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Backstepping control with radial basis function neural network for web transport systems

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ABSTRACT

Web transport system (WTS) is commonly used in the production and handling of web materials such as paper, fabric, corrugated iron, steel, and printing operations. These materials are easily damaged if the process performance is poor. Therefore, high technology in mechanics and precise control techniques are required in this system. In addition, because of parameter variation, strong nonlinearity, and many external noises, there are many challenges in controlling this process. This paper proposes a backstepping technique-based algorithm to control the web's tension and velocity. To solve the parameter variation, a radial basis function (RBF) neural network-based adaptation algorithm is developed to approximate the varied components in the control algorithm. The system stability is guaranteed using the Lyapunov stability theorem. Simulations in MATLAB/Simulink have been done and the effectiveness of the proposed control algorithm is verified. Tension and velocity tracking can be obtained with parameter variations.

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1. INTRODUCTION

Web transport system (WTS), which is one of the popular systems, is widely used in the production and handling of web materials [1]–[3] such as paper production, glass, oled materials, solar cells, fabrics, and printing operations [4], [5]. The materials have characteristics such as thin, continuous, elastic, and easy to be damaged during transportation and handling, so WTS requires not only high technology in terms of mechanics but also high requirements on control engineering. In fact, the controllers used for WTS are mainly proportional-integral (PI) and proportional-integral-derivative (PID) [6]–[8], feedforward control [9], and PID with feedforward control [10]. However, this is a linear control method, while WTS is a strongly nonlinear system, affected by external noise, so it does not always give the desired quality, but the often slow response, low stability, low accuracy, and challenge to meet the increasingly high requirements of today's modern production lines. Therefore, it is necessary to build a modern controller to overcome the disadvantages.

In recent years, various nonlinear control methods such as sliding mode control [11]–[13], intelligent control [14]–[16], backstepping control (BC) [17]–[19], and disturbance compensator [20] have been applied to improve the control quality for the system. These control methods can only improve performance when the system parameters are clearly known. However, the WTS system is a time-varying system, and the calculation of system parameters is quite complicated and less precise. To further improve the system performance, it is necessary to have an adaptive mechanism to track the system parameters' variation and radial basis function (RBF) neural network is an appropriate selection in many applications [21]–[24]. The paper proposes adaptive BC for WTS using RBF neural networks. The controller is designed using the backstepping technique while the system's time-varying parts are approximated by RBF neural network. The RBF network weight updating rules are proposed such as the system stability and desired system performance are guaranteed.

2. WEB TRANSPORT SYSTEM DYNAMIC MODELING

Let us consider a single-span WTS including an unwind roll and a rewind roll as shown in Figure 1. The guide rolls are ignored for simplicity. According to Newton's law and mass conservation, the nonlinear dynamic equations of web transport can be written as (1)-(3) [25]:

$$\dot{t}_w = c_1\omega_u + c_2\omega_r t_w + c_3\omega_r \tag{1}$$

$$\dot{\omega}_u = c_4 M_u + c_5 t_w + c_6\omega_u + c_7 w_u^2 \tag{2}$$

$$\dot{\omega}_r = c_8 M_r + c_9 t_w + c_{10}\omega_r + c_{11}\omega_r^2 \tag{3}$$

where $c_i, (i = 1, .., 11)$ are the time-dependent parameters defined as:

$$c_1 = \frac{r_u}{L}t_u - \frac{ESr_u}{L}; c_2 = -\frac{r_r}{L}; c_3 = \frac{ESr_r}{L}; c_4 = -\frac{1}{J_u}; c_5 = \frac{r_u}{J_u}; c_6 = -\frac{b_{fu}}{J_u}; c_7 = \frac{aw\rho r_u^3}{J_u}; c_8 = \frac{1}{J_r};$$
$$c_9 = -\frac{r_r}{J_r}; c_{10} = -\frac{b_{fr}}{J_r}; c_{11} = -\frac{aw\rho_r^3}{J_r};$$

In the definition of c_i, operating radius r_u, r_r and moment of inertia J_u, Jr, are calculated as:

$$r_u(t) = R_{u0} - \frac{\varphi}{2\pi}a; r_r(t) = R_{r0} + \frac{\varphi}{2\pi}a; J_u(t) = J_{u0} + \frac{1}{2}\rho w\pi(r_u^4 - R_c^4);$$
$$J_r(t) = J_{r0} + \frac{1}{2}\rho w\pi(r_r^4 - R_r^4)$$

Where t_w is web tension, w_u is unwind roll's angular velocity, w_r is rewind roll's angle velocity, M_u is unwind roll torque, M_r is rewind roll torque, r_u is unwind roll radius, R_{u0} is unwind roll's initial radius, r_r is rewind roll radius, R_{r0} is rewind roll's initial radius, J_u is the unwind roll's total moment of inertia, J_{u0} is unwind roll's initial total moment of inertia, J_r is rewind roll's total moment of inertia, J_{r0} is rewind roll's initial total moment of inertia, b_{f_u} is unwind roll vicious friction coefficient, b_{f_r} is rewind roll vicious friction coefficient, E is web elasticity, S is web cross-sectional area, L is web length, a is web thickness, w is web width, and p is web density.

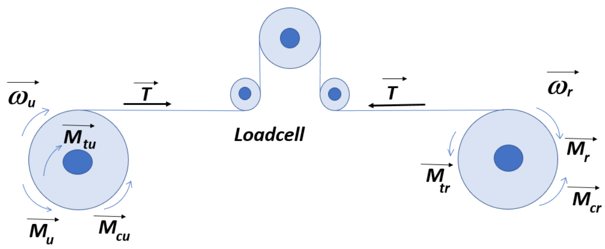

Figure 1. Single-span WTS

3. DESIGN A BACKSTEPPING CONTROL INCORPORATING RADIAL BASIS FUNCTION NEURAL NETWORK

At first, we define intermediate variables f_u, g_u, f_r, g_r as:

$$f_u = c_5 t_w + c_6 w_u + c_7 w_u^2; g_u = c_4; f_r = c_9 t_w + c_{10} w_r + c_{11} w_r^2; g_r = c_8$$

Then, the dynamical model (1)-(3) becomes (4)-(6):

$$\dot{t} = c_1 \omega_u + c_2 \omega_r t + c_3 \omega_r \tag{4}$$

$$\dot{\omega}_u = f_u + g_u M_u \tag{5}$$

$$\dot{\omega}_r = f_r + g_r M_r \tag{6}$$

The designing process is as:

– Step 1: defining tension tracking error variables as (7):

$$\Delta t_w = t_w - T_d \tag{7}$$

where T_d is reference web tension, then:

$$\Delta \dot{t}_w = \dot{t} - \dot{T}_d = c_1 \omega_u + c_2 \omega_r t + c_3 \omega_r - \dot{T}_d \tag{8}$$

Choose the Lyapunov function: $V_1 = \frac{1}{2} \Delta \dot{t}_w^2$. Taking the derivative of V_1 one can obtain as (9):

$$\dot{V}_1 = \Delta t_w \Delta \dot{t}_w = (c_1 \omega_u + c_2 \omega_r t + c_3 \omega_r - \dot{T}_d)(t - T_d) \tag{9}$$

In order to stabilize the subsystem, the condition $\dot{V}_1 \leq 0$ must be guaranteed. Thus, we choose (10):

$$c_1 \omega_u + c_2 \omega_r t + c_3 \omega_r - \dot{T}_d = -k_t (t - T_d) \tag{10}$$

where k_t is a positive real number, then:

$$\dot{V}_1 = -k_t (t - T_d)^2 = -k_t \Delta t_s^2 \leqslant 0; \forall k_t \geqslant 0 \tag{11}$$

From condition (10), we deduce the virtual control signal to stabilize the subsystem as (12):

$$F_{\omega_{ud}} = -\frac{1}{c_1} (c_2 t \omega_r + c_3 \omega_r - \dot{T}_d + k_t (t - T_d)) \tag{12}$$

– Step 2: defining unwind velocity tracking error variables as (13):

$$\Delta \omega_u = \omega_u - F_{\omega_{ud}} \tag{13}$$

Choose the Lyapunov function: $V_u = \frac{1}{2} (\Delta \omega_u)^2 = \frac{1}{2} (\omega_u - F_{\omega_{ud}})^2$. Taking the derivative of V_u:

$$\dot{V}_u = \Delta \omega_u \Delta \dot{\omega}_u = \Delta \omega_u (\dot{\omega}_u - \dot{F}_{\omega_{ud}}) = \Delta \omega_u (f_u + g_u M_u - \dot{F}_{\omega_{ud}}) \tag{14}$$

In order to obtain $\dot{V}_u \leq 0$ the control signal M_u is chosen as (15):

$$M_u = -\frac{1}{g_u} (f_u - \dot{F}_{\omega_{ud}} + k_{\omega_u} \Delta \omega_u) \tag{15}$$

where k_{ω_u} is a positive real number, then:

$$\dot{V}_u = -k_{\omega_u} (\Delta \omega_u)^2 \leqslant 0 \tag{16}$$

However f_u and g_u are difficult to determine precisely. Thus, we will approximate them by $\hat{f}_u$ and $\hat{g}_u$, respectively. The control signal then is calculated as (17):

$$M_u = -\frac{1}{\hat{g}_u}(\hat{f}_u - \dot{F}_{\omega_{ud}} + k_{\omega_u}\Delta\omega_u) \tag{17}$$

The derivative of V_u becomes (18):

$$\begin{aligned} \dot{V}_u &= \Delta\omega_u((f_u - \hat{f}_u) + \hat{f}_u + (g_u - \hat{g}_u)M_u + \hat{g}_u M_u - \dot{F}_{\omega_{ud}}) \\ &= \Delta\omega_u(f_u - \hat{f}_u) + \Delta\omega_u(g_u - \hat{g}_u)M_u - k_{\omega_u}(\Delta\omega_u)^2 \end{aligned} \tag{18}$$

Next, the approximation rules for f_u and g_u are proposed. Supposing that the function f_u can be computed by an ideal RBF as (19):

$$f_u = \bar{W}_u^T \bar{h}_u \tag{19}$$

Where $\bar{W}_u$ is the ideal weight vector of the neural network $\bar{W}_u = [W_{u1}^*, W_{u2}^*, ..., W_{um}^*]^T$, m is the number of neural in the network; and $\bar{h}_u$ is a Gaussian function vector $\bar{h}_u = [h_{u1}, h_{u2}, ..., h_{um}]^T$. The Gaussian function $h_{ui}, (i = 1, 2, ..., m)$, with inputs w_u, w_r, is defined as (20):

$$h_{ui} = \frac{exp(\frac{\|\omega_u - c_{1i}\|^2 + \|\omega_r - c_{2i}\|^2}{b_{ui}^2})}{\sum_{i=1}^m exp(\frac{\|\omega_u - c_{1i}\|^2 + \|\omega_r - c_{2i}\|^2}{b_{ui}^2})} \tag{20}$$

Where c_{1i} and c_{2i} are the position of the center of the RBF, b_{ui} is the width of the RBF. The approximation function $\hat{f}_u$ are calculated using RBF as (21) (Figure 2):

$$\hat{f}_u = \hat{W}_u^T \bar{h}_u \tag{21}$$

Where $\hat{W}_u = [W_{u1}, W_{u2}, ..., W_{um}]^T$ is weight vector. We have to establish the weight updating rule so that the system is stable. In addition, we also have to find the approximation rule for g_u. It is noted that $g_u = -1/J_u$, then there exists upper bound $g_u < g_{uM} < 0$.

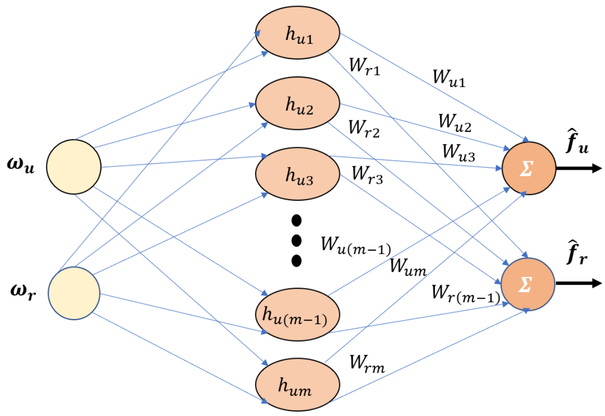

Figure 2. Schematic diagram of RBF neural network to approximate $\hat{f}_u$ and $\hat{f}_r$

Supposing that g_u can be approximated by $\hat{g}_u$. We define $\tilde{W}_u = \bar{W}_u - \hat{W}_u$; $\tilde{g}_u = g_u - \hat{g}_u$. Choose the Lyapunov candidate function V_{2u} as (22):

$$V_{2u} = V_u + \frac{1}{2}\tilde{W}_u^T\Gamma_u^{-1}\tilde{W}_u + \frac{1}{2}\eta_u\tilde{g}_u^2 = \frac{1}{2}(\Delta\omega_u)^2 + \frac{1}{2}\tilde{W}_u^T\Gamma_u^{-1}\tilde{W}_u + \frac{1}{2}\eta_u\tilde{g}_u^2 \tag{22}$$

where Γ_u is a positive definite diagonal matrix and η_u is a positive real number, then:

$$\begin{aligned} \dot{V}_{2u} &= \dot{V}_u + \tilde{W}_u^T\Gamma_u^{-1}\dot{\tilde{W}}_u + \eta_u\tilde{g}_u\dot{\tilde{g}}_u \\ &= \Delta\omega_u(f_u - \hat{f}_u) + \Delta\omega_u(g_u - \hat{g}_u)M_u - k_{\omega_u}(\Delta\omega_u)^2 + \tilde{W}_u^T\Gamma_u^{-1}\dot{\tilde{W}}_u + \eta_u\tilde{g}_u\dot{\tilde{g}}_u \\ &= \Delta\omega_u\tilde{W}_u^T h_u + \Delta\omega_u\tilde{g}_u M_u - k_{\omega_u}(\Delta\omega_u)^2 + \tilde{W}_u^T\Gamma_u^{-1}\dot{\tilde{W}}_u + \eta_u\tilde{g}_u\dot{\tilde{g}}_u \\ &= -k_{\omega_u}(\Delta\omega_u)^2 + \tilde{W}_u^T(\Delta\omega_u h_u + \Gamma_u^{-1}\dot{\tilde{W}}_u) + \tilde{g}_u(\Delta\omega_u M_u + \eta_u\dot{\tilde{g}}_u) \\ &= -k_{\omega_u}(\Delta\omega_u)^2 + \tilde{W}_u^T(\Delta\omega_u h_u - \Gamma_u^{-1}\dot{\hat{W}}_u) + \tilde{g}_u(\Delta\omega_u M_u - \eta_u\dot{\hat{g}}_u \end{aligned} \tag{23}$$

In order to guarantee system stability, i.e. $\dot{V}_{2u} \leq 0$ the following update laws are proposed:

$$\dot{\hat{g}}_u = \begin{cases} \eta_u^{-1}\Delta\omega_u M_u; \text{ if } \hat{g}_u < g_{uM} \\ \eta_u^{-1}\Delta\omega_u M_u; \text{ if } (\hat{g}_u = g_{uM})\&(\Delta\omega_u M_u < 0) \\ 0; \text{ if } (\hat{g}_u = g_u M)\&(\Delta\omega_u M_u \geq 0) \end{cases} \tag{24}$$

$$\dot{\hat{W}}_u = \Gamma_u \Delta\omega_u h_u \tag{25}$$

The update rule (24) can be interpreted as:

– If $\hat{g}_u < g_{uM}$, it means $\dot{\hat{g}}_u$ is within the allowed limit, then $\hat{g}_u$ can take any value and here we choose $\dot{\hat{g}}_u = \eta_u^{-1}\Delta\omega_u M_u$, then $\tilde{g}_u(\Delta\omega_u M_u - \eta_u\dot{\hat{g}}_u) = 0$.
– If $\hat{g}_u = \underline{g}_u$, it means $\hat{g}_u$ reaches the upper bound, then $\dot{\hat{g}}_u$ cannot choose a positive value. So if $\Delta\omega_u M_u <$ 0 then we will choose $\dot{\hat{g}}_u = \eta_u^{-1}\Delta\omega_u M_u < 0$, and $\tilde{g}_u(\Delta\omega_u M_u - \eta_u\dot{\hat{g}}_u) = 0$.
– If $\hat{g}_u = g_{uM}$ and $\Delta\omega_u M_u \geq 0$, we choose $\hat{g}_u = 0$. This keeps the value $\hat{g}_u$ equal to the upper bound value. Then, $\tilde{g}_u = g_u - \hat{g}_u = g_u - g_{uM} \leq 0$, deduce: $\tilde{g}_u(\Delta\omega_u M_u - \eta_u\dot{\hat{g}}_u) = \tilde{g}_u\Delta\omega_u M_u \leq 0$.

Thus, in all cases we always have (26):

$$\tilde{g}_u(\Delta\omega_u M_u - \eta_u\dot{\hat{g}}_u) \leq 0 \tag{26}$$

In addition, from the update rule (25), we have (27):

$$\tilde{W}_u^T(\Delta\omega_u h_u - \Gamma_u^{-1}\dot{\hat{W}}_u) = 0 \tag{27}$$

Thus:

$$\dot{V}_{2u} = -k_{\omega_u}(\Delta\omega_u)^2 + \tilde{W}_u^T(\Delta\omega_u h_u - \Gamma_u^{-1}\dot{\hat{W}}_u) + \tilde{g}_u(\Delta\omega_u M_u - \eta_u\dot{\hat{g}}_u) \leq -k_{\omega_u}(\Delta\omega_u)^2 \leq 0 \tag{28}$$

– Step 3: defining rewind velocity tracking error variables as (29):

$$\Delta\omega_r = \omega_r - \omega_{rd} \tag{29}$$

Where ω_{rd} is the reference velocity for the rewind roll. Choose the Lyapunov candidate function: $V_r = \frac{1}{2}(\Delta\omega_r)^2 = \frac{1}{2}(\omega_r - \omega_{rd})^2$. Taking the derivative of V_r:

$$\dot{V}_r = \Delta\omega_r\Delta\dot{\omega}_r = \Delta\omega_r(\dot{\omega}_r - \dot{\omega}_{rd}) = \Delta\omega_r(f_r + g_r M_r - \dot{\omega}_{rd}) \tag{30}$$

In order to obtain $\dot{V}_r \leq 0$ the control signal M_r is chosen as (31):

$$M_r = -\tfrac{1}{g_r}(f_r - \dot{\omega}_{rd} + k_{\omega_r}\Delta\omega_u) \tag{31}$$

where k_{ω_r} is a positive real number, then:

$$\dot{V}_r = -k_{\omega_r}(\Delta\omega_r)^2 \leq 0 \tag{32}$$

However f_r and g_r are difficult to determine precisely. Thus, we will approximate them by $\hat{f}_r$ and $\hat{g}_r$, respectively. Then, the control signal is calculated as (33):

$$M_r = -\tfrac{1}{\hat{g}_r}(\hat{f}_r - \dot{\omega}_{rd} + k_{\omega_r}\Delta\omega_r) \tag{33}$$

The derivative of V_r becomes (34):

$$\begin{aligned} \dot{V}_r &= \Delta\omega_r((f_r - \hat{f}_r) + \hat{f}_r + (g_r - \hat{g}_r)M_r + \hat{g}_r M_r - \dot{\omega}_{rd}) \\ &= \Delta\omega_r(f_r - \hat{f}_r) + \Delta\omega_r(g_r - \hat{g}_r)M_r - k_{\omega_r}(\Delta\omega_r)^2 \end{aligned} \tag{34}$$

Next, the approximation rules for f_r and g_r are proposed. Supposing that the function f_r can be computed by an ideal RBF as (35):

$$f_u = \bar{W}_r^T \bar{h}_r \tag{35}$$

Where $\bar{W}_r$ is the ideal weight vector of the neural network $\bar{W}_r = [W_{r1}^*, W_{r2}^*, ..., W_{rn}^*]^T$, n is the number of neural in the network, and $\bar{h}_r$ is a Gaussian function vector $\bar{h}_r = [h_{r1}, h_{r2}, ..., h_{rn}]^T$. The approximation function $\hat{f}_r$ are calculated using RBF as (36):

$$\hat{f}_r = \hat{W}_r^T \bar{h}_r \tag{36}$$

Where $\hat{W}_r = [W_{r1}, W_{r2}, ..., W_{rn}]^T$ is weight vector. We have to establish the weight updating rule so that the system is stable. In addition, we also have to find the approximation rule for g_r. It is noted that $g_r = 1/J_r$, then there exists lower bound $g_r \geq g_{rM} > 0$. Supposing that g_r can be approximated by $\hat{g}_r$. We define $\tilde{W}_r = \bar{W}_r - \hat{W}_r$; $\tilde{g}_r = g_r - \hat{g}_r$. Choose the Lyapunov candidate function V_{2r} as (37):

$$V_{2r} = V_r + \tfrac{1}{2}\tilde{W}_r^T \Gamma_r^{-1} \tilde{W}_r + \tfrac{1}{2}\eta_r \tilde{g}_r^2 = \tfrac{1}{2}(\Delta\omega_r)^2 + \tfrac{1}{2}\tilde{W}_r^T \Gamma_r^{-1} \tilde{W}_r + \tfrac{1}{2}\eta_r \tilde{g}_r^2 \tag{37}$$

where Γ_r is a positive definite diagonal matrix and η_r is a positive real number, then:

$$\begin{aligned}
\dot{V}_{2r} &= \dot{V}_r + \tilde{W}_r^T \Gamma_r^{-1} \dot{\tilde{W}}_r + \eta_r \tilde{g}_r \dot{\tilde{g}}_r \\
&= \Delta\omega_u (f_r - \hat{f}_r) + \Delta\omega_r (g_r - \hat{g}_r) M_r - k_{\omega_r} (\Delta\omega_r)^2 + \tilde{W}_r^T \Gamma_r^{-1} \dot{\tilde{W}}_r + \eta_r \tilde{g}_r \dot{\tilde{g}}_r \\
&= \Delta\omega_r \tilde{W}_r^T h_r + \Delta\omega_r \tilde{g}_r M_r - k_{\omega_r} (\Delta\omega_r)^2 + \tilde{W}_r^T \Gamma_r^{-1} \dot{\tilde{W}}_r + \eta_r \tilde{g}_r \dot{\tilde{g}}_r \\
&= -k_{\omega_r} (\Delta\omega_r)^2 + \tilde{W}_r^T (\Delta\omega_r h_r + \Gamma_r^{-1} \dot{\tilde{W}}_r) + \tilde{g}_r (\Delta\omega_u M_r + \eta_r \dot{\tilde{g}}_r) \\
&= -k_{\omega_r} (\Delta\omega_r)^2 + \tilde{W}_r^T (\Delta\omega_r h_r - \Gamma_r^{-1} \dot{\hat{W}}_r) + \tilde{g}_r (\Delta\omega_r M_r - \eta_r \dot{\hat{g}}_r)
\end{aligned}$$

In order to guarantee system stability, i.e. $\dot{V}_{2r} \leq 0$ the following update laws are proposed:

$$\dot{\hat{g}}_r = \begin{cases} \eta_r^{-1} \Delta\omega_r M_r; \text{ if } \hat{g}_r > g_{rM} \\ \eta_r^{-1} \Delta\omega_r M_r; \text{ if } (\hat{g}_r = g_{rM}) \& (\Delta\omega_r M_r > 0) \\ 0; \text{ if } (\hat{g}_r = g_r M) \& (\Delta\omega_r M_r \leq 0) \end{cases} \tag{38}$$

$$\dot{\hat{W}}_r = \Gamma_r \Delta\omega_r h_r \tag{39}$$

The update rule (38) can be interpreted as:

- If $\hat{g}_r > g_{rM}$, it means $\hat{g}_r$ is within the allowed limit, then $\dot{\hat{g}}_r$ can take any value and here we choose $\dot{\hat{g}}_r = \eta_r^{-1} \Delta\omega_r M_r$, then $\tilde{g}_r (\Delta\omega_r M_r - \eta_r \dot{\hat{g}}_r) = 0$.
- If $\hat{g}_r = g_{rM}$, it means $\hat{g}_r$ reaches the lower bound, then $\dot{\hat{g}}_r$ cannot choose a negative value. So if $\Delta\omega_r M_r > 0$ then we will choose $\dot{\hat{g}}_r = \eta_r^{-1} \Delta\omega_r M_r > 0$, and $\tilde{g}_r (\Delta\omega_r M_r - \eta_r \dot{\hat{g}}_r) = 0$.
- If $\hat{g}_r = g_{rM}$ and $\Delta\omega_r M_r \leq 0$, we choose $\dot{\hat{g}}_r = 0$. This keeps the value $\hat{g}_r$ equal to the lower bound value. Then, $\tilde{g}_r = g_r - \hat{g}_r = g_r - g_{rM} \geq 0$, deduce: $\tilde{g}_r (\Delta\omega_r M_r - \eta_r \dot{\hat{g}}_r) = \tilde{g}_r \Delta\omega_r M_r \leq 0$. Thus, in all cases we always have (40):

$$\tilde{g}_r (\Delta\omega_r M_r - \eta_r \dot{\hat{g}}_r) \leq 0 \tag{40}$$

In addition, from the update rule (39), we have (41):

$$\tilde{W}_r^T (\Delta\omega_r h_r - \Gamma_r^{-1} \dot{\hat{W}}_r) = 0 \tag{41}$$

Thus:

$$\dot{V}_{2r} = -k_{\omega_r} (\Delta\omega_r)^2 + \tilde{W}_r^T (\Delta\omega_r h_r + \Gamma_r^{-1} \dot{\hat{W}}_r) + \tilde{g}_r (\Delta\omega_r M_r - \eta_r \dot{\hat{g}}_r) \leq -k_{\omega_r} (\Delta\omega_r)^2 \leq 0 \tag{42}$$

The control laws, as well as the updating rules, have been developed successfully.

4. SIMULATION RESULT

Simulations have been conducted using MATLAB/Simulink to verify the effectiveness of the proposed control method. A comparison is also made between the proposed controller and conventional backstepping. The simulation parameters are: $R_{u0} = 0.1\ m$; $R_{r0} = 0.05\ m$; $b_{fu} = 0.00002533\ Nms$; $b_{fr} = 0.00002533\ Nms$; $J_{u0} = 1.5\ kg.m^2$; $J_{r0} = 0.5\ kg.m^2$; $a = 0.00005\ m$; $k_{wu} = 230$; $k_{wr} = 230$; and $k_t = 500$.

In the simulation, for both the conventional BC and the RBF-BC, the reference tension is 10 N. The rewind reference speed profile is as follows. The speed increases linearly from 0 to 2 m/s from 0 to 5 second. The speed is kept constant from 5 to 20 seconds. Finally, the speed decreases linearly from 20 to 25 second. Two situations are considered in the simulation including the system parameters are known precisely, i.e. the system parameter error is 0% and there are system parameter error 20%. In both considered situations, the simulation results are shown in Figure 3(a)-(f).

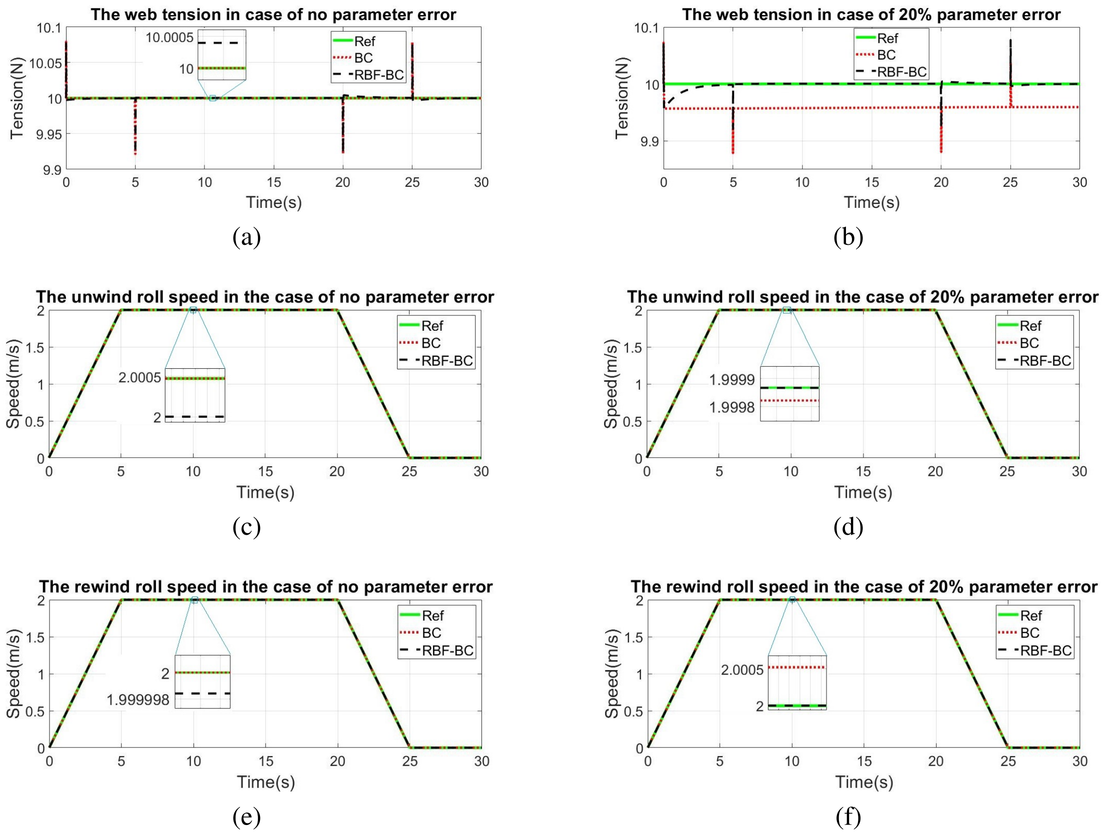

Figure 3. Simulation results with no parameter error and 20% parameter error: (a) tension-no parameter error, (b) tension-20% parameter error, (c) unwind roll speed-no parameter error, (d) unwind roll speed-20% parameter error, (e) rewind roll speed-no parameter error, and (f) rewind roll speed -20% parameter error

For the case of no error, at times 0, 5, 20, and 25 seconds, due to a sudden change in velocity, there are tension overshoots 0.8% as shown in Figure 3(a). After that, the tension returns back to the reference value. For the BC controller, the return time is very fast. But for RBF-BC, it takes about 1.2 s to return to the set value since the system parameters need to be estimated. In addition, at the steady state, for the RBF-BC, there exists a little steady-state error (0.006%). The unwind velocity in case BC and RBF-BC both track the reference value; however, in the case of RBF-BC there exists a little error (0.0025%) as shown in Figure 3(c). For the rewind roll, the velocity tracking is also obtained for both controllers as shown in Figure 3(e). When there are parameter errors for the BC controller, there is exists a difference between the actual tension and the reference value, the difference increases when the error increases.

For the case of 20% error, the difference is 0.45% as shown in Figure 3(b). For the RBF-BC controller, the difference between the actual and the reference value is much smaller. It is because the BC controller depends on the system parameter, but RBF-BC can adapt to parameter variation. This is the advantage of the proposed RBF-based controller. For both BC and RBF-BC controllers, velocity tracking is always guaranteed as shown in Figures 3(d) and (f). This is the advantage of a backstepping-based controller for WTS.

5. CONCLUSION

A BC coupled with a RBF neural network is proposed for WTS in this paper. The BC strongly depends on system parameters. Thus, the RBF is proposed to update the changing of the system parameter. The weight update rules of the neural network have been developed to stabilize the system and guarantee good performance. Simulation results demonstrate the effectiveness of the proposed controller compared to the conventional BC. In the future, we will continue to improve the performance of the controller to overcome the ”explosion of terms” phenomenon in the BC. We also consider implementing the proposed controller in a real system.

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