A Predictive Control-Based Approach to Networked Hammerstein Systems: Design and Stability Analysis

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***Abstract*—In this paper, a predictive control-based approach is proposed for a Hammerstein-type system which is closed through some form of network. The approach uses a two-step predictive controller to deal with the static input nonlinearity of the Hammerstein system and a delay and dropout compensation scheme to compensate for the communication constraints in a networked control environment. Theoretical results are presented for the closed-loop stability of the system. Simulation examples illustrating the validity of the approach are also presented.**

***Index Terms*—Delay and dropout compensation scheme (DDCS), Hammerstein system, networked control systems (NCSs), predictive control, two-step approach.**

I. Introduction

A CONTROL system is called a "networked control system" (NCS) when the direct connections used in conventional control systems between sensors, controllers, and actuators are replaced by some form of communication networks with limited resource [1]–[4]. This configuration, which is due to the network inserted, brings to the system lower cost, flexibility, the ability of remote control, etc., whereas the communication constraints of the network, e.g., the time delay of data exchange through the network (so-called "network-induced delay"), data packet dropout, quantization, medium access constraint, etc., greatly degrade the performance of the control systems, even making the system unstable under certain conditions. Such a configuration presents a new challenge to conventional control theories [5].

The limits to the performance of control systems in a networked control environment are caused primarily by network-induced delay and data packet dropout [5]. These communication constraints can mean in NCSs that the control signal for the plant is delayed or even unavailable, which results in an open loop system. The desire to obtain a better performance than that resulting from holding the last available control signal or using zero control during open loop intervals in NCSs has led to a model-based control architecture [6] and to a predictive control-based control architecture [7], [9]–[12]. The key idea of the model-based approach is that the knowledge of the plant dynamics is used to reduce the usage of the network, whereas in the predictive control-based approach proposed in [9], the plant dynamics is further used to produce future control signals to actively compensate for the random network-induced delay in the forward channel with the use of a corresponding time-delay compensator at the actuator side. A better performance can be expected since the predictive control-based approach takes greater advantage of the knowledge available.

In this paper, following the predictive control-based approach in [9], we extend its application to networked Hammerstein systems where a static nonlinear input process and random network-induced delays and data packet dropouts in both forward and backward channels exist. In order to deal with the static input nonlinearity of the Hammerstein system, a two-step design approach that is similar to that in [13] is applied, the key idea of which is to design for the linear part of the Hammerstein system first and then compensate for the input nonlinearity using an inverse process. The inaccuracy in compensation for the nonlinear input process is assumed to satisfy a sector constraint based on which the stability criteria of the closed-loop system are obtained. Compared with previous results, the main advantage of the predictive controller designed in this paper is that only delayed sensing data are used, whereas in [9], the previous control signals up to the current step were all required, which data will be shown later to be hard to obtain in practice (Remark 2). To correspond to the new predictive controller, a novel compensation scheme for the communication constraints, which is called the delay and dropout compensation scheme (DDCS), is designed, which consists of three components: a matrix selector at the controller side to compensate for the network-induced delay in the backward channel, a delay compensator at the actuator side to compensate for the network-induced delay and data packet dropout in the forward channel, and a horizon adjustor for the controller to compensate for the network jitter by adjusting the control horizon according to current network condition (see Fig. 1 for the whole structure). The implementation of DDCS makes the predictive control-based approach work well in a network-based environment.

The remainder of this paper is organized as follows. The design of the proposed approach is presented in Section II. Then, the theoretical results for the system stability and the simulation results are presented in Sections III and IV, respectively. The conclusions are given in Section V.

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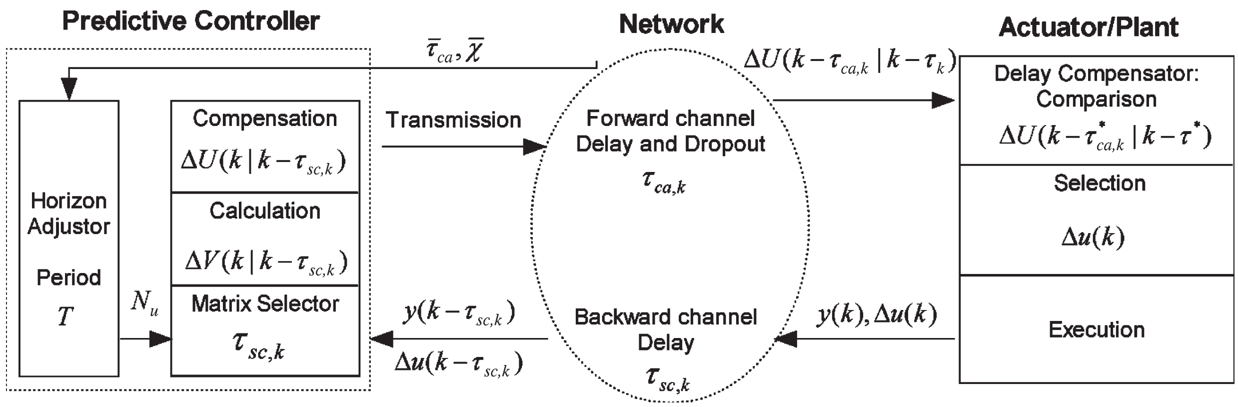

Fig. 1. Structure of networked predictive control system with input nonlinearity.

II. Design of Networked Predictive Control System With Input Nonlinearity

The following single-input–single-output Hammerstein system S is considered in this paper:

$$S: \begin{cases} x(k+1) = Ax(k) + bv(k) & \text{(1a)} \\ y(k) = cx(k) & \text{(1b)} \\ v(k) = f(u(k)) & \text{(1c)} \end{cases}$$

where $x \in \mathbb{R}^n$, $u, v, y \in \mathbb{R}$, and $f(\cdot) : \mathbb{R} \to \mathbb{R}$ is a memoryless static nonlinear function.

In this section, we present first the design details of the two-step predictive control approach to system S and then the design of DDCS to compensate for the network-induced delays and data packet dropout when such a system is implemented in a networked control environment.

A. Design of the Two-Step Predictive Control Approach

The key idea of the typical two-step predictive control approach is to design an intermediate control signal $v(k)$ of the linear part of system S [(1a) and (1b)] with a linear predictive control method (a linear generalized predictive control (LGPC) method is adopted in this paper) first and then obtain the real control signal $u(k)$ for system S from the nonlinear relationship $v(k) = f(u(k))$ [10], [13]. In a networked control environment, the typical two-step predictive control approach is modified as follows with the consideration of the network-induced delays.

1) Design of LGPC: In the presence of the network-induced delay, the following modified quadratic objective function is adopted:

$$J(N_1, N_2, N_u) = \sum_{j=N_1}^{N_2} q_j \left(\hat{y}(k+j|k-\tau_{\mathrm{sc},k}) - \omega(k+j)\right)^2 + \sum_{j=1}^{N_u} r_j \Delta v^2(k+j-1) \quad (2)$$

where N_1 and N_2 are the minimum and maximum prediction horizons, N_u is the control horizon, q_j, $N_1 \le j \le N_2$, and r_j, $1 \le j \le N_u$, are weighting factors, $\omega(k+j)$, $j = N_1, \ldots, N_2$, are the set points, $\Delta v(k) = v(k) - v(k-1)$ is the control increment, and $\hat{y}(k+j|k-\tau_{\mathrm{sc},k})$, $j = N_1, \ldots, N_2$, are the forward predictions of the system outputs, which are obtained on data up to time $k - \tau_{\mathrm{sc},k}$ and will be calculated in detail later, where $\tau_{\mathrm{sc},k}$ is the network-induced delay in the backward channel at time k.

Let $\bar{x}(k) = [\,x^{\mathrm{T}}(k) \quad v(k-1)\,]^{\mathrm{T}}$, then system S can be represented by S' as

$$S': \begin{cases} \bar{x}(k+1) = \bar{A}\bar{x}(k) + \bar{b}\Delta v(k) & \text{(3a)} \\ y(k) = \bar{c}\bar{x}(k) & \text{(3b)} \end{cases}$$

where $\bar{A} = \begin{pmatrix} A & b \\ 0 & 1 \end{pmatrix}$, $\bar{b} = \begin{pmatrix} b \\ 1 \end{pmatrix}$, and $\bar{c} = (\,c \quad 0\,)$. Thus, the j' step forward output prediction at time k' is

$$\hat{y}(k'+j'|k') = \bar{c}\bar{A}^{j'}\bar{x}(k') + \sum_{l'=0}^{j'-1} \bar{c}\bar{A}^{j'-l'-1}\bar{b}\Delta v(k'+l'|k').$$

Let $j' = j + \tau_{\mathrm{sc},k}$, $k' = k - \tau_{\mathrm{sc},k}$, and $l' = l + \tau_{\mathrm{sc},k}$. Then the forward output predictions at time k based on the information of the state on time $k - \tau_{\mathrm{sc},k}$ and control signals from time $k - \tau_{\mathrm{sc},k} - 1$ are

$$\hat{y}(k+j|k-\tau_{\mathrm{sc},k}) = \bar{c}\bar{A}^{j+\tau_{\mathrm{sc},k}}\bar{x}(k-\tau_{\mathrm{sc},k}) + \sum_{l=-\tau_{\mathrm{sc},k}}^{j-1} \bar{c}\bar{A}^{j-l-1}\bar{b}\Delta v(k+l|k-\tau_{\mathrm{sc},k}). \quad (4)$$

If the state vector x is not available, an observer must be included

$$\hat{x}(k+1|k) = A\hat{x}(k|k-1) + bv(k) + L\left(y_m(k) - c\hat{x}(k|k-1)\right) \quad (5)$$

where $y_m(k)$ is the measured output. If the plant is subject to white noise disturbances affecting the process and the output with known covariance matrices, the observer becomes a Kalman filter, and the gain L is calculated solving a Riccati equation.

Let $\hat{Y}(k|k-\tau_{\mathrm{sc},k}) = [\hat{y}(k+N_1|k-\tau_{\mathrm{sc},k}) \ \cdots \ \hat{y}(k+N_2|k-\tau_{\mathrm{sc},k})]^{\mathrm{T}}$, $\Delta V'(k|k-\tau_{\mathrm{sc},k}) = [\Delta v(k-\tau_{\mathrm{sc},k}|k-\tau_{\mathrm{sc},k}) \ \cdots \ \Delta v(k+N_u-1|k-\tau_{\mathrm{sc},k})]^{\mathrm{T}}$. Then

$$\hat{Y}(k|k-\tau_{\mathrm{sc},k}) = E_{\tau_{\mathrm{sc},k}}\bar{x}(k-\tau_{\mathrm{sc},k}) + F_{\tau_{\mathrm{sc},k}}\Delta V'(k|k-\tau_{\mathrm{sc},k}) \tag{6}$$

where $E_{\tau_{\mathrm{sc},k}} = [\,(\bar{c}\bar{A}^{N_1+\tau_{\mathrm{sc},k}})^{\mathrm{T}} \ \cdots \ (\bar{c}\bar{A}^{N_2+\tau_{\mathrm{sc},k}})^{\mathrm{T}}\,]^{\mathrm{T}}$ and $F_{\tau_{\mathrm{sc},k}}$ is an $(N_2-N_1+1)\times(N_u+\tau_{\mathrm{sc},k})$ matrix with the non-null entries defined by $(F_{\tau_{\mathrm{sc},k}})_{ij} = \bar{c}\bar{A}^{N_1+\tau_{\mathrm{sc},k}+i-j-1}\bar{b}$, $j-i \le N_1+\tau_{\mathrm{sc},k}-1$. Note here that $E_{\tau_{\mathrm{sc},k}}$ and $F_{\tau_{\mathrm{sc},k}}$ vary with different $\tau_{\mathrm{sc},k}$'s.

Let $\varpi_k = [\,\omega(k+N_1) \ \cdots \ \omega(k+N_2)\,]^{\mathrm{T}}$. Then the optimal predictive control increments from k to $k+N_u-1$ can be calculated by letting $\partial J(\cdot)/\partial\Delta V' = 0$

$$\Delta V(k|k-\tau_{\mathrm{sc},k}) = M_{\tau_{\mathrm{sc},k}}\left(\varpi_k - E_{\tau_{\mathrm{sc},k}}\bar{x}(k-\tau_{\mathrm{sc},k})\right) \tag{7}$$

where $\Delta V(k|k-\tau_{\mathrm{sc},k}) = [\Delta v(k|k-\tau_{\mathrm{sc},k}) \ \cdots \ \Delta v(k+N_u-1|k-\tau_{\mathrm{sc},k})]^{\mathrm{T}}$, $M_{\tau_{\mathrm{sc},k}} = H_{\tau_{\mathrm{sc},k}}(F^{\mathrm{T}}_{\tau_{\mathrm{sc},k}}QF_{\tau_{\mathrm{sc},k}}+R)^{-1}F^{\mathrm{T}}_{\tau_{\mathrm{sc},k}}Q$, Q and R are diagonal matrices with $Q_{i,i} = q_i$ and $R_{i,i} = r_i$, respectively, and $H_{\tau_{\mathrm{sc},k}} = [0_{N_u\times\tau_{\mathrm{sc},k}} \ I_{N_u\times N_u}]$, with $I_{N_u\times N_u}$ being the identity matrix with rank N_u.

Remark 1: Normally, the minimum prediction horizon can be set as one. Rewrite the maximum prediction horizon N_2 as N_p. The following constraint between N_u and N_p needs to be always held in order to implement the LGPC method successfully:

$$N_u \le N_p. \tag{8}$$

Remark 2: In [9], the previous control signals $v(k-1),\ldots,v(k-\tau_{\mathrm{sc},k})$ are used to calculate the predictive control sequence at time k. However, this information is hard to obtain for the controller in practice due to the random network-induced delays in both channels. As will be discussed further in Section II-B, in a networked predictive control environment, a sequence of future control signals is packed and sent to the actuator, and the actuator only selects one from the sequence according to the specific time delay in the forward channel. Therefore, the controller does not know the real control signal adopted by the actuator until it receives the information about the previous control signals applied to the actuator. Only in such a special case that, with no delay in the forward channel, the previous control signals are all known by the controller immediately. Therefore, in this paper, we develop a new method to deal with this problem, in which only the control and state (output) information at time $k-\tau_{\mathrm{sc},k}$ is used to generate the predictive control sequence, by including the control sequence from time $k-\tau_{\mathrm{sc},k}$ to $k-1$ as part of the predictive control sequence. As a result, the forward predictive control sequence obtained depends only on delayed sensing data at time $k-\tau_{\mathrm{sc},k}$ (7), which is always available to the controller [see Assumption A3)], thus enabling the approach to be feasible in practice.

2) Nonlinear Input Process: Assuming that the nonlinear function $f(\cdot)$ is invertible and denoting its inverse by $\hat{f}^{-1}(\cdot)$, then

$$\Delta u(k) = \hat{f}^{-1}\left(\Delta v(k)\right). \tag{9}$$

Thus, at every time instant k, the intermediate control increments $\Delta v(k)$, $k=1,2,\ldots,N_u$, can be obtained from (7), and then, the real control increments $\Delta u(k)$, $k=1,2,\ldots,N_u$, can be calculated from (9), thus enabling the control law to be derived for system S'.

If $\Delta u(k)$ can be calculated accurately using (9), thus enabling the function $\hat{f}^{-1}(\cdot)$ to be exactly known, then the system with compensation for the nonlinear input process is equivalent to LGPC, and the system is stable if and only if the linear part of system S with LGPC is stable. However, in practice, it is usually impossible to calculate $u(k)$ that accurately, i.e., $\hat{f}^{-1}(f(\cdot)) \ne 1(\cdot)$. This inaccuracy introduces to the LGPC a nonlinear disturbance, which makes the stability analysis difficult.

For simplicity of notation, let $\hat{\vec{f}}^{-1}(\cdot): \mathbb{R}^{N_u} \to \mathbb{R}^{N_u}$ with $\hat{\vec{f}}^{-1}(\Delta V(k|k-\tau_{\mathrm{sc},k})) = [\hat{f}^{-1}(\Delta v(k|k-\tau_{\mathrm{sc},k})) \ \cdots \ \hat{f}^{-1}(\Delta v(k+N_u-1|k-\tau_{\mathrm{sc},k}))]^{\mathrm{T}}$. Then, from the earlier discussion, the real predictive control increment sequence for system S can be represented by

$$\Delta U(k|k-\tau_{\mathrm{sc},k}) = \hat{\vec{f}}^{-1}(\Delta V(k|k-\tau_{\mathrm{sc},k}) \tag{10}$$

where $\Delta U(k|k-\tau_{\mathrm{sc},k}) = [\Delta u(k|k-\tau_{\mathrm{sc},k}) \ \cdots \ \Delta u(k+N_u-1|k-\tau_{\mathrm{sc},k})]^{\mathrm{T}}$.

Remark 3: Note that the control increment, instead of the control signal itself, is used in the compensation for the nonlinear input process in (9). Although the use of control increments complicates the problem in that the past control increments are also needed to determine the current control increment, it is inevitable since the objective function to be optimized takes the form of control increments. In order to implement the predictive controller in this paper, the past control increments are sent to the controller as well as the state information [see Assumption A3)], which is different from conventional control systems. Note that for a system without a nonlinear input process (1c), it makes no difference whether the intermediate control increment or the intermediate control signal itself is used to calculate the real control signal, whereas for system S, generally, these two methods give different control input at time k, i.e., $f(\Delta v(k)) \ne f(v(k)) - f(v(k-1))$.

B. Design of DDCS

To enable the predictive controller designed in this paper to work appropriately in a networked control environment, a DDCS is proposed to compensate for the network-induced delay and data packet dropout in NCSs.

The following assumptions are first made for the DDCS design.

A1) Each data packet containing the sensing data is sent with a time stamp to notify when it was sent from sensor to controller. This enables the network-induced delay in the backward channel for each data packet known to the controller. This information is then used to calculate the appropriate control predictions.

A2) At every time instant k, the control predictions $\Delta U(k|k-\tau_{\mathrm{sc},k})$ with time stamps k and $\tau_{\mathrm{sc},k}$ are packed into one data packet and sent to the actuator. These time stamps are to notify the time when it was sent and also the network-induced delay in the backward channel which the calculation of the control predictions was based on. This enables the network-induced delays in both channels for each control predictive sequence known to the actuator.

A3) The information of the control increment signal actually applied to the plant is also sent to the controller.

A4) The control horizon is chosen in such a way that the sum of the maximum network-induced delay in the forward channel (noted by $\bar{\tau}_{\rm ca}$) and the maximum number of continuous data packet dropout (noted by $\bar{\chi}$) is bounded by N_u, i.e.,

$$\bar{\tau}_{\rm ca} + \bar{\chi} \leq N_u - 1. \tag{11}$$

Remark 4: The data packet dropout is not treated as a long delay in this paper. They are simply ignored, and the measurement of the delay bound is only over those received successfully so that the delay bound can be assumed to be finite. In this way, the data packet dropout does not need to be specially treated. This can be compared with the approaches in [14] and [15], where the effect of the data packet dropout is explicitly considered.

Based on the aforementioned assumptions, the three components of the DDCS, the matrix selector, the delay compensator, and the horizon adjustor, which are to deal with the network-induced delay in the backward channel, network-induced delay and data packet dropout in the forward channel, and the network jitter, respectively, are presented in the following sections.

1) Compensation for the Random Network-Induced Delay in the Backward Channel—A Matrix Selector: Note that the matrices $E_{\tau_{{\rm sc},k}}$, $F_{\tau_{{\rm sc},k}}$, $M_{\tau_{{\rm sc},k}}$, and $H_{\tau_{{\rm sc},k}}$ are all needed to implement the predictive controller in (7), which vary with $\tau_{{\rm sc},k}$ and, if computed online, will present a great computation burden for the controller and introduce additional computation delay to the system. Fortunately, although these matrices vary with the delay in the backward channel, they can be calculated offline since all the matrices are fixed for a given $\tau_{\rm sc}$. This advantage enables us to calculate offline all the matrices with respect to the specific $\tau_{\rm sc}$'s, to store them in a device called the "matrix selector," and to just choose the appropriate ones from the matrix selector when calculating online the predictive control increments according to the current value of the delay $\tau_{{\rm sc},k}$, which is known to the controller from Assumption A1). In this way, the computation delay can be reduced to a certain extent.

Let $\mathcal{E}_{\rm sc} = \{E_0, E_1, \ldots, E_{\bar{\tau}_{\rm sc}}\}$, $\mathcal{F}_{\rm sc} = \{F_0, F_1, \ldots, F_{\bar{\tau}_{\rm sc}}\}$, $\mathcal{M}_{\rm sc} = \{M_0, M_1, \ldots, M_{\bar{\tau}_{\rm sc}}\}$, and $\mathcal{H}_{\rm sc} = \{H_0, H_1, \ldots, H_{\bar{\tau}_{\rm sc}}\}$, where $\bar{\tau}_{\rm sc}$ is the upper bound of the network-induced delay in the backward channel, then we have for any k (or $\tau_{{\rm sc},k}$), $E_{\tau_{{\rm sc},k}} \in \mathcal{E}_{\rm sc}$, $F_{\tau_{{\rm sc},k}} \in \mathcal{F}_{\rm sc}$, $M_{\tau_{{\rm sc},k}} \in \mathcal{M}_{\rm sc}$, and $H_{\tau_{{\rm sc},k}} \in \mathcal{H}_{\rm sc}$, respectively. For a practical implementation, these $4\times(\bar{\tau}_{\rm sc}+1)$ matrices are calculated offline and stored in the matrix selector for online use.

2) Compensation for the Random Network-Induced Delay and Data Packet Dropout in the Forward Channel—A Delay Compensator: As presented in Assumption A2), the predictive control increment sequence $\Delta U(k|k-\tau_{{\rm sc},k})$ is sent to the actuator all in one data packet. When a new sequence arrives at the actuator side, it is compared with the one already in the so-called "delay compensator" according to the time stamps (which notify the time when the sequences were sent from the controller), and only the one with the latest time stamp is stored. The delay compensator is specially designed for the actuator, and it can only store one control sequence (data packet) at any time. For example, denote the sequence that arrives at the actuator side as $\Delta U(k_1|k_1-\tau_{{\rm sc},k_1})$ with a time stamp k_1 and the one already in the delay compensator as $\Delta U(k_2|k_2-\tau_{{\rm sc},k_2})$ with a time stamp k_2. Then, if $k_1 > k_2$, $\Delta U(k_2|k_2-\tau_{{\rm sc},k_2})$ will be replaced by $\Delta U(k_1|k_1-\tau_{{\rm sc},k_1})$; otherwise, $\Delta U(k_1|k_1-\tau_{{\rm sc},k_1})$ will be simply discarded, and the delay compensator remains unchanged.

The comparison process is introduced at the actuator side due to the fact that different data packets may experience different delays in the forward channel, thereby producing a situation where, for example, a data packet sent earlier from the controller may arrive at the actuator later or may never arrive in the case of data packet dropout. As a result of the comparison process, the predictive control sequence stored in the delay compensator is always the latest one available at any specific time.

As for the actuator, it can be either time driven or event driven. The difference between the two driven methods lies in the trigger method that initiates the actuator. For time-driven actuator, the actuator is trigged to work at regular intervals, no matter whether the delay compensator is updated or not, whereas for event-driven actuator, it is only trigged by the update of the delay compensator, i.e., a new predictive control sequence is stored in the delay compensator. Whatever method is used, the actuator selects the appropriate control increment signal which can compensate for current network-induced delay in the forward channel from the predictive control increment sequence in the delay compensator at every execution time instant and then applies it to the plant. The method to choose the appropriate control increment signal at a specific time will be explained in detail in the next section. It is necessary to point this out that the appropriate control increment is always available using the delay compensator provided that Assumption A4) holds.

3) Compensation for the Network Jitter—A Horizon Adjustor: A larger control horizon generally leads to a better performance for a typical GPC implementation, whereas in a networked control environment, a larger control horizon means a greater computation burden for the controller and, more severely, a greater communication burden for the network, since more control predictions are computed and transmitted through the network (note that the size of the control predictive sequence is proportional to the control horizon N_u). This may result in network traffic congestion and makes the performance of the NCS worse on the contrary. Therefore, we argue that an appropriately chosen control horizon is important for the performance of the proposed approach, and hence, a horizon adjustor is proposed in this paper, which adjusts the control horizon N_u by taking account of the current network performance.

In the design of the horizon adjustor, the constraints for N_u [see (8) and (11)] should always be satisfied for the successful implementation of both the LGPC method and the delay compensator. Notice also that the period of updating the control horizon depends on the network conditions. A period of T can be used if the network condition does not change much during this period.

The horizon adjustor using a period T can therefore be obtained as

$$N_u(kT) = N_u\left((k-1)T\right) + \psi\left(\bar{\tau}_{\mathrm{ca}}(t), \bar{\chi}(t)\right) \quad (12a)$$

$$N_u(t) = N_u(kT), \qquad t \in [kT(k+1)T) \quad (12b)$$

with the constraints $\bar{\tau}_{\mathrm{ca}}(t) + \bar{\chi}(t) + 1 \le N_u \le N_p$ [constraints (8) and (11)], where $\bar{\tau}_{\mathrm{ca}}(t)$ and $\bar{\chi}(t)$ are the upper bounds of the network-induced delay and continuous data packet dropout in the forward channel during the next period of T, respectively, and $\psi(\cdot,\cdot)$ is an adjusting function to adjust the control horizon dynamically with the network conditions. Since the future network condition is unavailable in practice, previous information could be used instead. A simple form of $\psi(\cdot,\cdot)$ can then be

$$\psi(\bar{\tau}_{\mathrm{ca}}(t), \bar{\chi}(t)) = \rho_t \cdot (\bar{\tau}_{\mathrm{ca}}(t) + \bar{\chi}(t) - \bar{\tau}_{\mathrm{ca}}(t-1) - \bar{\chi}(t-1)) \quad (13)$$

where ρ_t is an adjusting factor to reflect the extent of the network jitter. ρ_t will be set to be large if the network jitter is severe and vice versa.

In the implementation of the horizon adjustor, N_p remains to be a constant which results in $\mathcal{E}_{\mathrm{sc}}$ unchanged. What is required is to calculate different sets of $F_{\tau_{\mathrm{sc},k}}$, $M_{\tau_{\mathrm{sc},k}}$, and $H_{\tau_{\mathrm{sc},k}}$ with respect to different N_u's offline and store them in the matrix selector for online use. N_p is chosen in such a way that the data packet containing the control predictions does not exceed the packet size limit of the network used even if $N_u = N_p$, which enables the control predictions to be packed into one data packet.

The two-step predictive control approach with DDCS can now be summarized as follows, within a specific period T of the horizon adjustor.

S1) Calculation. The predictive controller calculates the intermediate predictive control increment sequence $\Delta V(k|k-\tau_{\mathrm{sc},k})$ using (7) with the use of the proposed matrix selector and delayed information of states and control signals. The predictive control increment sequence $\Delta U(k|k-\tau_{\mathrm{sc},k})$ is then obtained by compensating for the nonlinear input process using (10).

S2) Forward transmission. $\Delta U(k|k-\tau_{\mathrm{sc},k})$ is packed and sent to the actuator simultaneously with time stamps k and $\tau_{\mathrm{sc},k}$.

S3) Comparison. The delay compensator updates its information according to the time stamps once a data packet arrives.

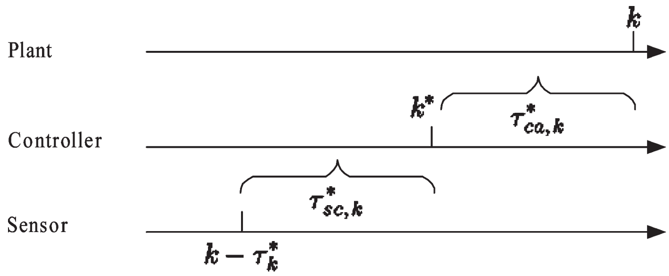

Fig. 2. Time delays of the control signal adopted by the actuator at time k.

S4) Execution. An appropriate control increment signal is picked out from the control sequence in the delay compensator and applied to the plant.

S5) Backward transmission. The information of the applied control increment with the sensing state is sent to the controller.

The structure of the predictive control-based approach with DDCS [the so-called "networked predictive control systems"(NPCSs)] is shown in Fig. 1.

III. Stability Analysis

In this section, the closed-loop formulation of such an NPCS with a nonlinear input process is derived, and then, the stability theorem is obtained by using a switched system theory under a sector constraint of the nonlinearity due to calculation inaccuracy.

A. Closed-Loop System

Let $\tau^*_{\mathrm{ca},k}$ denote the network-induced delay in the forward channel of the predictive control increment sequence, from which the control signal is picked out by the actuator at time instant k. The time when the sequence was sent from the controller side can then be read from its time stamp as

$$k^* = k - \tau^*_{\mathrm{ca},k} = \max_j \{j|\Delta U(j|j-\tau_{\mathrm{sc},j}) \in \Gamma_k\} \quad (14)$$

where Γ_k is the set of the predictive control increment sequences that is available during time interval $(k-1,k]$ at the actuator side, including not only the one in the delay compensator but also others that arrive at the actuator during this interval (see Fig. 2). From (10) and (14), the control signal adopted by the actuator at time k is obtained as

$$\begin{aligned}\Delta u(k) &= \Delta u\left(k|k-\tau^*_k\right)\\ &= d^{\mathrm{T}}_{\tau^*_{\mathrm{ca},k}} \Delta U\left(k-\tau^*_{\mathrm{ca},k}|k-\tau^*_k\right)\end{aligned} \quad (15)$$

where $d_{\tau^*_{\mathrm{ca},k}}$ is an $N_u \times 1$ matrix with all entries being zero, except that $(\tau^*_{\mathrm{ca},k}+1)$th is one, τ^*_k is the round trip time with respect to $\tau^*_{\mathrm{ca},k}$, i.e., $\tau^*_k = \tau^*_{\mathrm{ca},k} + \tau^*_{\mathrm{sc},k}$, and $\tau^*_{\mathrm{sc},k} = \tau_{\mathrm{sc},k^*}$.

From (7) and (10) and noticing for any vector V with an appropriate dimension, $d^{\mathrm{T}}_{\tau^*_{\mathrm{ca},k}} \hat{\vec{f}}^{-1}(V) = \hat{f}^{-1}(d^{\mathrm{T}}_{\tau^*_{\mathrm{ca},k}} V)$ recalling the definition of $\hat{\vec{f}}^{-1}(\cdot)$; thus, we obtain (assume that the set point $\omega = 0$ without loss of generality)

$$\begin{aligned}\Delta u(k) &= d^{\mathrm{T}}_{\tau^*_{\mathrm{ca},k}} \Delta U\left(k-\tau^*_{\mathrm{ca},k}|k-\tau^*_k\right)\\ &= d^{\mathrm{T}}_{\tau^*_{\mathrm{ca},k}} \hat{\vec{f}}^{-1}\left(\Delta V(k-\tau^*_{\mathrm{ca},k}|k-\tau^*_k)\right)\\ &= \hat{f}^{-1}\left(d^{\mathrm{T}}_{\tau^*_{\mathrm{ca},k}} \Delta V(k-\tau^*_{\mathrm{ca},k}|k-\tau^*_k)\right)\\ &= \hat{f}^{-1}\left(-K^*_{\tau,k}\bar{x}\left(k-\tau^*_k\right)\right) \end{aligned} \tag{16}$$

where $K^*_{\tau,k} = d^{\mathrm{T}}_{\tau^*_{\mathrm{ca},k}} M_{\tau_{\mathrm{sc},k}} E_{\tau_{\mathrm{sc},k}}$.[1] The real control increment for linear system [(1a) and (1b)] at time k can then be obtained as

$$\Delta v(k) = f\left(\Delta u(k)\right) = f \circ \hat{f}^{-1}\left(-K^*_{\tau,k}\bar{x}\left(k-\tau^*_k\right)\right) \tag{17}$$

where $f \circ \hat{f}^{-1}(\cdot) = f(\hat{f}^{-1}(\cdot))$ is the composite function of $f(\cdot)$ and $\hat{f}^{-1}(\cdot)$.

Let $X(k) = [\,\bar{x}^{\mathrm{T}}(k-\bar{\tau}) \quad \cdots \quad \bar{x}^{\mathrm{T}}(k)\,]^{\mathrm{T}}$, $w(k) = \Delta v(k)$. Then the closed-loop system can be represented by

$$S^*: \begin{cases} X(k+1) = \widetilde{A}X(k) + \widetilde{b}w(k) & \text{(18a)}\\ w(k) = f \circ \hat{f}^{-1}\left(-K^*_{\bar{\tau},k}X(k)\right) & \text{(18b)}\end{cases}$$

where $\widetilde{b} = [\,0_{n+1,1} \quad \cdots \quad 0_{n+1,1} \quad \bar{b}^{\mathrm{T}}_{n+1,1}\,]^{\mathrm{T}}$, $K^*_{\bar{\tau},k}$ is a $1 \times (\bar{\tau}+1)$ block matrix with a block size of $1 \times (n+1)$, and all its blocks are zero, except that $(\bar{\tau}+1-\tau^*_k)$th is $K^*_{\tau,k}$ (the set of all the possible $K^*_{\tau,k}$'s will be denoted by $\mathbb{K}$), and

$$\widetilde{A} = \begin{pmatrix} 0_{n+1} & I_{n+1} & & & \\ & 0_{n+1} & I_{n+1} & & \mathbf{0} \\ & & \ddots & \ddots & \\ & \mathbf{0} & & 0_{n+1} & I_{n+1} \\ & & & & \bar{A}\end{pmatrix}.$$

B. Stability Analysis

As has been pointed out in Section II-A2, the compensation for the nonlinear input process using (9) is generally not accurate, and this inaccuracy introduces to the linear part of the system [see (1a) and (1b)] a nonlinear disturbance, which appears in the form of $f \circ \hat{f}^{-1}(\cdot)$. Although, generally, $f \circ \hat{f}^{-1}(\cdot) \not\equiv 1$, it is reasonable to assume that the calculation error meets some accuracy requirement to a certain extent, which results in a sector constraint of the term $f \circ \hat{f}^{-1}(\cdot)$, as described in Assumption A5) as follows.[2]

A5) The nonlinearity due to the calculation inaccuracy is supposed to satisfy a sector constraint, i.e., there exist $0 < \underline{\varepsilon} \le \bar{\varepsilon} < \infty$, s.t.

$$\underline{\varepsilon}\alpha \le f \circ \hat{f}^{-1}(\alpha) \le \bar{\varepsilon}\alpha, \qquad \forall \alpha \in \mathbb{R}. \tag{19}$$

[1] Note that the value of $K^*_{\tau,k}$ varies with the delays in both channels, and thus, it has $(\bar{\tau}_{ca}+1)(\bar{\tau}_{sc}+1)$ different values in total.

[2] Note that, although it is reasonable to place a sector constraint as in Assumption A5) to $f \circ \hat{f}^{-1}(\cdot)$, it is somewhat conservative since the calculation of some strongly nonlinear function may not be that accurate and, thus, does not satisfy A5).

This constraint can be denoted by

$$f \circ \hat{f}^{-1}(\cdot) \in [\underline{\varepsilon}, \bar{\varepsilon}]. \tag{20}$$

Notice here that, generally, $0 < \underline{\varepsilon} \le 1 \le \bar{\varepsilon} < \infty$.

By using Assumption A4), we obtain that for any specific $\alpha \in \mathbb{R}$, there exists a real number ε_α, $\underline{\varepsilon} \le \varepsilon_\alpha \le \bar{\varepsilon}$, such that $f \circ \hat{f}^{-1}(\alpha) = \varepsilon_\alpha \alpha$; (18b) can thereby be rewritten as

$$\begin{aligned} w(k) &= f \circ \hat{f}^{-1}\left(-K^*_{\bar{\tau},k}X(k)\right)\\ &= -\varepsilon_k K^*_{\bar{\tau},k}X(k)\end{aligned} \tag{21}$$

where $\varepsilon_k \in [\underline{\varepsilon}, \bar{\varepsilon}]$ represents the compensation for the specific nonlinearity for the term $K^*_{\bar{\tau},k}X(k)$ at time k.

Recalling (18a) and (21), the closed-loop system S^* can then be written as

$$\begin{aligned} X(k+1) &= \widetilde{A}X(k) + \widetilde{b}w(k)\\ &= \left(\widetilde{A} - \varepsilon_k \widetilde{b}K^*_{\bar{\tau},k}\right)X(k)\\ &= \Lambda\left(\varepsilon_k, K^*_{\bar{\tau},k}\right)X(k)\end{aligned} \tag{22}$$

where the closed-loop matrix $\Lambda(\varepsilon_k, K^*_{\bar{\tau},k}) = \widetilde{A} - \varepsilon_k \widetilde{b}K^*_{\bar{\tau},k}$ has the form

$$\Lambda\left(\varepsilon_k, K^*_{\bar{\tau},k}\right) = \begin{pmatrix} 0_{n+1} & I_{n+1} & & & \\ & 0_{n+1} & I_{n+1} & & \mathbf{0} \\ & & \ddots & \ddots & \\ & \mathbf{0} & & 0_{n+1} & I_{n+1} \\ \cdots & -\varepsilon_k\bar{b}K^*_{\tau,k} & \cdots & & \bar{A}\end{pmatrix}.$$

The position and value of the term $-\varepsilon_k\bar{b}K^*_{\tau,k}$ depend on the specific delays in the both channels at time k, i.e., $(\Lambda(\varepsilon_k, K^*_{\bar{\tau},k}))_{\bar{\tau}+1,j} = -\varepsilon_k\bar{b}K^*_{\tau,k}$, $j = \tau^*_k = 1, 2, \ldots, \bar{\tau}$, and $(\Lambda(\varepsilon_k, K^*_{\bar{\tau},k}))_{\bar{\tau}+1,\bar{\tau}+1} = \bar{A} - \varepsilon_k\bar{b}K^*_{\tau,k}$, if $\tau^*_k = \bar{\tau}+1$.

Theorem 1: The closed-loop system S^* is stable if A4) holds and there exists a positive definite solution $P = P^{\mathrm{T}} > 0$ for the following $2(\bar{\tau}_{\mathrm{ca}}+1)(\bar{\tau}_{\mathrm{sc}}+1)$ LMIs:

$$\Lambda^{\mathrm{T}}\left(\underline{\varepsilon}, K^*_{\bar{\tau},k}\right)P\Lambda\left(\underline{\varepsilon}, K^*_{\bar{\tau},k}\right) - P \le 0 \tag{23a}$$

$$\Lambda^{\mathrm{T}}\left(\bar{\varepsilon}, K^*_{\bar{\tau},k}\right)P\Lambda\left(\bar{\varepsilon}, K^*_{\bar{\tau},k}\right) - P \le 0 \tag{23b}$$

where $K^*_{\bar{\tau},k} \in \mathbb{K}$.

Proof: Let $V(k) = X^{\mathrm{T}}(k)PX(k)$ be a Lyapunov function candidate, then the incremental $V(k)$ for system S^* can be obtained using (22)

$$\begin{aligned}\Delta V(k) &= X^{\mathrm{T}}(k)\left(\Lambda\left(\varepsilon_k, K^*_{\bar{\tau},k}\right)^{\mathrm{T}}P\Lambda\left(\varepsilon_k, K^*_{\bar{\tau},k}\right) - P\right)X(k)\\ &= X^{\mathrm{T}}(k)\Big(\widetilde{A}^{\mathrm{T}}P\widetilde{A} - P - \varepsilon_k\widetilde{A}^{\mathrm{T}}P\widetilde{b}K^*_{\bar{\tau},k} - \varepsilon_k K^{*T}_{\bar{\tau},k}\widetilde{b}^{\mathrm{T}}P\widetilde{A}\\ &\qquad + \varepsilon_k^2 K^{*T}_{\bar{\tau},k}\widetilde{b}^{\mathrm{T}}P\widetilde{b}K^*_{\bar{\tau},k}\Big)X(k)\\ &\triangleq X^{\mathrm{T}}(k)\mathcal{A}\left(\varepsilon_k, K^*_{\bar{\tau},k}\right)X(k)\end{aligned} \tag{24}$$

where $\varepsilon_k \in [\underline{\varepsilon}, \bar{\varepsilon}]$ and $K^*_{\bar{\tau},k} \in \mathbb{K}$.

Notice that for any $\varepsilon_k \in [\underline{\varepsilon}, \bar{\varepsilon}]$, there exists $0 \le \lambda_k \le 1$ s.t. $\varepsilon_k = \lambda_k \underline{\varepsilon} + (1-\lambda_k)\bar{\varepsilon}$, and thus, we obtain by substituting this into (24)

$$\mathcal{A}\left(\varepsilon_k, K^*_{\bar{\tau},k}\right) = \lambda_k \mathcal{A}\left(\underline{\varepsilon}, K^*_{\bar{\tau},k}\right) + (1-\lambda_k)\mathcal{A}\left(\bar{\varepsilon}, K^*_{\bar{\tau},k}\right) - \lambda_k(1-\lambda_k)(\underline{\varepsilon}-\bar{\varepsilon})^2 K^{*T}_{\bar{\tau},k}\widetilde{b}^{\mathrm{T}} P \widetilde{b} K^*_{\bar{\tau},k}. \quad (25)$$

From (23a), (23b), and (24), $\mathcal{A}(\underline{\varepsilon}, K^*_{\bar{\tau},k})$ and $\mathcal{A}(\bar{\varepsilon}, K^*_{\bar{\tau},k})$ are seminegative definite for all $K^*_{\bar{\tau},k} \in \mathbb{K}$. Notice that P is symmetric positive definite and that $K^{*T}_{\bar{\tau},k}\widetilde{b}^{\mathrm{T}} P \widetilde{b} K^*_{\bar{\tau},k}$ is semipositive definite as a symmetric matrix, thus enabling $\mathcal{A}(\varepsilon_k, K^*_{\bar{\tau},k})$ to be seminegative definite for any $\varepsilon_k \in [\underline{\varepsilon}, \bar{\varepsilon}]$ and $K^*_{\bar{\tau},k} \in \mathbb{K}$, which completes the proof. ■

Remark 5: It is necessary to point this out that according to Assumption A5) and Theorem 1, what is required for the stability of the system is to satisfactorily meet the sector constraint in (20) no matter how the inverse function $\hat{f}^{-1}(\cdot)$ is calculated. It implies that the function $f(\cdot)$ does not need to be theoretically invertible as long as its inverse can be obtained by a numerical method and satisfies the sector constraint [one can refer to [16] and the references therein for more information of the calculation of $\hat{f}^{-1}(\cdot)$].

Remark 6: When the horizon adjuster is also considered, the feedback gain $K^*_{\bar{\tau},k}$ in (16) will depend on a different control horizon N_u and can be rewritten as $K^*_{\bar{\tau},N_u,k}$. Thus, the set $\mathbb{K}$ now consists of all the possible $K^*_{\bar{\tau},N_u,k}$, $\min_t(\tau_{\mathrm{ca}}(t) + \chi(t)) + 1 \le N_u \le N_p$. A similar stability criterion to Theorem 1 can then be obtained analogously.

The following two special conditions are also considered for the stability of the closed-loop system.

C1) The network-induced delays in both channels are constant (noted by τ^0_{sc} and τ^0_{ca}, respectively).

C2) The calculation of the inverse of the nonlinear function is accurate.

The following corollary can be easily obtained by using Theorem 1.

Corollary 1: The closed-loop system S^* is stable if any one of the following three conditions holds.

1) A4) and C1) hold, and there exists a positive definite solution $P = P^{\mathrm{T}} > 0$ for the following two LMIs:

$$\Lambda^{\mathrm{T}}\left(\underline{\varepsilon}, K^*_{\bar{\tau},k}\right) P \Lambda\left(\underline{\varepsilon}, K^*_{\bar{\tau},k}\right) - P \le 0 \quad (26a)$$

$$\Lambda^{\mathrm{T}}\left(\bar{\varepsilon}, K^*_{\bar{\tau},k}\right) P \Lambda\left(\bar{\varepsilon}, K^*_{\bar{\tau},k}\right) - P \le 0 \quad (26b)$$

where $\tau_{\mathrm{sc},k} \equiv \tau^0_{\mathrm{sc}}$, $\tau_{\mathrm{ca},k} \equiv \tau^0_{\mathrm{ca}}$, and $K^*_{\bar{\tau},k}$ is therefore fixed.

2) C2) holds, and there exists a positive definite solution $P = P^{\mathrm{T}} > 0$ for the following $(\bar{\tau}_{\mathrm{ca}}+1)(\bar{\tau}_{\mathrm{sc}}+1)$ LMIs:

$$\Lambda^{\mathrm{T}}\left(1, K^*_{\bar{\tau},k}\right) P \Lambda\left(1, K^*_{\bar{\tau},k}\right) - P \le 0 \quad (27)$$

where $K^*_{\bar{\tau},k} \in \mathbb{K}$.

3) Both of C1) and C2) hold, and there exists a positive definite solution $P = P^{\mathrm{T}} > 0$ for the following LMI:

$$\Lambda^{\mathrm{T}}\left(1, K^*_{\bar{\tau},k}\right) P \Lambda\left(1, K^*_{\bar{\tau},k}\right) - P \le 0 \quad (28)$$

where $\tau_{\mathrm{sc},k} \equiv \tau^0_{\mathrm{sc}}$, $\tau_{\mathrm{ca},k} \equiv \tau^0_{\mathrm{ca}}$, and $K^*_{\bar{\tau},k}$ is therefore fixed.

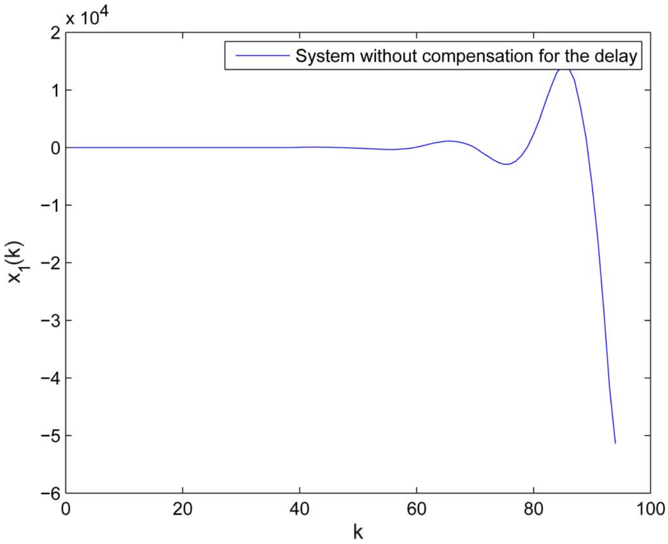

Fig. 3. State evolution using LQR method.

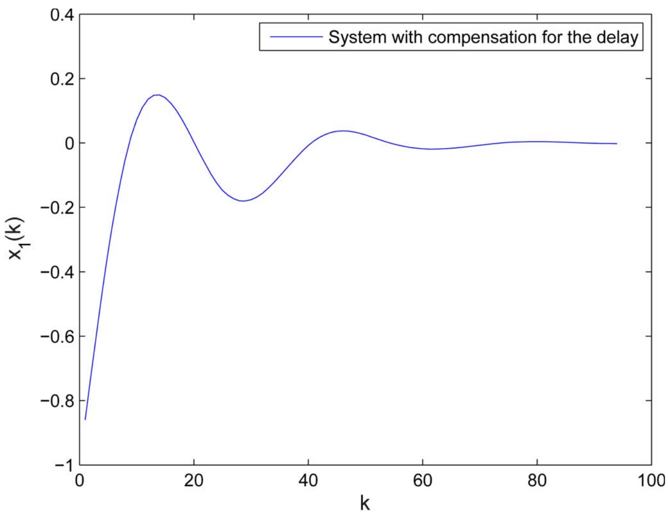

Fig. 4. State evolution using the approach in this paper.

IV. SIMULATION

In this section, a second-order Hammerstein model is adopted to illustrate the effectiveness of the proposed approach. The system matrices in (1a) and (1b) of system S are set as follows which is open-loop unstable:

$$A = \begin{pmatrix} 0.98 & 0.1 \\ 0 & 1 \end{pmatrix} \quad b = \begin{pmatrix} 0.04 \\ 0.1 \end{pmatrix} \quad c = (1 \quad 0).$$

We first use this linear system [see (1a) and (1b)] to illustrate the effectiveness of the proposed predictive controller and the compensation scheme DDCS for the communication constraints. In order to do this by comparison, the linear quadratic optimal (LQR) control method is used to design a state feedback law for this system without consideration of the communication constraints, which yields the feedback gain $K_{\mathrm{LQR}} = [\,0.7044 \quad 1.3611\,]$. The simulation result shows that it is unstable using this LQR control when there is random delays in both channels (the upper bounds of the delays are $\bar{\tau} = 3$, $\bar{\tau}_{\mathrm{ca}} = 2$, and $\bar{\tau}_{\mathrm{sc}} = 1$, see Fig. 3), whereas it is stable

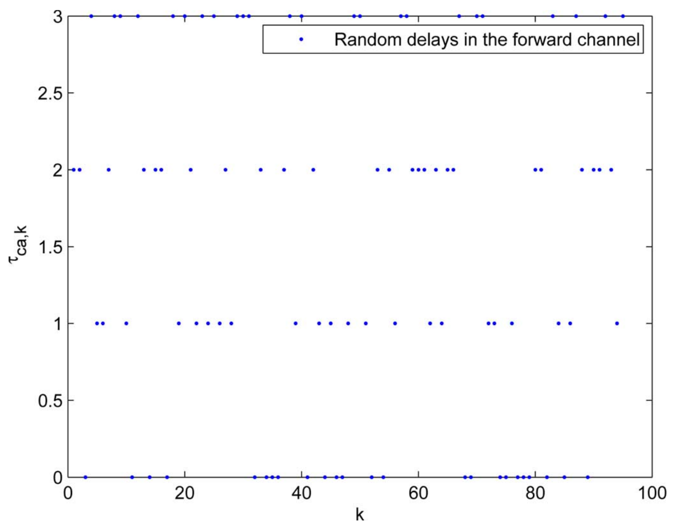

Fig. 5. Random delays in the forward channel.

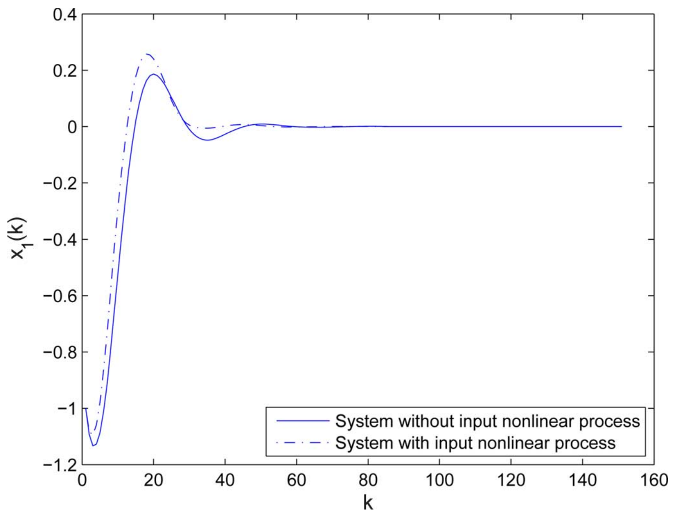

Fig. 6. Effectiveness of the compensation for the input nonlinear process.

using the proposed approach in this paper (Fig. 4). The random delays in the forward channel are shown in Fig. 5. Other parameters of the simulation are chosen as $N_u = 8$, $N_p = 10$, and the initial state $x_0 = [-1 \quad -1]^{\mathrm{T}}$. The delays in both channels are set to vary randomly within their upper bounds.

Note the fact that with an inverse process to compensate for the static input nonlinearity in the Hammerstein system, from (18b), we know that the system performance only depends on the accuracy of this compensation process, i.e., the size of the sector constraint $[\underline{\varepsilon}, \bar{\varepsilon}]$ for $f \circ \hat{f}^{-1}(\cdot)$ [see (20)]. In this simulation, we set $[\underline{\varepsilon}, \bar{\varepsilon}] = [0.5, 1.5]$, which means that there is approximately 50% error in the compensation for the input nonlinearity, whereas the input nonlinear function $f(\cdot)$ can be of any form provided that this compensation accuracy is satisfied. All the other parameters are set as the same as the aforementioned ones. Such a system with those parameters can be proved to be stable using Theorem 1.

The effect of the compensation for the input nonlinearity is shown in Fig. 6, from which it is seen that the compensation accuracy for the input nonlinearity is effective.

V. Conclusion

In this paper, a novel approach with the integration of the two-step predictive control method and a DDCS is proposed for a Hemmerstein system in a networked control environment. In the approach, the predictive controller for the linear part of the system is first designed by using delayed sensing data, and the nonlinear input can be viewed as a nonlinear disturbance after a compensation scheme. The communication constraints considered in this paper, i.e., random delays in both channels and data packet dropout in the forward channel, are dealt with by the DDCS, which consists of three components configured at both the controller and actuator sides. The stability theorem for the closed-loop system is obtained by using switched system theory. Simulation work has also been done to illustrate the effectiveness of the proposed approach.

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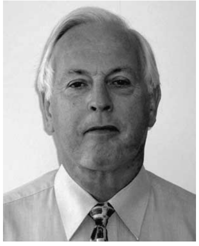

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