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Time-delay estimator and disturbance observer based on neural network in networked control system

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Abstract

In this paper, we deal with the control problem of network induced delays and randomly varying time-delay controlled plant under the effect of disturbances and noise in networked control systems (NCS). In a time-delay NCS it becomes more challenging to attain stability when the disturbances and noise interference appear in form of a time-varying signal in the close loop of the NCS. These in turn make the conventional control methods, e.g., normal mathematical model of Smith predictor, more complicated when the aim is to meet quality requirements of the NCS. To overcome these inherent challenges, we mainly analyze the existing techniques, and then propose a novel method to efficiently reduce the effect of time-delays, disturbances, and noise interference for highly efficient and accurate control purposes. Specifically, we introduce a joint solution of time-delay estimator and disturbance observer in which the outer loop with an adaptive Smith predictor is utilized to compensate time-delays for the whole NCS while the inner loop with disturbance observer is to eliminate the disturbances and noise interference. By using neural network identification and the estimation method, the proposed model provides many outstanding advantages such as high adaptation, robust stability, and fast response. The simulation results generated via TrueTime Beta2.0 platform demonstrate that our design significantly improves the performance of NCS.

Keywords: *disturbance observer, networked control system, neural network, Smith predictor, time-delay estimator*

1. Introduction

In the last two decades, networked control systems (NCS) have garnered intensive attention from researchers. A basic structure of NCS can be described as depicted in Figure 1.

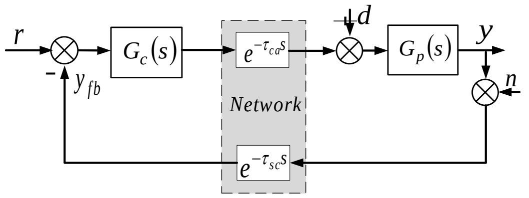

Figure 1 Structure of NCS

The most serious problems causing less efficient NCS performance, instability, and even collapse, are randomly varying time-delays (RVTD) and disturbances. These problems can be addressed in two principle ways, one being a time-delay compensation and the other a disturbance observer (DOB).

Concerning time-delay compensation, many different control methodologies have been proposed to reduce the effect of time-delays in the process control loop. Among them, the Smith predictor is widely used as an effective compensator for large time-delay control systems (Astrom, Hang, & Lim, 2003; Bahill, 1983; Cuenca, Gacia, Albertos, & Salt, 2011; Cuenca, Salt, Casanova, & Piza, 2010). Under the effect of RVTD, adaptive Smith predictive technique consisting of the on-line time-delay estimation and an adaptive control schemes can be adopted as a feasible solution. In this regard, the existing approaches mainly focused on either control scheme through the use of appropriate Lyapunov-Krasovskii functionals (Hong & Lee, 2003) or estimation methods (Dang, Guan, Li, & Zhang, 2012; Dang, Guan, Tran, & Li, 2011; Huang, Kuo, & Tseng, 2007; Kenji & Kouhei, 2008). Especially, related to time-delay estimation methods, as a simple technique, time-delay is considered either constant or slowly varying forms (Agarwal & Canudas, 1987; Tran, Guan, Dang, Cheng, & Yuan, 2013). The combined effect of these two forms of time-delay is reduced by approximately transforming them into frequency domain. More sophisticatedly, despite the fact that time-delay is randomly varying in a slow or fast manner. It is mitigated by applying the neuro-fuzzy based time-delay estimation using discrete cosine transform coefficients (Shaltaf, 2007; Shaltaf & Mohammad, 2009). Furthermore, the problem of RVTD was efficiently overcome in our previous work (Dang, Guan, Li, & Zhang, 2012; Dang, Guan, Tran, & Li, 2011) by a combination design of control and estimation schemes or by implying gain and phase margin method (Tran, Guan, Dang, Cheng, & Yuan, 2013). However, the mentioned methods did not consider the presence of disturbances and noise in the close loop of the NCS, which may cause the designs to be less efficient.

In connection with disturbance rejection, the basic concepts of disturbance observers have been studied in some other works (Chiang, Chen, Liu, & Hsu, 2001; Koofigar, 2014; Lee, Park, Lee, Lee, Jeong, Yoon, Chun, & Choi, 2012). Disturbance is usually assumed to be an exogenous signal, which can be compensated efficiently by the feedback signal from the disturbance estimator. In practice, due to the fact that the disturbances of communication networks have a direct effect on the overall delay of a system. The authors (Kenji & Kouhei, 2008; Kaya, 2003) propose a design method for a communication disturbance observers to compensate unknown time-delay (Kenji & Kouhei, 2008). More importantly, robustness and disturbance rejection performance based criteria for designing DOB were carefully studied by further taking into account the effect of sensor noise (Choi, Yang, Chung, Kim, & Suh, 2003; Yang, Choi, Chung, Suh, & Oh, 2002). Considering the disturbances caused by congestion problems, the authors (Grieco & Mascolo, 2002) presented an end-to-end congestion control algorithm in high-speed ATM networks using the Smith principle composed with feed forward disturbance compensation to improve the performance of the control system. Aiming at rejecting the effect of exogenous disturbance in the close loop and achieving tracking control, a novel discrete control scheme combined by a repetitive control and a novel disturbance observer feature inside the internal model was proposed (Na, Castello, Grino, & Ren, 2002). To avoid the steady state error of a step input, ramp input, or acceleration input, Yashiro have proposed a novel communication disturbance observer using a band-pass filter (Yashiro, & Kouhei, 2008). However, all of the above methods only considered the objects to a limited extent resulting in restricted achievement in a complicated NCS.

In fact, although the problem of performance control with disturbance attenuation for time-delay systems has drawn a lot of attention in recent years (Yoo, Park, & Choi, 2009; Zhao & Wang, 2011), the characteristics of communication networks with network-induced time delays are considered as certain input delays. Therefore, the performance control with disturbance attenuation has not been addressed for systems with uncertain time-varying input delays. Note that for systems with uncertain time-varying input delays, it becomes more difficult to analyze the disturbance attenuation because the state variation depends on both the current state and history state of the exterior disturbance input.

As can be observed from the above discussion, the conventional methods could not be applied efficiently because the characteristics of time-delay, disturbance, and noise are actually occurring in randomly varying forms. In this paper, we cope with all the randomly varying problems by taking the following approaches. Firstly, we investigate the stability of NCS under the effect of disturbances and noise. Secondly, we propose a new approach by using a time-delay estimator and a disturbance observer based on neural net-work. In this approach, the outer loop with an adaptive Smith predictor is utilized to compensate the RVTD for the whole NCS while the inner loop with disturbance observer is devised to reject the randomly varying disturbances and noise. Finally, by means of further joint assessment of the fuzzy adaptive controller and DOB results demonstrate that our design significantly improves the performance of NCS.

The remainder of this paper is organized as follows. In Section II, we analyze the proposed Smith predictor structure of NCS under the effect of time-delays, disturbances, and noise. We introduce a method to design the disturbance observer based on neural network for NCS in Section III. Section IV is dedicated to designing the fuzzy adaptive controller in connection with the proposed model for simulation. Simulation results are given in Section V and Section VI draws concluding remarks.

2. Problem formulation

2.1 Structure of NCS

A structure of overall NCS with disturbance observer and adaptive Smith predictor can be described as in Figure 2. Typically, it includes the controlled plant model with time-delay, $G_p(s)e^{-\tau(k)_p s}$, the model of controller, $G_c(s)$, an input r and an output y. The signals d and n represent the input exogenous external disturbance and measurement sensor noise, respectively.

The disturbance observer can generate an estimated value of disturbance to suppress the actual disturbance d in the inner loop of the system. Network induced delays are characterized by controller-to-actuator delays, τ_{ca}, sensor-to-controller delay, τ_{sc}, and time-delay of the plant. In practice, the controlled plant always generates a certain delay together with τ_{ca} and τ_{sc}, defined by an approximate value τ_p. This makes the problem of time-delay compensation more challenging. Thus, the adaptive Smith predictor is added to the NCS model as shown in Figure 2 for the purpose of eliminating the time-delays of the overall system. Based on the adaptive Smith predictor, the time-delay compensation is easier to obtain because the objective is now equivalent to suppressing the delay caused by τ_p.

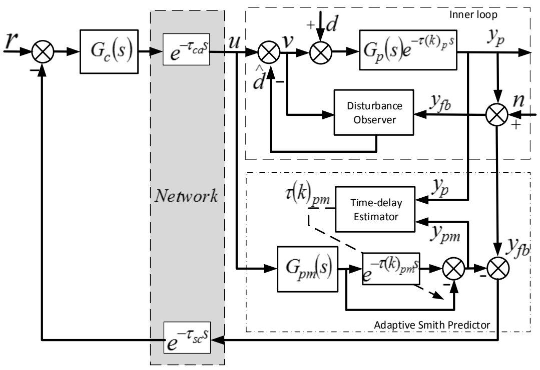

Figure 2 Structure of NCS with time-delays estimator and disturbance observer

2.2 Disturbance observer in the inner loop of NCS

The structure of the DOB is shown in Figure 3, where $G(s)=G_p(s)e^{-\tau(k)_p s}$ and $G_n(s)$ represent the real time-delay plant and its corresponding nominal model, respectively. $Q(s)$ is defined as a stable low-pass filter.

From Figure 3, the plant output $y_p(s)$ can be expressed as

$$y_p(s)=T_{y_pu}(s)u(s)+T_{y_pd}(s)d(s)+T_{y_pn}(s)n(s) \quad (1)$$

where

$$T_{y_pu}(s)=\frac{G(s)G_n(s)}{G_n(s)+Q(s)(G(s)-G_n(s))} \quad (2)$$

$$T_{y_pd}(s)=\frac{G(s)G_n(s)(1-Q(s))}{G_n(s)+Q(s)(G(s)-G_n(s))} \quad (3)$$

$$T_{y_pn}(s)=\frac{G(s)}{G_n(s)+Q(s)(G(s)-G_n(s))} \quad (4)$$

From (2), (3), and (4), it can be seen that in the low frequency range, we have $Q(s)\approx 1$. It means that $T_{y_pu}(s)\approx G_n(s)$, $T_{y_pn}(s)\approx 1$, and $T_{y_pd}(s)\approx 0$. As a result, $y_p(s)\approx G_n(s)u(s)+n(s)$ and thus the DOB can reject the disturbance as well as compensate for the model mismatch. In contrast, when the frequency range is high, i.e., $Q(s)\approx 0$. In this case, $y_p(s)\approx G_n(s)u(s)+G(s)d(s)$, the disturbance observer in the inner loop is useless in terms of disturbance attenuation but the effect of sensor noise on the output signal is completely removed. Assuming that all the transfer functions are stable, the real uncertain closed loop system becomes the nominal closed loop system without disturbance so that the disturbance rejection performance and robustness of system can be enhanced. Another important problem is how to design the low pass filter $Q(s)$ so that all the closed loops in the system are internally stable for given plants. In this paper, we follow the form of $Q(s)$ proposed by Choi (Choi, Yang, Chung, Kim, & Suh, 2003) and Shima (Shima, & Jo, 2009) as seen below:

$$Q(s)=\frac{c_k(\tau s)^k+c_{k-1}(\tau s)^{k-1}+\ldots+c_0}{(\tau s)^l+a_{l-1}(\tau s)^{l-1}+\ldots+a_1(\tau s)+a_0} \quad (5)$$

Where $\tau>0$ is the filter time constant, $k\le l-j, k, l$, and j are arbitrary nonnegative integers.

The trade-off of designing $Q(s)$ is achieved by selecting the values of the cut-off frequency $\omega=1/\tau$ and the numerator order. The purpose here is how to find these two values so that the design of $Q(s)G_n^{-1}(s)$ as shown in Figure 3 becomes proper and implementable. The detailed design of $Q(s)$ will be described in the next section.

2.3 Smith predictor in the outer loop of NCS

As mentioned above, the controlled plant always generates a certain delay together with τ_{ca} and τ_{sc} to form τ_p which makes the problem of time-delay compensation more difficult to solve. By applying the Smith predictor to the NCS model as shown in Figure 2, the time-delay compensation becomes feasible and actually equivalent to suppressing the delay caused by τ_p. In fact, the plant model is easily available while the delays in the network are not due to varying and random characteristics. Therefore, it is difficult for the Smith predictor to attain full suppression of delays. To deal with this problem, in our previous work, a novel Smith predictor was proposed (Dang, Guan, Tran, & Li, 2011; Dang, Guan, Li, & Zhang, 2012; Dang, Nguyen, & Nguyen, 2015) but without considering the effect of disturbances and noise, especially the effect of disturbances, which may reduce the performance of NCS. The NCS needs to be equipped with an adaptive DOB to cope with disturbances. To do so, we can independently tune the performance of either compensating time-delay with the adaptive Smith predictor or rejecting disturbances through DOB.

In this section, we concentrate on analyzing the Smith predictor structure in the outer loop, as illustrated in Figure 2, while the DOB provides the best performance to completely reject the disturbances from the outer loop. In this case, we have $d = \hat{d}$, i.e. $\hat{d}$ is the output of DOB.

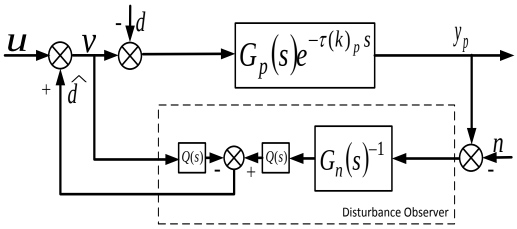

Figure 3 Structure of disturbance observer in inner loop of NCS

The close loop transfer function of NCS is approximately given by:

$$\frac{y_p(s)}{y_r(s)} = \frac{G_c(s)e^{-\tau_{ca}s}G_p(s)e^{-\tau_p s}}{1+G_c(s)G_{pm}(s)+G_c(s)e^{-\tau_{ca}s}(G_p(s)e^{-\tau_p s}-G_{pm}(s)e^{-\tau_{pm}s})e^{-\tau_{sc}s}} \tag{6}$$

We further have $\tau_p = \tau_{pm}$ t and $G_p = G_{pm}$ by assuming that the prediction model is determined exactly.

Consequently, by reducing (6), we obtain

$$\frac{y_p(s)}{y_r(s)} = \frac{G_c(s)e^{-\tau_{ca}s}G_p(s)e^{-\tau_p s}}{1+G_c(s)G_p(s)} \tag{7}$$

Finally, we achieve the transfer function of NCS as below

$$\frac{y_p(s)}{y_r(s)} = \frac{G_c(s)G_p(s)}{1+G_c(s)G_p(s)}e^{-\tau_{ca}s}e^{-\tau_p s} \tag{8}$$

As can be seen from (8), the effect of delays of network and controlled plant is completely eliminated from the denominator of NCS transfer function. Since, the NCS can be divided into two parts, the first part is the closed loop control system and the other is considered as the gain blocks before the output. Practically, it is difficult to attain this result because of the four following reasons:

- If the plant model is not determined exactly, the nominal control system may be instable.
- In case the delay of the plant cannot be estimated exactly, the difference between τ_{pm} and τ_p is considerable, and thus the stability performance of NCS becomes unacceptable.
- When the time-delay of the system randomly varies in a large range, the time-delay estimator is over bounded. In this case, the output response of NCS is certainly unstable.
- Even when the plant model can be determined exactly, the delay models of network, plant, and disturbances are randomly varying and difficult to identify.

The detailed solutions for the above existing problems will be analyzed in the following Sections.

3. Design of disturbance observer based neural network

There are many kinds of disturbances in the NCS including external and internal disturbances, caused by electromagnetic interference, dynamic condition of network, congestion, packet dropout, etc. The disturbance attenuation issues for a class of NCS under uncertain access delay and packet dropout effects are considered and (Zhao, & Wang, 2011) have previously studied the finite-time H_∞ control problem for NCS with time-varying exogenous disturbances. The disturbance observer based controller has been widely employed in industrial applications thanks to its powerful ability to eliminate the disturbance and compensate the uncertainty of plant performance (Gao & Ding, 2007; Kato, Muis, & Ohnishi, 2006; Lai & Hsu, 2010; Shima & Jo, 2009; Zhong & Rico, 2001). In this section, the neural network based disturbance observer (NDOB) is derived for any unknown time-delay plants or uncertain disturbances.

3.1 Inverse time-delay plant model design

The proposed model of NDOB is shown in Figure 4, the neural network unit is an inverse model of the plant $G(s) = G_p(s)e^{-\tau(k)_p s}$.

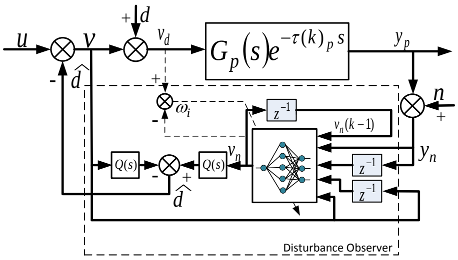

Figure 4 The proposed model of NDOB

To ensure the fast convergence in training of neural network, we use Levenberg-Marquardt algorithm to design the second-order training speed approach without computing an exact form of a Hessian matrix. The Newton methods are based on the second-order Taylor series expansion with the following weight vector

$$\begin{aligned} E(\mathrm{w}_{k+1}) &= E(\mathrm{w}_k + \Delta\mathrm{w}_k) \\ &= E(\mathrm{w}_k) + g_k^T \Delta\mathrm{w}_k + \frac{1}{2}\Delta_k^T H_k \mathrm{w}_k \end{aligned} \quad (9)$$

where $\Delta\mathrm{w}_k$, which is given by the Newton method, is written as

$$\Delta\mathrm{w}_k = g_k^T(-H_k^{-1}) \quad (10)$$

$$\mathrm{w}_{k+1} = \mathrm{w}_k - g_k^T(-H_k^{-1}) \quad (11)$$

where the vector $\Delta\mathrm{w}_k = g_k^T(-H_k^{-1})$ is known as the Newton direction if the Hessian matrix H_k is positive definite. Indeed, the complicated computation of the Hessian matrix for the fast convergence of neural network training can be reduced under the assumption that the error function is some kind of squared sum, the Hessian matrix based on the Gauss-Newton and Levenberg-Marquardt approach can be approximated by

$$H_k = J^T(\mathrm{w}_k)J(\mathrm{w}_k) \quad (12)$$

$$g_k = J^T(\mathrm{w}_k)E(\mathrm{w}_k) \quad (13)$$

The performance index to be optimized is defined as

$$F(\mathrm{w}_k) = E_n^T(\mathrm{w}_k)E_n(\mathrm{w}_k) \quad (14)$$

where $\mathrm{w}_k = \left[\mathrm{w}_1\mathrm{w}_2\ldots w_k\right]^T$ consists of all the weights of the network, $\mathrm{E}_n(w_k) = \left[\varepsilon_{11}\ldots\varepsilon_{n1}\varepsilon_{12}\ldots\varepsilon_{k1}\ldots\varepsilon_{1p}\ldots\varepsilon_{np}\right]^T$ is the cumulative error vector comprising of the error for all the training examples, p is the number of patterns, k is the number of the weights, and n is the number of the network outputs. The Jacobian matrix in (12) is defined as

$$J(w_k) = \begin{vmatrix} \frac{\partial_{e_{11}}}{\partial_{W_1}} & \frac{\partial_{e_{11}}}{\partial_{W_2}} & \cdots & \frac{\partial_{e_{11}}}{\partial_{W_k}} \\ \frac{\partial_{e_{21}}}{\partial_{W_1}} & \frac{\partial_{e_{21}}}{\partial_{W_2}} & \cdots & \frac{\partial_{e_{21}}}{\partial_{W_k}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial_{e_{np}}}{\partial_{W_1}} & \frac{\partial_{e_{np}}}{\partial_{W_2}} & \cdots & \frac{\partial_{e_{np}}}{\partial_{W_k}} \end{vmatrix} \quad (15)$$

where *np* is the number of time steps to be evaluated. The Gauss-Newton method can be written as an update rule with scaling factor $\mathrm{w}_k = \left[\mathrm{w}_1\mathrm{w}_2\ldots w_k\right]^T$ as below

$$W_{k+1} = W_{k+1} - (J^T(w_k)J(w_k) + \mu I(w_k))^{-1} J^T(w_k)E_T(w_k) \quad (16)$$

where I is identity unit matrix and $J(w_k)$ is Jacobian of m output errors with respect to k weights of the neural network.

In this study, we choose a four-layered feed forward neural network including an input layer, two hidden layers, and an output layer, by adopting 5-8-12-1 structure network. The input layer has five inputs: $v_n(k-1)$, $v(k)$, $v(k-1)$, $y_n(k)$, and $y_n(k-1)$. The two hidden layers include eight neurons for the first layer and twelve neurons for the second layer, with sigmoid activation function. The output layer has one linear neuron. The training epoch is with 500 steps (using a sampling time of 0.01sec), but the number of steps can vary from 1 to 10000 or even higher. The training process consists of two phases. In the first phase, the initial learning parameters are built by a trained off-line. In the second phase, based on the initial learning results, a trained online is executed and stopped until the algorithm completely converges.

3.2 Optimal Q-filter design

The low pass filter, i.e. known as the Q-filter, has the cut-off frequency shown in Bode diagram in Figure 5. The relative degree of the Q-filter is the major tuning knob for the trade-off between the disturbance attenuation performance and the robustness of the original system. Different relative degrees of the Q-filter achieve different disturbance attenuation performances. Besides relative degrees, the cut-off frequency of the Q-filter is another key design parameter. When the cut-off frequency of Q-filter is too high, the overall system may actually be in a worse robustness status which can be seen from the variation of the phase margin of the overall closed-loop system. It seems quite hard to achieve a good disturbance attenuation performance while simultaneously maintaining the phase margin not to be lost.

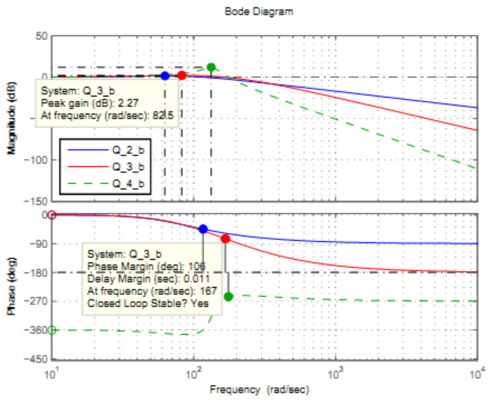

Figure 5 Choosing Q-filter according to numerator order

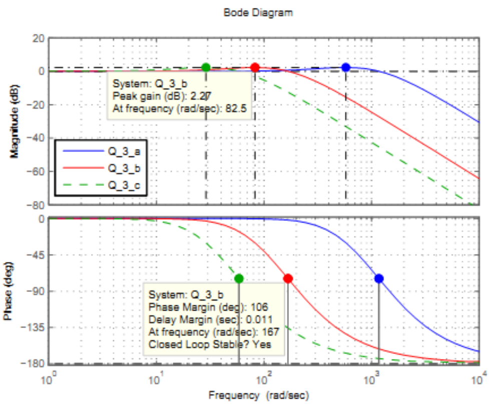

Figure 6 Choosing Q-filter according to cut-off frequency

Yang proposed two criteria for the relative degree (Yang, Choi, Chung, Suh, & Oh, 2002), numerator order, and filter time constant of the Q-filter.

Criterion 1 (Yang, Choi, Chung, Suh, & Oh, 2002): When the relative degree of the Q-filter decreases, the robustness of the EDOB system becomes better. If the relative degree of the Q-filter holds the same value, the robustness is directly proportional to the order of the denominator.

Criterion 2 (Yang, Choi, Chung, Suh, & Oh, 2002): If we increase the numerator order of the Q-filter, the property of disturbance attenuation is improved. In case the numerator order does not change, the property of disturbance attenuation is better if the filter time constant is smaller and has a wider frequency range.

Remark 1: In fact, the EDOB system with the Q-filter is equivalent to the NDOB with Q-filter in our study.

To solve the optimal problem of trade-off between robust stability and performance of the NDOB following the above criterions, we choose the Q-filter according to cut-off frequency and numerator order of the filter as shown in Table 1.

First, we selected $\tau = 0.007$ and changed the numerator order of Q-filter is *2, 3,* and *4*, respectively. The results are shown in Figure 5, $Q(s) = Q\_3\_c$ with the larger numerator, which may increase the performance of NDOB whereas the robustness will be reduced if the denominator has constant value. In case, $Q(s) = Q\_3\_a$ with the smaller numerator, the resulting low performance of the NDOB is not a good selection. So, we choose $Q(s) = Q\_3\_b$ with the numerator order equals 3, which proves to be the best choice with a peak gain of 2.7dB, and a frequency of 82.5 rad/sec, as well as a phase margin of 106 degree with a delay margin of 0.011sec at a frequency equaling 167 rad/sec.

Finally, we selected numerator order of Q-filter at 3 as the best solution and then changed the filter time constant of the Q-filter to $\tau = 0.001$ in $Q(s) = Q\_3\_a$, $\tau = 0.007$ in $Q(s) = Q\_3\_b$, and $\tau = 0.02$ in $Q(s) = Q\_3\_c$ presents as in Table 1. The bode plot is shown in Figure 6, $Q(s) = Q\_3\_a$ with a small time constant filter, thus we can open a wider frequency range for disturbance rejection. The disturbance attenuation performance becomes better but it may reduce the robustness of the system. In the opposite case, $Q(s) = Q\_3\_c$ with a large filter time constant, the robustness of the system is certainly increased but the performance in turn is unsatisfactory. Thus, the best selection is $Q(s) = Q\_3\_b$ which is the optimal solution in terms of both robust stability and performance of the NDOB.

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4. NCS under the effect of both time-delays and disturbance

The proposed NCS model in Figure 7 includes the fuzzy adaptive PID controller, the adaptive Smith predictor for compensating time-delays, and the NDOB for rejecting disturbances. In previous sections, the NDOB based on neural network could eliminate the disturbances but could not compensate the time-delays. In order to further compensate for the effect of time-delays, we design a neural network time-delays estimator along with fuzzy adaptive controller and NDOB in an adaptive NCS Smith predictor model.

4.1 Fuzzy adaptive PID controller design

Table 1 The parameters of Q-filter following the changing of the filter time constant and numerator order

Q-filter	Filter time constant (t)	Numerator order
Q_2_ b	0.007	2
Q_3_ b	0.007	3
Q_4_ b	0.007	4
Q_3_ a	0.001	3
Q_3_ b	0.007	3
Q_3_ c	0.02	3

Following our previous works, the fuzzy PID controllers with automatic tuning concepts are deployed (Dang, Guan, Tran, & Li, 2011). But, because the objects in the NCS are now more complicated than those mentioned (Dang, Guan, Tran, & Li, 2011), we have to change the properties of fuzzy inference systems in order to increase the stability of the system. In particular, we consider the fuzzy modulator with an input, e_f, and a triple-output, K_p, K_i and K_d, as depicted in Figure 7.

The process of the fuzzy inference system is connected with membership functions, fuzzy logic operators, and if-then rules. In this paper, by applying Mamdani's fuzzy inference method, we have the membership function collections as below

e_f : PB ; PM ; PS ; ZZ ; NS ; NM ; NB

e_{fc} : PB ; PM ; PS ; ZZ ; NS ; NM ; NB

u_f : B ; M ; S

Our fuzzy rules are set as same as in Table1,

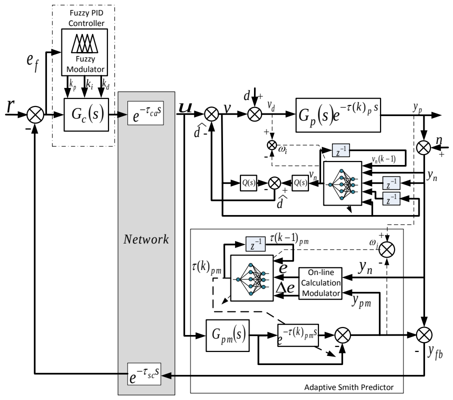

Figure 7 Proposed NCS model under the effect of both time-delays and disturbance

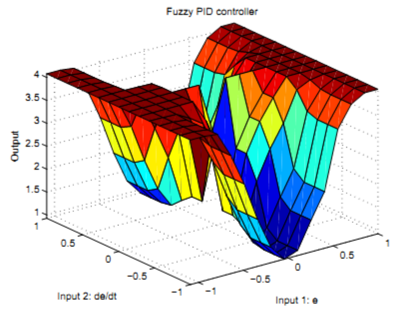

Figure 8 Optimal fuzzy PID controller surface

Table 2, and Table 3 of the article (Dang, Guan, Tran, & Li, 2011). In order to design a Mamdani fuzzy logic with a compact rule base, the rule notation form in which w_k is a binary variable determined by the consequence of the rule given as follows

• Rule k : If e is M_j and e_{fc} is N_i then u_f is w_k

The control output u_f of the fuzzy controller is computed via the center of gravity of the fuzzy set as

$$u_f = \frac{\sum_{k=1}^{N} w_k \mu_k(w_k)}{\sum_{k=1}^{N} \mu_k(w_k)} \qquad (17)$$

where N is quantitative number and $\mu_k(w_k)$ is the fired degree from w_k.

The fuzzy inference system can adjust K_p, K_i and K_d of the PID controller according to e_f, and e_{fc}. The PID parameters are tuned by

$$u(k) = K_p(k)e(k) + K_i(k)\int_0^k e(t)dt + K_p(k)\frac{de(k)}{dk} \qquad (18)$$

By conducting experimental studies, we find out that the optimal fuzzy PID controller corresponds to its control surface as illustrated in Figure 8.

4.2 Time-delays estimator design based on neural network

Assuming that the NDOB gains the highest performance, the disturbances can be rejected from the inner loop of NCS. Thus, from Figure 7 we have

$$y_n(s) = G_p(s)e^{-\tau_p s}u(s) \quad (19)$$

$$y_{pm}(s) = G_{pm}(s)e^{-\tau_{pm} s}u(s) \quad (20)$$

Practically, y_n and y_{pm} are asynchronous, even highly divergent if the difference between τ_p and τ_{pm} is considerable. As a result, the Smith predictor becomes invalid. To obtain $\tau_p \cong \tau_{pm}$, let us define an area *A (k)*, which slowly increases and reaches a certain constant when y_n and y_{pm} overlap. According to Dang (Dang, Guan, Tran, & Li, 2011), the area *A(k)* can be described as

$$A(k) = \int_0^k \left| y_n(t) - y_{pm}(t) \right| dt \quad (21)$$

We have $\tau_p \cong \tau_{pm}$ with the assumption that $G_p(s) \cong G_{pm}(s)$, the NCS under the effect of both disturbances and time-delays can be reduced to the equivalent equation (8) as the non-time-delayed-disturbance control system. The neural network time-delay estimator shown in the outer loop of Figure 7 has two important components. The first one is an on-line calculation modulator consisting of: a double-input, y_n and y_{pm}, and a double-output, e and Δe.

The outputs at every sampling time are given by Dang (Dang, Guan, Tran, & Li, 2011).

$$e(k+1) = A(k+1) - A(k) \quad (22)$$

$$\Delta e(k+1) = e(k+1) - e(k) \quad (23)$$

The second one is the designed RVTD neural network estimator compensating the RVTD for NCS using the method presented in the paper (Dang, Guan, Li, & Zhang, 2012). In this way, the adaptiveness of the neural network controller is much better than that of the fuzzy controller in (Dang, Guan, Tran, & Li, 2011), especially under the nonlinear and randomly varying characteristics of the elements. To ensure fast convergence in the neural network estimation scheme, we use the second order training Levenberg-Marquardt algorithm without computing an exact form of the Hessian matrix. Actually, under the assumption that the error function is some kind of squared sum, to reduce the complicated computation of Hessian matrix for the fast convergence requirement, the Hessian matrix can be approximated by equation (12). The performance index to be optimized and the Jacobian matrix are defined as (14) and (15), respectively.

In this study, we choose a fourth-layered feed forward the neural network including input layer, two hidden layers, and output layer, by adopting 3-8-10-1 the structure network can be adjusted following (16). The input layer has three inputs, $\tau_{pm}(k-1)$, $e(k)$ and $\Delta e(k)$. The hidden layers include five and ten neurons per layer with a sigmoid activation function. The output layer has one linear neuron. The training epoch is equal to or less than 3000 so that the neural network output can identify the RVTD of the overall system in Figure 7. The training process consists of two phases. In the first phase, initial learning parameters are built by a trained offline. In the second phase, based on the initial learning results, a trained online is executed and stopped until the algorithm is completely converged.

5. Simulation experiment

5.1 Simulation design

We use the simulation software TrueTime2.0 Beta1 based on CSMA/AMP (Anton, Henriksson, & Martin, 2009). We deploy the NCS consisting of sensor nodes, controller nodes, actuator nodes, interference nodes and controlled plant. If the network is busy, the sender node should wait until the network is free to transmit data. If a collision occurs (i.e., more than one transmission is being started within 1 microsecond), the message with the highest priority will be considered to be transmitted first. If two messages with the same transmission priority are received simultaneously, an arbitrary choice is made to send one of them. We select parameters of the network as follows:

- The data rate: 80.000 bits/s
- Minimum frame size: 80 bits
- The probability distribution of data packet dropout (DPD): from 0 to 1
- The sampling period of sensor: 0.01s
- The reference signal r is step function from 0 to 2

Suppose that the unknown periodic disturbance is in the form of

$$d(t) = A(\sin(2\pi 1.3t) + \sin(2\pi 0.4t)) \qquad (24)$$

where A is the amplitude of the unknown periodic disturbance. The form of the noise is given by

$$n(t) = 0.001\sin(2\pi 50t) \qquad (25)$$

where t is uniform random in the range of [0-10]. The controlled plant is used by following the form of the transfer function (Dang, Guan, Tran, & Li, 2011),

$$G_p(s)e^{-\tau(k)_p s} = \frac{700}{s^2 + 30s + 5} e^{-\tau(k)_p s} \qquad (26)$$

The time-delay is in the shape of sinusoidal signals (Shaltaf & Abdallah, 2000).

$$\tau(k)_p(t) = 0.3\sin(2\pi(3 + 0.1t_{dl}^2)) \qquad (27)$$

where t_{dl} is uniform random in the range of [0-10].

5.2 Experimental simulation results

To evaluate the performance and the stability of the proposed NCS model, we carefully analyze responses of the control signal, the output signal, and the tracking error, in case t_{dl} in (28) is equal to 5. Assuming that, the NCS works in the worse conditions, under the effect of disturbances (25), noise (26), and time-delays (i.e. delay of the network and the plant (28)). Figure 9 shows the output responses of the NCS in two cases: the first case is the responses of the NCS with NDOB and the other is the responses of the NCS without NDOB. The output response of the first case has small amplitude fluctuations around the equilibrium point while the other output response under the effect of disturbances has higher fluctuations that makes the system more difficult to control. Moreover, when the disturbance is sufficiently large, the output response of NCS may lead to gravitational instability.

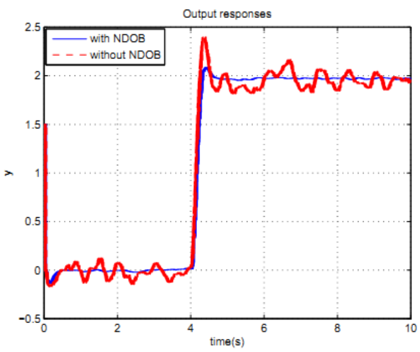

Figure 9 The output response of proposed model in case of with and without NDOB

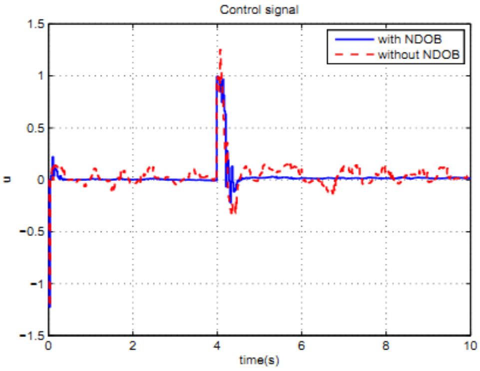

Figure 10 The control signal of proposed model with and without NDOB

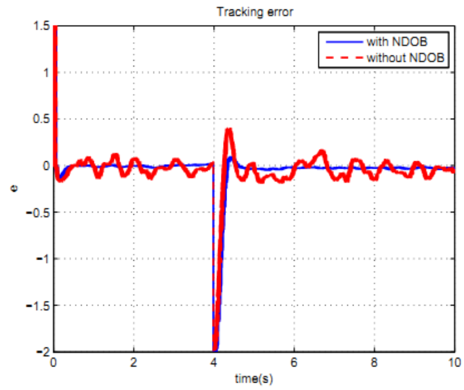

Figure 11 The tracking error of proposed model with and without NDOB

The results in Figure 10 and Figure 11 show the control signal and the tracking error of the NCS, respectively. We can see clearly that, at the beginning of the stage when the input signal changes from 0 to 2, the control signal oscillates with large amplitude from the equilibrium position. After a short period of oscillation, the control signal returns to a relatively stable situation. It means that the proposed control scheme provides a very good adaptation under the effect of time-delays. In terms of rejecting disturbance, the tracking error of NCS with NDOB in Figure 11 demonstrates that the performance of the NCS is improved.

Moreover, in the above cases, the NCS is in stable conditions. When the state of the system is with different probability distributions of data packet dropout, we can investigate more general efficiency of the proposed method. Figure 12, Figure 13, and Figure 14 show the experimental results in 3 cases of probability distribution of data packet dropout: DPD = 0.1, DPD = 0.3, and DPD = 0.5. In case of DPD ≤

0.3, the output and control signals indicate that the system is stable with good quality. When the probability of data packet dropout is higher, e.g. 0.3 ≤ DPD < 0.5, the output responses of the system retains stability at an acceptable level. However, the output responses become unacceptable if DPD is greater than or equal to 0.5. In summary, the response status of the system can be described in details as featured in Table 2. We conclude that, the system gains high stability under the effect of both internal and external disturbances changing in large range.

Table 2 Status of the proposed system under effect of external disturbance and packet dropout ($t_{dl} = 5$)

A	Ranges of data packet dropout (DPD)			
	0.1	0.3	0.5	> 0.5
0.01	Stable	Stable	Stable	Unstable
0.05	Stable	Stable	Stable	Unstable
0.2	Stable	Stable	Unstable	Unstable
0.5	Stable	Unstable	Unstable	Unstable
> 0.5	Unstable	Unstable	Unstable	Unstable

Table 3 Status of the proposed system under effect of time-delay and packet dropout ($A = 0.01$)

t_{dl}	Ranges of data packet dropout (DPD)			
	0.1	0.3	0.5	> 0.5
0	Stable	Stable	Stable	Unstable
5	Stable	Stable	Stable	Unstable
10	Stable	Stable	Stable	Unstable
15	Stable	Stable	Stable	Unstable
20	Stable	Stable	Stable	Unstable

Finally, we consider the NCS under the effect of time-delay, external disturbance and data packet dropout. The status of the proposed system is shown in detail in Table 3. The system is stable in every case of time-delay for the range of [0 − 20] and DPD ≤ 0.5, but becomes unacceptable in all other cases. These results show that the proposed NCS model can completely eliminate the effect of time-delay when NCS is operating in acceptable conditions.

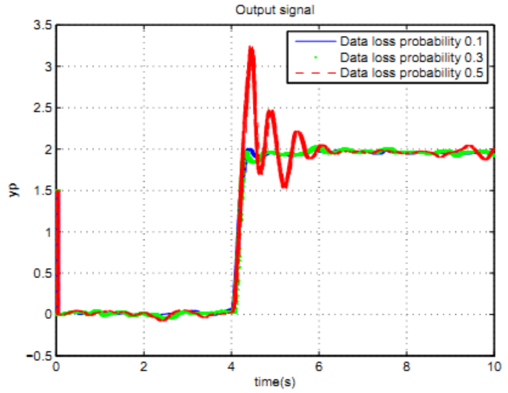

Figure 12 The output response of proposed model with different probability distribution of data packet

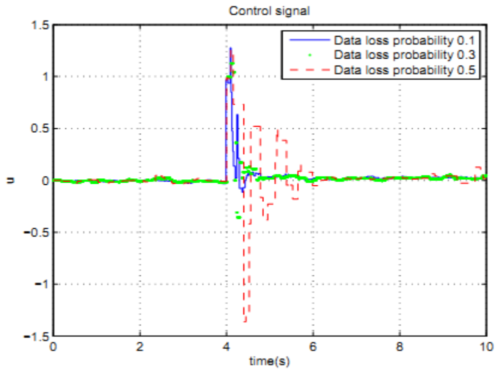

Figure 13. The control signal of proposed model with different probability distribution of data packet dropouts

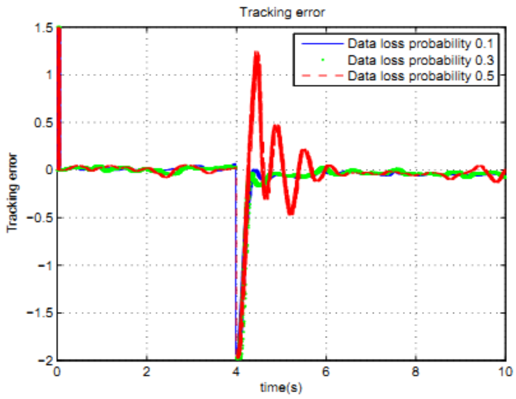

Figure 14 The tracking error of proposed model with different probability distribution of data packet dropouts

7. Conclusions

In this paper, in order to mitigate the effect of RVTD and disturbances, we carefully take into account the two following case studies. Firstly, we analyze the stability of the considered method under the effect of disturbances and noise without NDOB. Secondly, we propose a novel approach by using the Smith predictor combined with the NDOB in the NCS model. Consequently, both the time-delays and disturbances are eliminated from the NCS. The results show that our approach provides better performance and can be successfully applied to practical engineering purposes when faced with some control problems related to time-delay and disturbances. In the future, this study can be extended by considering the robustness of NCS with uncertain plant model under the effect of time-delays, disturbances, and noise interference.

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