A Robust Sliding Mode Control With RBFNN Compensation For Uncertain Networked Control System

Liman Yang[1] Yunhua Li[1] Li Zuo[2]

1. School of Automation Science and Electrical Engineering
Beijing University of Aeronautics and Astronautics
Beijing, China
ylm@buaa.edu.cn

2. Department of Electrical Engineering
Beijing Institute of Petrochemical Technology
Beijing, China
zuoli@bipt.edu.cn

***Abstract*—For the uncertain NCS with stochastic network delay less than one period, a sort of RBFNN-DSMC algorithm combining discrete sliding mode control and RBF neural network is presented. In view of the coupling influence of time-variable delay and plant model error as well as exterior disturbance, RBFNN is used to approach the equivalent disturbance online and output assistant control quantity so as to restrain uncertainty with the discrete sliding mode controller with delay compensation together. Simulation study indicates that the above-mentioned algorithm has good control performance and robustness for the uncertain NCS.**

***Keywords*—networked control system, sliding mode control, RBF neural network, delay, disturbance**

I. INTRODUCTION

The concept of Networked Control System (NCS) was proposed in 1980s, which was called Integrated Communication and Control Systems (ICCS) at that moment [1]. It is a closed-loop feedback control system closed by real-time communication network. In a network environment, all the control devices such as monitors, controllers, actuators and sensors are distributed and are simply linked together with network interfaces such as Field-bus, Industry Ethernet or mobile net so as to achieve coordination and resources sharing efficiently. In convention, network-based mechatronic control system is termed as NCS [2]. The NCS can provide an effective and reliable way to realize motion synthesis and coordinated control of the complex mechatronic systems including multiple distributed mechanisms. It is the essential technology for cooperation working of large-scale manufacture equipments and field robots under network conditions [3].

In recent years, the study works focus on the system modeling and stability analysis, control strategy, network scheduling, and integrated design methods etc, in which controller design is a significant aspect. Due to the common phenomena introduced by network communication such as time-variable delay, data-package dropout, empty sampling etc., an NCS is a typical discrete stochastic system. Therefore, a number of scholars choose to study the optimal control and stability problems of NCS according to stochastic system. Nilsson models delay as independent stochastic variable and Markov Chain, and studies system stability and the LQG optimal control problem via time-stamp and measuring signals [4]. Aiming at the NCS whose time delay is longer than a sampling period, Hu Shousong and Zhu Qixin assume that the time delay has a known probability distribution function and design the stochastic optimal controllers to make the corresponding systems exponentially mean square stable[5]. Qiu Zhanzhi adopts Lyapunov stability theory and LMI approach to get the robust control law and existing conditions in view of the dynamic output feedback NCS [6].Additionally, there is a kind of based-delay estimation online control strategy. As in [7], a new delay-estimating online without time stamp is proposed for NCS with delay less than one period, and the sliding mode controller based on online estimation and offline calculation is designed. In [8], the router tracking information is utilized to estimate time delay for wide area network, and a model predictive controller with delay compensation is put forward. Besides uncertainty by network transmission, there are many uncertain factors in controlled plant itself as parameter perturbation, non-modeling dynamic, exterior disturbance and measuring noises etc. For an NCS with uncertain structure parameters in [9], a sliding mode feedback controller is designed, and the maximum delay allowed boundary to guarantee stability is given through Lyapunov method. In [10], the long delay NCS with slow time-variable characteristic is transferred as the augmented state model with certain delay and a variable-parameter discrete sliding mode controller with disturbance observer is designed.

However, the model's mismatch and exterior disturbance might couple with time-variable delay so as to complicate the uncertainty that can be regarded as a nonlinear function. As a typical intelligent control method, the neural network has the advantage of approximating nonlinear function and also has self-learning, adaptive and parallel processing abilities.

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Therefore, a sort of robust sliding mode control algorithm combined with RBFNN (Radial Base Function neural network) is proposed for uncertain NCS in this paper.

The organization is as follows. Firstly, aiming at the nominal system under short network delay conditions, a DSMC (discrete sliding mode control) based on delay estimation online design is described. Then, considering the model's uncertainty, the RBFNN-DSMC algorithm is designed, in which the complicated disturbances by time-delay's estimating error, parameter perturbation and exteriors disturbance are taken as a limited nonlinear function, and RBFNN is structured to imitate ones online and output assistant control part so as to restrain the disturbances' influence with the DSMC together. Finally, stability analysis and simulation verification are given out.

II. DESIGN OF NCS SLIDING MODE CONTROLLER BASED ON THE DELAY ESTIMATION ONLINE

Firstly, the assumptions are given as follows. The sensing and controlling data are transmitted by single package in the closed loop; The network-delay from sensor to controller d_{sc} and that of from controller to actuator d_{ca} are both less than one sampling period, as well as the controller's CPU computing delay d_{c} is relative small, which are satisfied $d_{\text{sc}}+d_{\text{ca}}+d_{\text{c}}<T$; Moreover tasks' average delay and super as well as inferior boundary are known; There is no dropout of data package. Sensor is triggered by time, and controller and actuator are triggered by event.

Then, the forward and feedback delays are merged into τ, Considering the certain controlled plant with state feedback for easy analysis, and supposing the input and output of controller are represented as ω and u, state vector is X, network and plant can be modeled together and the continuous time model is given.

$$\begin{cases} \dot{X}(t)=A_{\text{p}}X(t)+B_{\text{p}}u(t-\tau_k) \\ \omega(t)=X(t) \end{cases} \tag{1}$$

where $X\in R^{\text{n}}$, $u\in R^{\text{m}}$, A_{p} and B_{p} are coefficient matrixes with proper dimensions.

According to assumption, control signals u_{k-1}, u_k must act orderly on controlled plant in time segment $[kT,(k+1)T]$ subjected to sensor clock, therefore the discrete model is further given.

$$\begin{cases} X_{k+1}=AX_k+B_0(\tau_k)u_k+B_1(\tau_k)u_{k-1} \\ \omega_k=X_k \end{cases} \tag{2}$$

where $B_0(\tau_k)=\int_0^{T-\tau_k} e^{A_{\text{p}}t}dt\cdot B_{\text{p}}$, $B_1(\tau_k)=\int_{T-\tau_k}^{T} e^{A_{\text{p}}t}dt\cdot B_{\text{p}}$ and $A=e^{A_{\text{p}}T}$.

Because τ_k is a stochastic time-varying serial, this model is a parameter stochastic time-varying system. Adopt the method of online delay estimation and offline parameters calculation to design the sliding mode controller.

For system described by (4), design the sliding mode controller by normal method firstly. Choose switch function $s_k=[s_{1k}\ \ \dots\ \ s_{mk}]^T=GX_k$ and $G\in R^{m\times n}$ to make system stable gradually on switch surface.

Design the reaching law as follows

$$s_{k+1}=(I-\delta T)s_k-\eta(s_k)\operatorname{sgn}s_k$$
$$\eta(s_{ik})=\begin{cases}\varepsilon_i T & ,|s_{ik}|>\Delta_i \\ 2(1-\delta_i T)|s_{ik}| & ,|s_{ik}|\le\Delta_i\end{cases} \quad \Delta_i=\frac{\varepsilon_i T+\phi}{\delta_i T} \tag{3}$$

where $\delta=\operatorname{diag}(\delta_1,\dots,\delta_m)$, $\eta=\operatorname{diag}(\eta_1,\dots,\eta_m)$, $0<\delta_i T<1$, $\varepsilon_i>0$, and ϕ is a lesser positive integer and related to the variance of equivalent disturbance. Combining (2) to get

$$u_k=\Gamma(X_k,\bar{\tau})=-(GB_0(\bar{\tau}))^{-1}(GAX_k+GB_1(\bar{\tau})u_{k-1} -(I-\delta T)s_k+\eta(s_k)\operatorname{sgn}s_k) \tag{4}$$

where $\bar{\tau}$ is segment function value of τ_k that can be obtained by estimation online. Here, to decrease the calculation quantity we consider segmenting the variant section of τ_k and taking a constant $\bar{\tau}$ to close to τ_k in each segment. $B_0(\bar{\tau})$ and $B_1(\bar{\tau})$ can be calculated offline in advance to get a set of parameter list. While computing online, judge the magnitude of τ_k and then check the list to get the corresponding $B_0(\bar{\tau})$ $B_1(\bar{\tau})$ to close to $B_0(\tau_k)$ and $B_1(\tau_k)$. The particulars can be seen in [7].

III. THE ROBUST SLIDING MODE CONTROL BASED ON RBFNN

A. RBF Neural Network

The typical structure of RBF neural network is shown as Fig. 1. Without universality, one node is set in latent layer, which can be expanded to multiple-nodes structure. The weight of link from input to output is 1. The latent layer consists in a group of radial base functions. The parameters of every latent node are center vector and base width vector. There are many kinds of radial base function. Usually, Gauss base function is chosen [11].

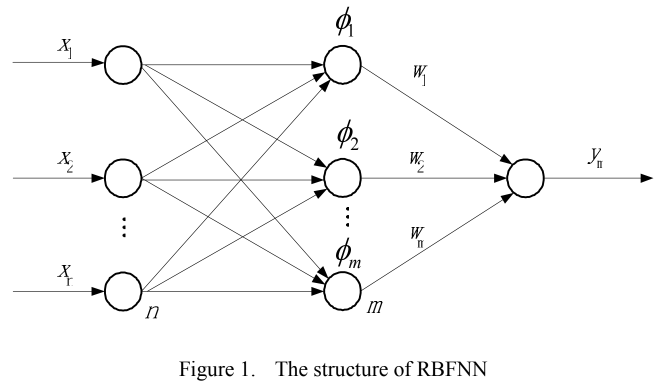


Figure 1. The structure of RBFNN

There are n input nodes and m latent nodes in above network. $X=\left[x_1,x_2,x_3,\cdots,x_n\right]^T$ is input vector. $\Phi=\left[\phi_1,\phi_2,\cdots,\phi_j,\cdots,\phi_m\right]^T$ is RBF vector. ϕ_j is Gauss base function described as $\phi_j=\exp\left(-\dfrac{\left\|\mathbf{X}-\mathbf{C}_j\right\|^2}{2\sigma_j^2}\right)$ $j=1,2,3,\cdots,m$, where $\mathbf{C}_j$ and σ_j are the center vector and base width vector of jth latent node, and can be wrote as $\mathbf{C}_j=[c_{j1},c_{j2},\cdots,c_{ji},\cdots,c_{jn}]$ and $\sigma=\left[\sigma_1,\sigma_2,\cdots,\sigma_m\right]^T$. The weight vector of link from latent layer to output layer is $W=\left[w_1,w_2\cdots,w_j,\cdots w_m\right]^T$.

The relationship of network input and output can be seen as a mapping: $f(\mathbf{X}):R^n\rightarrow R$

$$y=f(\mathbf{X})=\mathbf{W}^{\mathrm{T}}\mathbf{\Phi}=\sum_{j=1}^{m}w_j\exp\left(-\frac{\left\|\mathbf{X}-\mathbf{C}_j\right\|^2}{2\sigma_j^2}\right) \tag{5}$$

An RFBNN is constructed and trained by learning process to decide the parameters like as C_j, σ_j and w_j so as to set up the map from input to output.

B. The Robust Sliding Mode Control Based On RBFNN

Considering the uncertainty on the base of plant model in section 2, the model error, exterior disturbance and delay estimating error can be equivalent to a disturbance ψ_k, so that the discrete model of system is given as

$$X_{k+1}=AX_k+B_0(\overline{\tau})u_k+B_1(\overline{\tau})u_{k-1}+\psi_k \tag{6}$$

ψ_k includes multiple uncertain factors, which the time-variable delay make it difficult to model and get the boundary of uncertainty. Therefore, an RBFNN is adopted to imitate ψ_k by adaptive learning and output assistant control part so as to restrain the disturbances' influence with above mentioned DSMC together. The control principal is shown in Fig. 2.

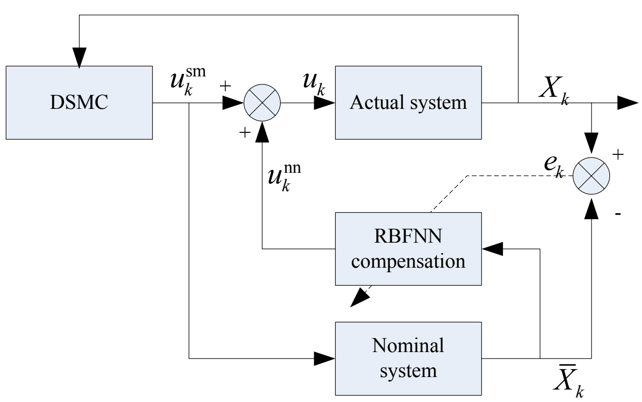


Figure 2. The principal of the sliding mode control with RBFNN compensation

In the Fig.2, control quantity u_k include two parts u_k^{sm} and u_k^{nn}. u_k^{sm} is the output of DSMC according to the nominal system to control the certainty part. u_k^{nn} is the compensating control quantity of RBFNN output to counteract the uncertainty. X_k and $\overline{X}_k$ represent the state output of the actual system and nominal system individually.

According to the method in section 2 to design sliding control law, i.e. u_k^{sm}

$$\begin{aligned}u_k^{\mathrm{sm}}=&-(GB_0(\overline{\tau}))^{-1}(GAX_k+GB_1(\overline{\tau})u_{k-1}\\&-(I-\delta T)s_k+\eta(s_k)\operatorname{sgn}s_k)\end{aligned} \tag{7}$$

Apply u_k^{sm} to the nominal system to get the ideal output of next moment as

$$\overline{X}_{k+1}=AX_k+B_0(\overline{\tau})u_k^{\mathrm{sm}}+B_1(\overline{\tau})u_{k-1} \tag{8}$$

Adopting the RBF network structure as Fig.1 and taking $\overline{X}_{k+1}$ as the input vector of the network, we can get the compensating control law u_k^{nn} as

$$u_k^{\mathrm{nn}}=\sum_{j=1}^{m}w_j\phi_j(\overline{X}_{k+1})=\sum_{j=1}^{m}w_j\exp\left(-\frac{\left\|\overline{X}_{k+1}-\mathbf{C}_j\right\|^2}{2\sigma_j^2}\right) \tag{9}$$

Combine (7) and (9), we can acquire the final output of RBFNN-DSMC controller as

$$u_k=u_k^{\mathrm{sm}}+u_k^{\mathrm{nn}} \tag{10}$$

The design target of u_k^{nn} is to degrade influence of the equivalent disturbance ψ_k. Observe the dynamic equation of switch function as

$s_{k+1}=GX_{k+1}=GAX_k+GB_0(\overline{\tau})(u_k^{\mathrm{sm}}+u_k^{\mathrm{nn}})+B_1(\overline{\tau})u_{k-1}+G\psi_k$ Take (7) into above equation to get

$$s_{k+1}=(I-\delta T)s_k-\eta(s_k)\operatorname{sgn}s_k+G\psi_k+GB_0(\overline{\tau})u_k^{\mathrm{nn}} \tag{11}$$

Thus, the target value of u_k^{nn} is $\overline{u}_k^{\mathrm{nn}}=-(GB_0(\overline{\tau}))^{-1}G\psi_k$. Here, ψ_k is unknown but can be responded by the difference between actual system output and nominal ones. Combine (6), (8) and (10), then get

$$e_{k+1}=X_{k+1}-\overline{X}_{k+1}=B_0(\overline{\tau})u_k^{\mathrm{nn}}+\psi_k \tag{12}$$

The difference between RBFNN output and target value is written as

$$\Delta u_k^{\mathrm{nn}}=u_k^{\mathrm{nn}}-\overline{u}_k^{\mathrm{nn}}=(GB_0(\overline{\tau}))^{-1}G(X_{k+1}-\overline{X}_{k+1}) \tag{13}$$

The online learning of RBFNN will adjust the link weigh W along the direction of decreasing $\left\|\Delta u_k^{\mathrm{nn}}\right\|$. To shorten the learning time, the dead band is introduced, so that the objective function of error is chosen as

$$J(k)=\begin{cases}0.5[\Delta u_k^{\mathrm{nn}}]^{\mathrm{T}}\Delta u_k^{\mathrm{nn}} & \left\|\Delta u_k^{\mathrm{nn}}\right\|>\xi \\ 0 & \left\|\Delta u_k^{\mathrm{nn}}\right\|\le\xi\end{cases} \qquad (14)$$

where ξ is a positive constant. It represents the learning will stop when Δu_k^{nn} enters into a certain neighborhood ξ of origin; otherwise, the learning will continue. The grads-descending approach is used to adjust weight W, get

$$\begin{aligned}w_j(k+1)=w_j(k)-\rho_j\nabla_{w_j}J(k)+\alpha_j(w_j(k)\\ -w_j(k-1))\quad (j=1,2,\ldots,m)\end{aligned} \qquad (15)$$

where ρ_j is learning speed, α_j is momentum factor, and $\nabla_{w_j}J(k)$ is revising quantity. Here $\nabla_{w_j}J(k)$ is obtained by (16).

$$\nabla_{w_j}J(k)=\frac{\partial J(k)}{\partial\Delta u_k^{\mathrm{nn}}}\frac{\partial\Delta u_k^{\mathrm{nn}}}{\partial w_j(k)}=\Delta u_k^{\mathrm{nn}}\phi_j(\bar{X}_{k+1}) \qquad (16)$$

So the weight $w_j(k)$ is given according the learning law as

$$\begin{aligned}w_j(k+1)=w_j(k)-\rho_j\Delta u_k^{\mathrm{nn}}\phi_j(\bar{X}_{k+1})+\alpha_j(w_j(k)\\ -w_j(k-1))\qquad (j=1,2,\ldots,m)\end{aligned} \qquad (17)$$

In the same way, the learning algorithm of node center and width parameters can be get

$$\begin{cases}\sigma_j(k+1)=\sigma_j(k)-\rho_j\Delta\sigma_j(k)+\alpha_j(\sigma_j(k)-\sigma_j(k-1)) \\ \Delta\sigma_j(k)=\Delta u_k^{\mathrm{nn}}w_j\phi_j\dfrac{\left\|\bar{X}-\boldsymbol{C}_j\right\|^2}{\sigma_j^3} \\ c_{ji}(k+1)=c_{ji}(k)-\rho_j\Delta c_{ji}(k)+\alpha_j(c_{ji}(k)-c_{ji}(k-1)) \\ \Delta c_{ji}=\Delta u_k^{\mathrm{nn}}w_j\phi_j\dfrac{x_j-c_{ji}}{\sigma_j^2} \qquad ,\begin{pmatrix}j=1,2,\ldots,m\\ i=1,2,\ldots,n\end{pmatrix}\end{cases} \qquad (18)$$

Here, the choice of latent nerve cells' number and weight initial value is an important problem, because unsuitable choice might induce the slow convergence even radiation or vibration. We can adopt the clustering approach [11] to decide the initial value of node center C_j and width σ_j, and the RBF center should be set in the region of important data of input space. In the actual system, the control quantity is limited, and the ideal model's state variety bound can be predicted. For the designed RBF network here, the important data occur near by switch surface, so that it will enhance the algorithm efficiency and convergent speed to combine system characteristic to choose the proper initial value of node center and width.

C. Analysis of Stability

For the uncertain NCS described as (6), the RBFNN-DSMC control law is composed of (7), (9) and (10). When the difference of output control quantity of RBF network and expected target value is less than a certain bound, the above controller has robustness for complex uncertainty by stochastic time-variable delay, model error and exterior disturbance. Due to the optimal approximating ability of RBFNN, it can approximate consistently any continuous function in a bicompact set if only network is large enough [12]. Therefore, we suppose the network output satisfies $\left\|\Delta u_k^{\mathrm{nn}}\right\|\le\xi$ and analyze the stability of the algorithm under this precondition.

Take $u_k^{\mathrm{nn}}=\bar{u}_k^{\mathrm{nn}}+\Delta u_k^{\mathrm{nn}}$ and $\bar{u}_k^{\mathrm{nn}}=-(GB_0(\bar{\tau}))^{-1}G\psi_k$ into the switch function's dynamic equation (11), then get

$$s_{k+1}=(I-\delta T)s_k-\eta(s_k)\operatorname{sgn}s_k+GB_0(\bar{\tau})\Delta u_k^{\mathrm{nn}} \qquad (19)$$

Set $\upsilon_k=GB_0(\bar{\tau})\Delta u_k^{\mathrm{nn}}=[\upsilon_{1k}\quad\upsilon_{2k}\cdots\upsilon_{mk}]^{\mathrm{T}}$, to get $\upsilon_{ik}=\sum_{l=1}^{n}\sum_{j=1}^{m}g_{il}b_{lj}(\bar{\tau})\Delta u_{jk}^{\mathrm{nn}}$, $i=1,\ldots,m$. $B_0(\bar{\tau})$ is time-variable parameter, but due to $\tau_{\min}\le\bar{\tau}\le\tau_{\max}$, $b_{lj}(\bar{\tau})$ has an exact boundary. Accordingly, υ_{ik} is bounded when $\left\|\Delta u_k^{\mathrm{nn}}\right\|\le\xi$, and might as well suppose $\left|\upsilon_{ik}\right|<\phi$, where ϕ is a positive constant. The switch boundary of sliding mode reaching law is selected as $\Delta_i=\dfrac{\varepsilon_i T+\phi}{\delta_i T}$, and system state traces will inevitably enter and stabilize in a boundary layer of switch surface $s_k=0$ after some moment, as well as the boundary layer width is $\Delta_i^{'}=\dfrac{\phi}{\delta_i T}$. The detailed proof can be seen from the theorem 1 in [7].

IV. Simulation Study

To verify the design methods above mentioned, simulation study targeting a reversal pendulum control system is carried out. Using Truetime software on MATLAB flat, the corresponding networked control system is modeled and simulated.

The linear continuous model of reversal pendulum is given

$$\begin{bmatrix}\dot{x}_1(t)\\ \dot{x}_2(t)\end{bmatrix}=\begin{bmatrix}0 & 1\\ -9.8 & -0.2\end{bmatrix}\begin{bmatrix}x_1(t)\\ x_2(t)\end{bmatrix}+\begin{bmatrix}0\\ 10\end{bmatrix}u(t) \qquad (20)$$

Set sampling period $T=10\mathrm{ms}$. In network, sensor is triggered by time, controller and actuator are triggered by event, a disturbing node simulates other periodic and abrupt transmitting tasks to make loop-delay become a random serial and satisfy $\tau_k\in[0,T]$. Discrete the model (20) according to the type of (2), then get

$$\begin{aligned}\begin{bmatrix}x_1(k+1)\\ x_2(k+1)\end{bmatrix}=\begin{bmatrix}0.9980 & 0.0199\\ -0.1955 & 0.9941\end{bmatrix}\begin{bmatrix}x_1(k)\\ x_2(k)\end{bmatrix}\\ +B_0(\tau_k)u(k)+B_1(\tau_k)u(k-1)\end{aligned} \qquad (21)$$

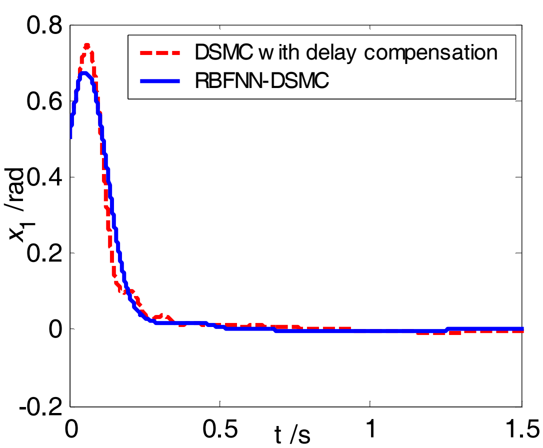
Suppose that the initial value of state system is $[x_{10} \quad x_{20}]^{\mathrm{T}} = [0.5 \quad 3.14]^{\mathrm{T}}$ and control target is $[x_1 \quad x_2]^{\mathrm{T}} = [0 \quad 0]^{\mathrm{T}}$.

Take the (21) as the nominal system of controlled plant, and suppose existing parameter vibration and disturbance

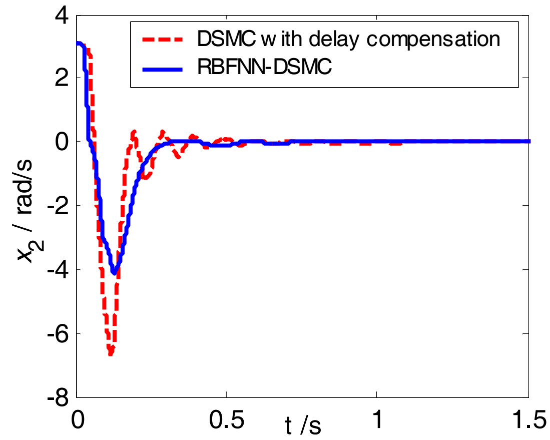
$$\Delta A = \begin{bmatrix} 0 & 0.5 \\ 4 & -0.2 \end{bmatrix}, \ \Delta B = \begin{bmatrix} 0 \\ -3 \end{bmatrix} \text{ and } d = \begin{bmatrix} 0 \\ 1.2 + 5\sin(4t) \end{bmatrix}.$$

Set up the network communication environment, network bandwidth is 125kbit/s, and state feedback and control signal are transmitted by network using TEE mode. Thus, the random network-delays satisfy $\max(d_{\mathrm{sc}}(k) + d_{\mathrm{ca}}(k)) + d_{\mathrm{c}} < T$. Calculate the measuring data to get average delay parameter $d_{\mathrm{sc}}^{\mathrm{avg}} = 3.6715\mathrm{ms}$ and $d_{\mathrm{ca}}^{\mathrm{avg}} = 3.3155\mathrm{ms}$, as well as super boundary $d_{\mathrm{sa}}^{\mathrm{sup}} = \max\limits_{k \in N}(d_{\mathrm{sc}}(k) + d_{\mathrm{ca}}(k)) = 12.582\mathrm{ms}$ and inferior boundary delay $d_{\mathrm{sa}}^{\mathrm{inf}} = \min\limits_{k \in N}(d_{\mathrm{sc}}(k) + d_{\mathrm{ca}}(k)) = 4.32\mathrm{ms}$, where N is delay sample set.

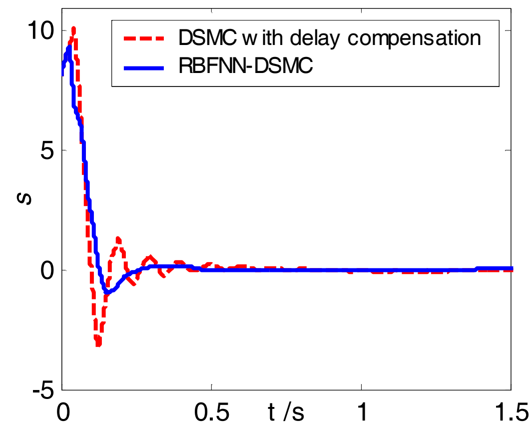
Considering the coupling influence of network delay and plant uncertainty, the above-mentioned RBFNN-DSMC algorithm and the DSMC with only delay-compensation [7] are simulated and compared. The controller parameters are set as $G = [10 \quad 1], \varepsilon T = 2, \delta T = 0.3$. Six neural cells are chosen in the latent layer of RBFNN, where center initial value is $\boldsymbol{C}(0) = \begin{bmatrix} 1.5 & 1 & 0.5 & 0 & -0.5 & -1 \\ 1.5 & 1 & 0.5 & 0 & -0.5 & -1 \end{bmatrix}^{\mathrm{T}}$, base width initial value is $\sigma_j(0) = 0.3 \quad (j = 1, \ldots, 6)$, output layer link weight is $w_j(0) = 0 \quad (j = 1, \ldots, 6)$, the weight superior boundary is $W_{\max} = 4$, learning velocity and momentum factor are $\rho = 0.25$, $\alpha = 0.05$ individually. The results of simulation are shown in Fig.3.



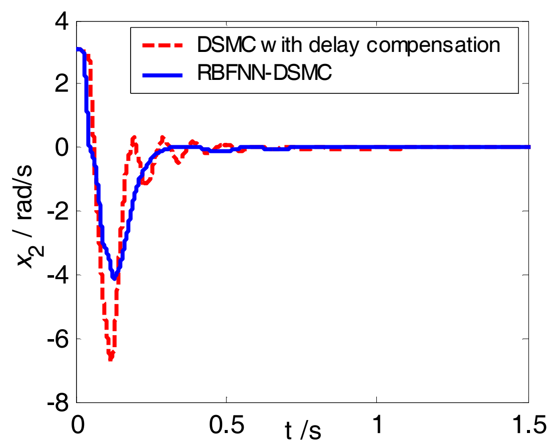
(a) Response curve of x_1



(b) Response curve of x_2



(c) Response curve of switch function s



(d) Control quantity u

Figure 3. Response curve and control curve of RBFNN-DSMC and DSMC only with delay compensation

Simulation results indicate that the DSMC only with delay compensation can stabilize the system finally with light vibration while the network delay and plant uncertainty act together, but the dynamic process is not good enough. The RBFNN-DSMC through RBF network to close and compensate the disturbance online can restrain effectively the delay-estimating error and other uncertain factors so as to obtain the better static and dynamic performance.

V. CONCLUSION

For the networked control system under stochastic network delay less than one period, the model's mismatch and exterior disturbance might couple with time-variable delay so as to complicate the uncertainty. To upgrade the control performance and robustness, a sort of RBFNN-DSMC algorithm combining discrete sliding mode control and RBF neural network is designed. In this way, RBFNN can learn adaptively the uncertainty online and output assistant control part so as to compensate the complicated disturbances' influence with the DSMC together, and also restrain the sliding mode vibration. The proposed algorithm is verified good for the uncertain NCS stable by the simulation of a reversal pendulum control system.

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