hat{x}_{i,n_i} + W_{i,n_i-1}^T \varphi_{i,n_i-1}(y_i) + \lambda_{i,n_i-1} \left(\hat{x}_{i,n_i-1} - \hat{\hat{x}}_{i,n_i-1} \right) \\ \dot{\hat{\hat{x}}}_{i,n_i} = u_i + W_{i,n_i}^T \varphi_{i,n_i}(y_i) + \lambda_{i,n_i} \left(\hat{x}_{i,n_i} - \hat{\hat{x}}_{i,n_i} \right) \end{cases} \tag{7}$$

where $\lambda_{i,j} > 0$ $(1 \le i \le N, \ 1 \le j \le n_i)$ is a designed constant. Define the prediction error as

$$\delta_{i,j} = \hat{x}_{i,j} - \hat{\hat{x}}_{i,j} \tag{8}$$

From (5) and (7), we have

$$\dot{\delta}_{i,j} = k_{i,j}(y_i - \hat{x}_{i,1}) - \lambda_{i,j} \left(\hat{x}_{i,j} - \hat{\hat{x}}_{i,j} \right) \tag{9}$$

3. **Composite Adaptive NN Dynamic Surface Control.**

Step $i.1$: Define the first error surface $s_{i,1}$ as

$$s_{i,1} = x_{i,1} \tag{10}$$

Expressing $x_{i,2}$ in terms of its estimate as $x_{i,2} = \hat{x}_{i,2} + e_{i,2}$, the time derivative of $s_{i,1}$ is

$$\dot{s}_{i,1} = \hat{x}_{i,2} + W_{i,1}^T \varphi_{i,1}(y_i) + \tilde{W}_{i,1}^T \varphi_{i,1}(y_i) + e_2 + \Delta_{i,1} + \varepsilon_{i,1} \tag{11}$$

where $\tilde{W}_{i,j} = W_{i,j}^* - W_{i,j}$. Choose the first virtual control function $\hat{x}_{i,2,d}$ as follows:

$$\hat{x}_{i,2,d} = -c_{i,1} s_{i,1} - W_{i,1}^T \varphi_{i,1}(y_i) \tag{12}$$

where $c_{i,1} > 0$ is a design parameter.

Introduce a new state variable $\hat{x}_{i,2,c}$ and let $\hat{x}_{i,2,d}$ pass through a first-order filter with a constant $\tau_{i,2} > 0$, and the dynamics of $\hat{x}_{i,2,c}$ can be expressed as

$$\tau_{i,2} \dot{\hat{x}}_{i,2,c} + \hat{x}_{i,2,c} = \hat{x}_{i,2,d}, \quad \hat{x}_{i,2,c}(0) = \hat{x}_{i,2,d}(0) \tag{13}$$

Define the following compensating signal to remove the defect known error $\hat{x}_{i,2,c} - \hat{x}_{i,2,d}$

$$\dot{z}_{i,1} = -c_{i,1}z_{i,1} + z_{i,2} + (\hat{x}_{i,2,c} - \hat{x}_{i,2,d}), \quad z_{i,1}(0) = 0 \tag{14}$$

where $z_{i,2}$ will be defined in the next step.

Define the compensated tracking error signals as $\chi_{i,1} = s_{i,1} - z_{i,1}$ and $\chi_{i,2} = s_{i,2} - z_{i,2}$, and choose the adaptive law of parameter $W_{i,1}$ as

$$\dot{W}_{i,1} = \gamma_{i,1}\left(\chi_{i,1} + \frac{\delta_{i,1}}{\bar{\gamma}_{i,1}}\right)\varphi_{i,1}(x_{i,1}) - \sigma_{i,1}W_{i,1} \tag{15}$$

where $\gamma_{i,1} > 0$, $\bar{\gamma}_{i,1} > 0$ and $\sigma_{i,1} > 0$ are design parameters.

Step i, j $(2 \le j \le n_i - 1)$: Define the i_jth error surface $s_{i,j}$ as

$$s_{i,j} = \hat{x}_{i,j} - \hat{x}_{i,j,c} \tag{16}$$

where $\hat{x}_{i,j,c}$ will be defined in (18). Choose the i_jth virtual control function $\hat{x}_{i,j+1,d}$ as follows:

$$\hat{x}_{i,j+1,d} = -c_{i,j}s_{i,j} - W_{i,j}^T\varphi_{i,j}(y_i) - s_{i,j-1} + \dot{\hat{x}}_{i,j,c} - k_{i,j}(y_i - \hat{x}_{i,1}) \tag{17}$$

where $c_{i,j} > 0$ is a design parameter.

Introduce a new state variable $\hat{x}_{i,j+1,c}$ and let $\hat{x}_{i,j+1,d}$ pass through a first-order filter with a constant $\tau_{i,j+1} > 0$; the dynamics of $\hat{x}_{i,j+1,c}$ can be expressed as

$$\tau_{i,j+1}\dot{\hat{x}}_{i,j+1,c} + \hat{x}_{i,j+1,c} = \hat{x}_{i,j+1,d}, \quad \hat{x}_{i,j+1,c}(0) = \hat{x}_{i,j+1,d}(0) \tag{18}$$

Define the following compensating signal to remove the defect known error $\hat{x}_{i,j+1,c} - \hat{x}_{i,j+1,d}$

$$\dot{z}_{i,j} = -c_{i,j}z_{i,j} - z_{i,j-1} + z_{i,j+1} + (\hat{x}_{i,j+1,c} - \hat{x}_{i,j+1,d}), \quad z_{i,j}(0) = 0 \tag{19}$$

Define the compensated tracking error signal $\chi_{i,j} = s_{i,j} - z_{i,j}$, and choose the parameter adaptive law of $W_{i,j}$ as

$$\dot{W}_{i,j} = \gamma_{i,j}\left(\chi_{i,j} + \frac{\delta_{i,j}}{\bar{\gamma}_{i,j}}\right)\varphi_{i,j}(y_i) - \sigma_{i,j}W_{i,j} \tag{20}$$

where $\gamma_{i,j} > 0$, $\bar{\gamma}_{i,j} > 0$ and $\sigma_{i,j} > 0$ are design parameters.

Step $i.n_i$: In the last step, define the error surface s_{i,n_i} as

$$s_{i,n_i} = \hat{x}_{i,n_i} - \hat{x}_{i,n_i,c} \tag{21}$$

Choose the actual control input u_i as

$$u_i = -c_{i,n_i}s_{i,n_i} - W_{i,n_i}^T\varphi_{i,n_i}(y_i) - s_{i,n_i-1} + \dot{\hat{x}}_{i,n_i,c} - k_{i,n_i}(y_i - \hat{x}_{i,1}) \tag{22}$$

where $c_{i,n_i} > 0$ is a design parameter. Define the following compensating signal

$$\dot{z}_{i,n_i} = -c_{i,n_i}z_{i,n_i} - z_{i,n_i-1}, \quad z_{i,n_i}(0) = 0 \tag{23}$$

Define the compensated signal $\chi_{i,n_i} = s_{i,n_i} - z_{i,n_i}$ and the prediction error

$$\delta_{i,n_i} = \hat{x}_{i,n_i} - \hat{\hat{x}}_{i,n_i} \tag{24}$$

where $\hat{\hat{x}}_{i,n_i}$ is obtained from the following serial-parallel estimation model:

$$\dot{\hat{\hat{x}}}_{i,n_i} = u_i + W_{i,n_i}^T\varphi_{i,n_i}(y_i) + \lambda_{i,n_i}\left(\hat{x}_{i,n_i} - \hat{\hat{x}}_{i,n_i}\right), \quad \hat{\hat{x}}_{i,n_i}(0) = \hat{x}_{i,n_i}(0) \tag{25}$$

where $\lambda_{i,n_i} > 0$ are design parameters. Choose the adaptive function W_{i,n_i} as

$$\dot{W}_{i,n_i} = \gamma_{i,n_i}\left(\chi_{i,n_i} + \frac{\delta_{i,n_i}}{\bar{\gamma}_{i,n_i}}\right)\varphi_{i,n_i}(y_i) - \sigma_{i,n_i}W_{i,n_i} \tag{26}$$

where $\gamma_{i,n_i} > 0$, $\bar{\gamma}_{i,n_i} > 0$ and $\sigma_{i,n_i} > 0$ are design parameters.

4. **Stability Analysis.**

Theorem 4.1. *For nonlinear strict-feedback system (1) with unmeasured states, under Assumption 2.1, the controller (22), state observer (5) and serial-parallel estimation models (7), together with the virtual control functions (12) and (17), parameter adaptive laws (15), (20) and (26), guarantee that all signals of the closed-loop system are bounded.*

Proof: Consider the Lyapunov function candidate

$$V = \frac{1}{2}\sum_{i=1}^{N} e_i^T P_i e_i + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{n_i}\chi_{i,j}^2 + \sum_{i=1}^{N}\sum_{j=1}^{n_i}\frac{1}{2\bar{\gamma}_{i,j}}\delta_{i,j}^2 + \sum_{i=1}^{N}\sum_{j=1}^{n_i}\frac{1}{2\gamma_{i,j}}\tilde{W}_{i,j}^T\tilde{W}_{i,j} \tag{27}$$

The time derivative of V_i along with (6) and (9) is

$$\begin{aligned}\dot{V} = &-\sum_{i=1}^{N} e_i^T Q_i e_i + \sum_{i=1}^{N} e_i^T P_i\left(\varepsilon_i + \sum_{j=1}^{n_i} B_{i,j}\tilde{W}_{i,j}^T\varphi_{i,j} + \Delta_i\right) + \sum_{i=1}^{N}\sum_{j=1}^{n_i}\chi_{i,j}\dot{\chi}_{i,j} \\ &+ \sum_{i=1}^{N}\sum_{j=1}^{n_i}\frac{1}{\bar{\gamma}_{i,j}}\delta_{i,j}\dot{\delta}_{i,j} + \sum_{i=1}^{N}\sum_{j=1}^{n_i}\frac{1}{\gamma_{i,j}}\tilde{W}_{i,j}^T\dot{\tilde{W}}_{i,j}\end{aligned} \tag{28}$$

By using Assumption 2.1, and the Young's inequality, we have the following inequalities

$$e_i^T P_i\varepsilon_i \le \|e_i\|^2 + \frac{1}{4}\|P_i\|^2\sum_{j=1}^{n_i}\varepsilon_{i,j}^{*2} \tag{29}$$

$$e_i^T P_i\sum_{j=1}^{n_i} B_{i,j}W_{i,j}^{*T}\varphi_{i,j}(y_i) - W_{i,j}^T\varphi_{i,j}^T(y_i) \le \|e_i\|^2\|P_i\|^2 + \sum_{j=1}^{n_i}\tilde{W}_{i,j}^T\tilde{W}_{i,j} \tag{30}$$

$$e_i^T P_i\Delta_i \le \frac{1}{2}\|e_i\|^2\|P_i\|^2 + \frac{1}{2}n_i\sum_{j=1}^{N} y_j^2 \tag{31}$$

where $p_i = \lambda_{\min}(Q_i) + \frac{3}{2}\|P_i\|^2 + 1$. From (5), (16) and (19), we have

$$\dot{\chi}_{i,j} = \tilde{W}_{i,j}^T\varphi_{i,j}(y_i) - c_{i,j}\chi_{i,j} - \chi_{i,j-1} + \chi_{i,j+1} - \tilde{W}_{i,j}^T\varphi_{i,j}(y_i) \tag{32}$$

From (5) and (7), we have

$$\dot{\delta}_{i,j} = \tilde{W}_{i,j}^T\varphi_{i,j}(y_i) + k_{i,j}(y_i - \hat{x}_{i,1}) - \lambda_{i,j}\delta_{i,j} - \tilde{W}_{i,j}^T\varphi_{i,j}(y_i) \tag{33}$$

Substituting (29)-(33) into (28) yields

$$\begin{aligned}\dot{V} \le &-\sum_{i=1}^{N} p_i\|e_i\|^2 + \sum_{i=1}^{N}\sum_{j=1}^{n_i}\tilde{W}_{i,j}^T\tilde{W}_{i,j} + \omega + \frac{1}{2}n_i\sum_{i=1}^{N}\sum_{j=1}^{N} y_j^2 + \sum_{i=1}^{N} y_i^2 \\ &+ \sum_{i=1}^{N}\sum_{j=1}^{n_i}\chi_{i,j}\left[\tilde{W}_{i,j}^T\varphi_{i,j}(y_i) - c_{i,j}\chi_{i,j} - \chi_{i,j-1} + \chi_{i,j+1} - \tilde{W}_{i,j}^T\varphi_{i,j}(y_i)\right] \\ &+ \sum_{i=1}^{N}\sum_{j=1}^{n_i}\frac{1}{\bar{\gamma}_{i,j}}\delta_{i,j}\left[\tilde{W}_{i,j}^T\varphi_{i,j}(y_i) + k_{i,j}(y_i - \hat{x}_{i,1}) - \lambda_{i,j}\delta_{i,j} - \tilde{W}_{i,j}^T\varphi_{i,j}(y_i)\right] \\ &+ \sum_{i=1}^{N}\sum_{j=1}^{n_i}\frac{1}{\gamma_{i,j}}\tilde{W}_{i,j}^T\dot{\tilde{W}}_{i,j}\end{aligned} \tag{34}$$

where $\chi_{i,n_i+1} = 0$, and $\omega = \frac{1}{4}\sum_{i=1}^{N}\sum_{j=1}^{n_i}\|P_i\|^2\varepsilon_{i,j}^{*2}$. By using the Young's inequality, we have the following inequalities

$$\begin{aligned}\dot{V} \leq &-\sum_{i=1}^{N}(p_i-1)\|e\|^2 - \sum_{i=1}^{N}\sum_{j=1}^{n_i}\left(c_{i,j}-\bar{N}\right)\chi_{i,j}^2 - \sum_{i=1}^{N}\sum_{j=1}^{n_i}\left(\frac{\lambda_{i,j}}{\bar{\gamma}_{i,j}} - \frac{k_{i,j}^2+1}{4}\right)\delta_{i,j}^2 \\ &-\sum_{i=1}^{N}\sum_{j=1}^{n_i}\left(\frac{\sigma_{i,j}}{2\gamma_{i,j}}-3\right)\tilde{W}_{i,j}^T\tilde{W}_{i,j} + \omega^* + \bar{N}\sum_{i=1}^{N}z_{i,1}^2\end{aligned} \tag{35}$$

where $\bar{N} = 1 + \max_{1\leq i\leq N}\{n_i\}$ and $\omega^* = \omega + \sum_{i=1}^{N}\sum_{j=1}^{n_i}\frac{\sigma_{i,j}}{2\gamma_{i,j}}W_{i,j}^{*T}W_{i,j}^*$. Choose the design parameters $c_{i,j}$, $\lambda_{i,j}$, $\bar{\gamma}_{i,j}$, $\sigma_{i,j}$ and $\gamma_{i,j}$ such that $p_i - 1 > 0$, $c_{i,j} - \bar{N} > 0$, $\frac{\lambda_{i,j}}{\bar{\gamma}_{i,j}} - \frac{k_{i,j}^2+1}{4} > 0$ and $\frac{\sigma_{i,j}}{2\gamma_{i,j}} - 3 > 0$, respectively. Defining $C = \min\{C_1,\ldots,C_{n_i}\}$ and $C_i = \min\Big\{2(p_i-1)/\lambda_{\max}(P_i), 2(c_{i,j} - \bar{N}), 2\left(\frac{\lambda_{i,j}}{\bar{\gamma}_{i,j}} - \frac{k_{i,j}^2+1}{4}\right), 2\left(\frac{\sigma_{i,j}}{2\gamma_{i,j}}-3\right)\Big\}$, one can obtain

$$\dot{V} \leq -CV + D \tag{36}$$

where $D = \omega^* + \bar{N}\sum_{i=1}^{N}\bar{z}_{i,1}^2$, and $\bar{z}_{i,1}$ is a positive constant, satisfies $|z_{i,1}| \leq \bar{z}_{i,1}$. The solution of (36) can be written as

$$V(t) \leq V(0)e^{-Ct} + \frac{D}{C} \tag{37}$$

From (37), we can obtain that all the signals in the closed-loop system are bounded.

5. **Simulation.** Consider the following large-scale nonlinear systems,

$$\begin{cases}\dot{x}_{1,1} = x_{1,2} + f_{1,1}(y_1) + \Delta_{1,1}(y_1,y_2)\\ \dot{x}_{1,2} = u_1 + f_{1,2}(y_1) + \Delta_{1,2}(y_1,y_2)\\ y_1 = x_{1,1}\end{cases} \tag{38}$$

$$\begin{cases}\dot{x}_{2,1} = x_{2,2} + f_{2,1}(y_2) + \Delta_{2,1}(y_1,y_2)\\ \dot{x}_{2,2} = u_2 + f_{2,2}(y_2) + \Delta_{2,2}(y_1,y_2)\\ y_2 = x_{2,1}\end{cases} \tag{39}$$

where $f_{1,1} = 0$, $f_{1,2} = \sin(x_{1,1})$, $f_{2,1} = 0$, $f_{2,2} = \sin(x_{2,1})$, $\Delta_{1,1} = 0$, $\Delta_{1,2} = \sin(x_{2,1})$, $\Delta_{2,1} = 0$, $\Delta_{2,2} = \sin(x_{1,1})$.

The simulation results are shown by Figure 1 and Figure 2. Figure 1 shows the curves of $x_{1,1}$ (solid line) and $x_{2,1}$ (dotted line). Figure 2 shows the curves of u_1 (solid line) and u_2 (dotted line).

6. **Conclusions.** In this paper, a hybrid adaptive NN output-feedback dynamic surface control design has been proposed for a class of uncertain interconnected nonlinear systems with unmeasured states. NN state observers have been designed for estimating the unmeasured states. Based on the dynamic surface control design technique and serial-parallel estimation model, new NN adaptive controllers with the composite parameter adaptive laws have been developed. It has been proved that all the signals of the closed-loop system are bounded and the system output can follow the given bounded reference signal. The proposed control algorithm can not only solve the problems of states unmeasured and "explosion of complexity", but also obtain the better identification effect and smaller tracking error than the previous control methods. Future research will be concentrated on composite adaptive NN control design for large-scale nonlinear uncertain systems with input constraints based on the results of this paper.

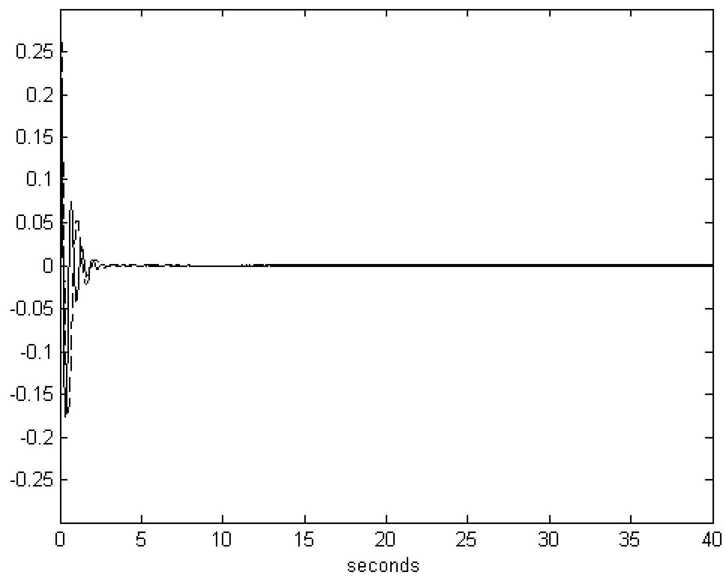

Figure 1. The curves of $x_{1,1}$ (solid line) and $x_{2,1}$ (dotted line)

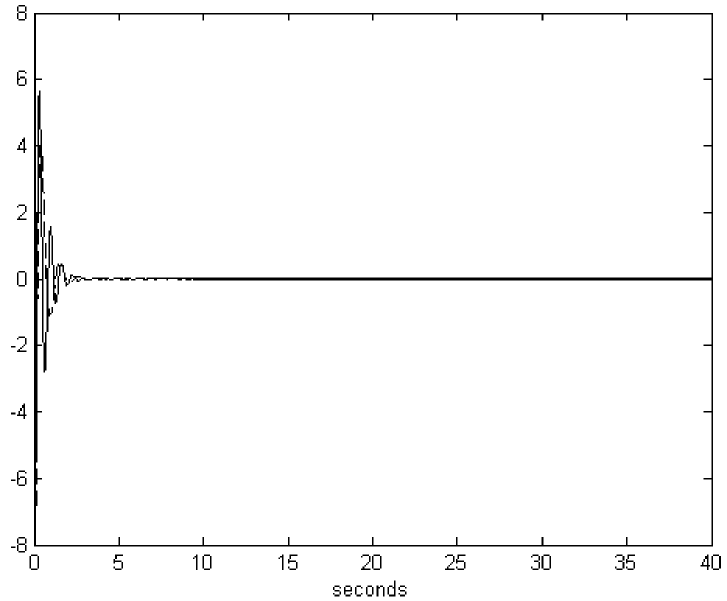

Figure 2. The curves of u_1 (solid line) and u_2 (dotted line)

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