Model-based predictive controller design for a class of nonlinear networked systems with communication delays and data loss*

An Bao-Ran(安宝冉)[a)†] and Liu Guo-Ping(刘国平)[a)b)]

[a)] *Center for Control Theory and Guidance Technology, Harbin Institute of Technology, Harbin* 150080, *China*
[b)] *School of Engineering, University of South Wales, Pontypridd CF*37 1*DL, United Kingdom*

(Received 29 November 2013; revised manuscript received 14 March 2014; published online 10 June 2014)

This paper discusses the model-based predictive controller design of networked nonlinear systems with communication delay and data loss. Based on the analysis of the closed-loop networked predictive control systems, the model-based networked predictive control strategy can compensate for communication delay and data loss in an active way. The designed model-based predictive controller can also guarantee the stability of the closed-loop networked system. The simulation results demonstrate the feasibility and efficacy of the proposed model-based predictive controller design scheme.

Keywords: communication delays, data loss, model-based networked predictive control

PACS: 02.30.Yy, 05.90.+m, 02.30.Ks **DOI:** 10.1088/1674-1056/23/8/080202

1. Introduction

In recent years, control applications in which the control loop is closed through a real-time communication network have received growing attention in control engineering, since the developments in microprocessors and network abilities provide a convenient way for the remote monitoring and adjustment of large distributed plants.[1–3] These systems, usually referred to as Networked Control Systems (NCSs), have many advantages such as low cost, easy maintenance, and reduced power consumption, together with more and more applications in industry, such as traffic, process control, spacecraft, energy and power management, and rehabilitation treatments.[4–9] However, the introduction of communication networks in control loops leads to some inevitable issues, including network-induced delay, data packet disorder, and data packet dropout, which can significantly degrade the system performance or even make the system unstable in certain conditions. These issues need to be taken into account when NCSs are analyzed and designed.

To guarantee the performance of the control system, there are many control strategies presented in the current literature for the design and analysis of NCSs, e.g., the augmented discrete-time model method,[10] the switched system approach,[11] the queuing method,[12] robust control,[13] stochastic optimal control,[14] state feedback control,[15] fuzzy logic modulation,[16] event-based control,[17] impulsive control,[18] and hybrid systems stability analysis.[19] However, many of these methods are restricted by some strict assumptions on NCSs and are passive to reduce the effect of the communication delay and data loss in a conservative way for linear time-invariant systems. In fact, a challenging issue that compensates for communication delays actively and overcoming data dropouts is a really hard task if the closed-loop NCSs are required to design in a less conservative way.

Considering the NCSs to be controlled are subjected to communication constraints and nonlinearities, the model-based networked predictive control (MB-NPC) scheme is presented in this paper. The basic idea of MB-NPC is that the explicit model of the plant is used to estimate the future behaviors of the plant and give an appropriate control signal to compensate for communication delays and data dropout. This paper utilizes a model-based networked predictive control scheme to compensate for communication delays in both the feedback and forward communication channels and also to cope with data dropout in an active way. It proposes a design strategy of the predictive controller for networked nonlinear systems under suitable assumptions.

This paper is organized as follows. Some background of the problem formulation and the MB-NPC scheme are presented in Section 2. Section 3 describes the stability analysis of the model-based networked predictive control system. Simulation results are given in Section 4 to demonstrate the feasibility and efficiency of the proposed model-based predictive method. The conclusion drawn from the present study is presented in Section 5.

2. Nonlinear plant and MB-NPC scheme

A graphical representation of the MB-NPC system is shown in Fig. 1.

*Project supported by the Key Program for the National Natural Science Foundation of China (Grant No. 61333003) and the General Program for the National Natural Science Foundation of China (Grant No. 61273104).

†Corresponding author. E-mail: baoran.an@hit.edu.cn

© 2014 Chinese Physical Society and IOP Publishing Ltd

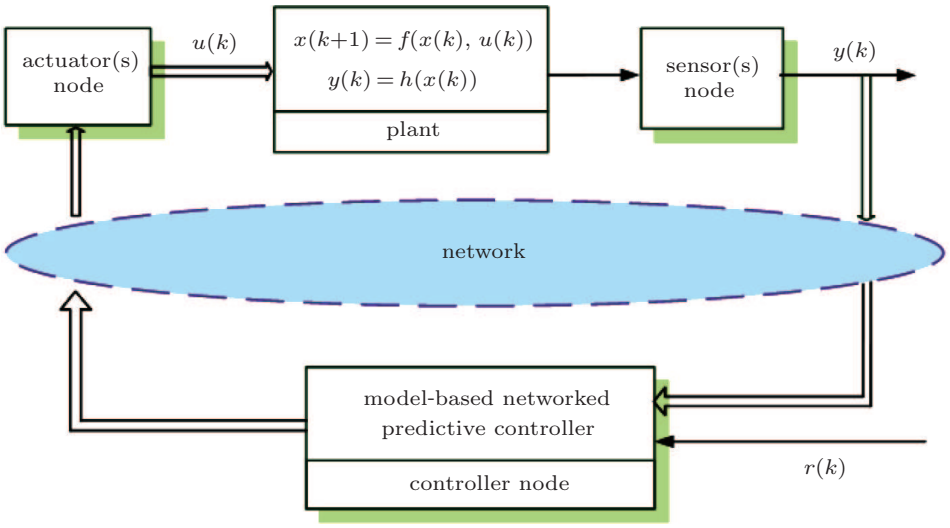


Fig. 1. (color online) Model-based networked predictive control system.

In a practical NCS, the communication network can be located in the forward channel (i.e., from the controller to the actuator) and/or the feedback channel (i.e., from the sensor to the controller). When a data packet fails to arrive at its destination within a certain transmission deadline, for example, the upper bound of the communication delay, data loss occurs. Based on physical networks, it is natural to assume that only a finite number of consecutive packet-dropouts can be tolerated by NCSs. Similarly, the communication delays in the feedback and forward channels of NCSs should also be bounded. In order to design the MB-NPC approach, the following assumptions are made.

Assumption 1 The communication delay in the feedback channel is bounded by $n_{\rm b}$; the communication delay in the forward channel is bounded by $n_{\rm f}$.

Assumption 2 The number of consecutive data dropouts in both the feedback channel and the forward channel is bounded by $n_{\rm d}$.

Assumption 3 All data are time-stamped, that is, they contain the information on when they were delivered by the transmission side.

Remark 1 Because the proposed predictive control sequence is based on time, the time stamp of the data transmitted through the network is very important for NCSs. In this regard, the time clocks in the components of NCSs are assumed to have been synchronized by a proper synchronization mechanism.[20,21] Since this paper mainly focuses on the predictive controller design problem, the synchronization issue will not be discussed in detail here.

2.1. Nonlinear plant to be controlled

In the current paper, a nonlinear plant to be controlled through the network is described by the following discrete-time dynamic equation:

$$\begin{aligned} x(k+1) &= f(x(k),u(k)),\\ y(k) &= h(x(k)), \end{aligned} \tag{1}$$

where $x(k) \in \mathcal{R}^n$ denotes the state of the system, $u(k) \in \mathcal{R}$ denotes the control input and $y(k) \in \mathcal{R}$ denotes the measured output. $f(\cdot,\cdot) : \mathcal{R}^n \times \mathcal{R} \to \mathcal{R}^n$ is an n-dimensional smooth vector field. In addition, it is assumed that the states of the nonlinear system (1) are not straightforwardly measurable.

For the implementation of the MB-NPC scheme, a state observer is employed to estimate the state variables and a local feedback linearizing controller is designed for the nonlinear plant (1) in the following.

2.1.1. State observer

Let $u_{[r]}(k)$ and $y_{[r]}(k)$ be the following vectors:

$$\begin{aligned} u_{[r]}(k) &= \begin{pmatrix} u(k+r-1)\\ u(k+r-2)\\ \vdots\\ u(k) \end{pmatrix},\\ y_{[r]}(k) &= \begin{pmatrix} y(k+r-1)\\ y(k+r-2)\\ \vdots\\ y(k) \end{pmatrix}. \end{aligned} \tag{2}$$

For any integer $m \geq 1$, f^m is defined as follows:

$$f^{m+1}(x(k),u_{[m+1]}(k)) = f(f^m(x(k),u_{[m]}(k)),u(k+m)), \tag{3}$$

where $f^1(x(k),u_{[1]}(k)) = f(x(k),u(k))$. Hence, the value of the state and measured output at time $k+m$ can be written as

$$\begin{aligned} x(k+m) &= f^m(x(k),u_{[m]}(k)),\\ y(k+m) &= h^{\circ} f^m(x(k),u_{[m]}(k)), \end{aligned} \tag{4}$$

where '$\circ$' denotes the composition operator.

Definition 1[22] Given a $\mathcal{C}^\infty$ function $h:\mathcal{R}^n\to\mathcal{R}^1$ and the smooth vector field $f(x,u)$ on $\mathcal{R}^n\times\mathcal{R}$, the observability matrix $\mathcal{Q}(x,u_{[n-1]})$ is defined as

$$\begin{aligned}\mathcal{Q}(x,u_{[n-1]}) &= \frac{\mathrm{d}}{\mathrm{d}x}\begin{pmatrix} h^\circ f^{n-1}(x,u_{[n-1]}) \\ h^\circ f^{n-2}(x,u_{[n-2]}) \\ \vdots \\ h^\circ f^1(x,u_{[1]}) \\ h(x)\end{pmatrix} \\ &= \frac{\mathrm{d}\phi(x,u_{[n-1]})}{\mathrm{d}x}. \end{aligned} \tag{5}$$

In the linear case, i.e., $f(x)=Ax+Bu$ and $h(x)=Cx$, the matrix (5) reduces to the well-known observability matrix.

By introducing the nonlinear transformation function $\phi(\cdot,\cdot)$ on the basis of Eqs. (2), (3), and (4), it can be obtained that

$$\begin{aligned} & y_{[n]}(k-n+1) \\ &= \begin{pmatrix} y(k) \\ y(k-1) \\ \vdots \\ y(k-n+2) \\ y(k-n+1)\end{pmatrix} \\ &= \phi(x(k-n+1),u_{[n-1]}(k-n+1)) \\ &= \begin{pmatrix} h^\circ f^{n-1}(x(k-n+1),u_{[n-1]}(k-n+1)) \\ h^\circ f^{n-2}(x(k-n+1),u_{[n-2]}(k-n+1)) \\ \vdots \\ h^\circ f^1(x(k-n+1),u_{[1]}(k-n+1)) \\ h(x(k-n+1))\end{pmatrix}. \end{aligned} \tag{6}$$

If the nonlinear plant (1) satisfies the following conditions:

Condition 1 The observability matrix $\mathcal{Q}(x,u_{[n-1]})$ has full rank for all $(x,u_{[n-1]})$.

Condition 2 The nonlinear algebraic equation (6) has a unique solution

$$x(k-n+1)=\phi^{-1}(y_{[n]}(k-n+1),u_{[n-1]}(k-n+1))$$

for all $(y_{[n]},u_{[n-1]})$. Also, $\phi^{-1}(\cdot,\cdot)$ denotes the inverse transformation of Eq. (6).

Then a state observer can be designed in the following[23]

$$\begin{aligned} \chi(k) &= \phi^{-1}(y_{[n]}(k-n+1),u_{[n-1]}(k-n+1)), \\ \hat{x}(k) &= f^{n-1}(\chi(k),u_{[n-1]}(k-n+1)), \end{aligned} \tag{7}$$

where $\hat{x}(k)\in\mathcal{R}^n$ denotes the state estimation for time k based on the information of $u_{[n-1]}(k-n+1)$ and $y_{[n]}(k-n+1)$.

Remark 2 There is a variety of observer design algorithms for discrete time nonlinear systems in the literature.[24,25] Compared with the existing nonlinear observers, the state estimation algorithm has the following main characteristics: (i) a nonlinear change of coordinates is not required; (ii) iterations to obtain state estimation are not employed; (iii) if the observer gets the explicit knowledge of the ϕ^{-1} function, the calculation is very straightforward; (iv) equations are computationally simple and easily implementable.

2.1.2. Local feedback linearizing controller

For a local feedback linearizing control law, it is necessary that the nonlinear system (1) can be linearized by state-coordinate change and feedback. In the following, an important definition related to the linearization is introduced.

Definition 2[26] The relative degree of the nonlinear system (1) is globally defined as the smallest integer ς such that $\partial/\partial u(h^\circ f^\varsigma)\neq 0$.

Construct a state-coordinate change

$$\begin{aligned} z(k) &= \begin{pmatrix} z_1(k) \\ z_2(k) \\ \cdots \\ z_n(k)\end{pmatrix} = \begin{pmatrix} h(x(k)) \\ h^\circ f(x(k),u(k)) \\ \cdots \\ h^\circ f^{n-1}(x(k),u(k))\end{pmatrix} \\ &= \varphi(x(k),u(k)) \end{aligned} \tag{8}$$

and a new input variable

$$v(k)=h^\circ f^n(x(k),u(k)). \tag{9}$$

Many researchers have studied linearization by coordinate change and feedback for nonlinear systems.[26–28] Closed-loop stability analysis is a challenging problem. Sufficient conditions for asymptotic stability are given by Kurtz and Henson for fully feedback linearizable systems.[29] Suppose the following conditions hold:

Condition 1 $\varsigma=n$.

Condition 2 The nonlinear state feedback

$$u(k)=\gamma(x(k),v(k)) \tag{10}$$

is a unique solution of the nonlinear algebraic equation (9) for all $x(k)\in\mathcal{R}^n$ and all $v(k)\in\mathcal{R}$.

Condition 3 $z(k)=\varphi(x(k),u(k))$ is a globally defined diffeomorphism, such that the nonlinear state feedback (10) yields the linear form

$$\begin{aligned} z(k+1) &= Az(k)+Bv(k), \\ y(k) &= Cz(k), \end{aligned} \tag{11}$$

where A, B, and C are:

$$A=\begin{pmatrix} 0 & 1 & 0 & \ldots & 0 & 0 \\ 0 & 0 & 1 & \ldots & 0 & 0 \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & 0 & \ldots & 0 & 1 \\ 0 & 0 & 0 & \ldots & 0 & 0\end{pmatrix}_{n\times n},$$

$$B=\begin{pmatrix} 0 \\ 0 \\ \ldots \\ 0 \\ 1\end{pmatrix}_{n\times 1}, \quad C=\begin{pmatrix} 1 & 0 & \ldots & 0 & 0\end{pmatrix}_{1\times n}.$$

Condition 4 The origin of the linear system (11) is stabilized with the pole-placement control law

$$\begin{aligned} v(k) &= -K\varphi(x(k),u(k)) = -Kz(k) \\ &= -k_n z_n(k) - k_{n-1} z_{n-1}(k) - \cdots - k_1 z_1(k), \end{aligned} \quad (12)$$

where k_i are adjustable controller parameters such that the eigenvalues of the matrix $A-BK$ are contained inside the unit circle.

Then, $x(k)=0$ is a globally asymptotically stable fixed point of the closed-loop system comprising Eqs. (1), (10), and (12).

2.2. MB-NPC scheme

From Assumptions 1–3, let $\tau_{\rm f} = n_{\rm f} + n_{\rm d}$ and $\tau_{\rm b} = n_{\rm b} + n_{\rm d}$. To obtain the states of the nonlinear plant on the controller side, a state estimation on the basis of Eq. (7) can be designed in the following:

$$\begin{aligned} \chi(k-\tau_{\rm b}) &= \phi^{-1}(y_{[n]}(k-\tau_{\rm b}-n+1), u_{[n-1]}(k-\tau_{\rm b}-n+1)), \\ \hat{x}(k-\tau_{\rm b}) &= f^{n-1}(\chi(k-\tau_{\rm b}), u_{[n-1]}(k-\tau_{\rm b}-n+1)), \end{aligned} \quad (13)$$

where $\hat{x}(k-i) \in \mathcal{R}^n$ denotes the state estimation for time $k-i$ based on the information of $u_{[n-1]}(k-i-n+1)$ and $y_{[n]}(k-i-n+1)$.

Although the state estimation equation (13) gives a one-step estimation of the states at time $k-\tau_{\rm b}$, the state predictions from time $k-\tau_{\rm b}+1$ and $k+\tau_{\rm f}$ are still not known. On the basis of the information available on the controller side, the state predictions from $k-\tau_{\rm b}+1$ and $k+\tau_{\rm f}$ can be obtained by

$$\begin{aligned} &\hat{x}(k-\tau_{\rm b}+1|k-\tau_{\rm b}) \\ &= f(\hat{x}(k-\tau_{\rm b}), u(k-\tau_{\rm b})), \\ &\hat{x}(k-\tau_{\rm b}+i|k-\tau_{\rm b}) \\ &= f(\hat{x}(k-\tau_{\rm b}+i-1|k-\tau_{\rm b}), u(k-\tau_{\rm b}+i-1)), \end{aligned} \quad (14)$$

where $i = 2,3,\ldots,\tau_{\rm b}+\tau_{\rm f}$. Clearly, both $\tau_{\rm b}$ and $\tau_{\rm f}$ are fixed. Based on the nonlinear plant model, all control inputs from $u(k-\tau_{\rm b})$ to $u(k+\tau_{\rm f}-1)$ are available on the controller side, although some of them are not applied to the plant at time t.

When the states of the plant are estimated, the observer-based state-feedback nonlinear controller is designed in this paper. The control prediction on the controller side is generated as follows:

$$u(k+\tau_{\rm f}|k-\tau_{\rm b}) = \gamma(\hat{x}(k+\tau_{\rm f}|k-\tau_{\rm b}), v(k+\tau_{\rm f}|k-\tau_{\rm b})). \quad (15)$$

On the actuator side, the control input will be taken as

$$\begin{aligned} u(k) &= u(k|k-\tau_{\rm b}-\tau_{\rm f}) \\ &= \gamma(\hat{x}(k|k-\tau_{\rm b}-\tau_{\rm f}), v(k|k-\tau_{\rm b}-\tau_{\rm f})). \end{aligned} \quad (16)$$

Similarly, the feedback in the linearized system (11) can be rewritten as

$$\begin{aligned} v(k) &= v(k|k-\tau_{\rm b}-\tau_{\rm f}) \\ &= h^{\circ} f^n(\hat{x}(k|k-\tau_{\rm b}-\tau_{\rm f}), u(k|k-\tau_{\rm b}-\tau_{\rm f})) \\ &= -K\varphi(\hat{x}(k|k-\tau_{\rm b}-\tau_{\rm f}), u(k|k-\tau_{\rm b}-\tau_{\rm f})). \end{aligned} \quad (17)$$

It is clear that the communication delays can be compensated by the above control strategy.

In order to deal with data loss, the following packet-based transmission method is adopted. Taking into account the output data loss in the feedback channel, one data packet of the output sequence at time k is sent from the sensor side to the controller side in the following:

$$\begin{pmatrix} y(k) \\ y(k-1) \\ \cdots \\ y(k-n_{\rm d}) \end{pmatrix}. \quad (18)$$

Similarly, to prevent the control data loss in the forward channel, the following predictive control sequence is sent from the controller side to the actuator side:

$$\begin{pmatrix} u(k+\tau_{\rm f}|k-\tau_{\rm b}) \\ u(k+\tau_{\rm f}-1|k-\tau_{\rm b}-1) \\ \cdots \\ u(k+n_{\rm f}|k-\tau_{\rm b}-n_{\rm d}) \end{pmatrix}. \quad (19)$$

On the basis of the time stamp of the transmitted data, two data buffers are used to reorder the received data. One is for the control input data on the actuator side, and the other is for the output data on the controller side. Therefore, under Assumptions 2 and 3, the output on the controller side and the control input on the actuator side are always available for use.

Remark 3 The networked predictive scheme was also proposed by Ouyang.[30] However, the state observer used a nonlinear change of coordinates in Ouyang's method. In this paper, a nonlinear change of coordinates is not required in state estimation.

3. Closed-loop stability analysis of MB-NPC system

Since communication delays and the MB-NPC scheme are involved, the stability analysis for networked nonlinear control systems plays a significant role in the design of the predictive controller, which is derived hereinafter.

Theorem 1 Consider the networked nonlinear system (1) with communication delays and data loss, where the communication delays are bounded by $n_{\rm b}$ and $n_{\rm f}$ in the feedback and forward channels and the number of consecutive data dropouts is bounded by $n_{\rm d}$ in both the feedback and forward channels. If all the conditions in Subsection 2.1 hold, the closed-loop system comprising Eqs. (1), (16), and (17) is asymptotically stable if and only if the eigenvalues of the matrix $A-BK$ lie in the unit circle.

Proof From Eq. (6), it can be obtained that

$$\begin{aligned} & x(k-\tau_{\rm b}-n+1) \\ &= \phi^{-1}(y_{[n]}(k-\tau_{\rm b}-n+1), u_{[n-1]}(k-\tau_{\rm b}-n+1)) \\ &= \chi(k-\tau_{\rm b}), \end{aligned} \tag{20}$$

where $k \geq \tau_{\rm b}+n-1$. From Eqs. (4) and (13), it can be obtained that $\forall\, k \geq \tau_{\rm b}+n-1$,

$$\begin{aligned} & \hat{x}(k-\tau_{\rm b}) \\ &= f^{n-1}(\chi(k-\tau_{\rm b}), u_{[n-1]}(k-\tau_{\rm b}-n+1)) \\ &= f^{n-1}(x(k-\tau_{\rm b}-n+1), u_{[n-1]}(k-\tau_{\rm b}-n+1)) \\ &= x(k-\tau_{\rm b}). \end{aligned} \tag{21}$$

Similarly,

$$\begin{aligned} \hat{x}(k-\tau_{\rm b}+1|k-\tau_{\rm b}) &= f(\hat{x}(k-\tau_{\rm b}), u(k-\tau_{\rm b})) \\ &= f(x(k-\tau_{\rm b}), u(k-\tau_{\rm b})) \\ &= x(k-\tau_{\rm b}+1), \end{aligned} \tag{22}$$

which uses Eq. (14). Using the above equation recursively results in

$$\hat{x}(k+\tau_{\rm f}|k-\tau_{\rm b}) = x(k+\tau_{\rm f}). \tag{23}$$

Let $k+\tau_{\rm f}$ be replaced by k in the above equation, which gives

$$\hat{x}(k|k-\tau_{\rm b}-\tau_{\rm f}) = x(k). \tag{24}$$

From the MB-NPC scheme, the control input of the nonlinear plant in Eq. (21) is

$$\begin{aligned} u(k) &= u(k|k-\tau_{\rm b}-\tau_{\rm f}) \\ &= \gamma(\hat{x}(k|k-\tau_{\rm b}-\tau_{\rm f}), -K\varphi(\hat{x}(k|k-\tau_{\rm b}-\tau_{\rm f}))) \\ &= \gamma(x(k), -K\varphi(x(k))). \end{aligned} \tag{25}$$

Substituting $\hat{x}(k|k-\tau_{\rm b}-\tau_{\rm f})$, $u(k|k-\tau_{\rm b}-\tau_{\rm f})$ into Eq. (17) by Eqs. (24) and (25) yields Eqs. (11) and (12). Thus, the closed-loop networked nonlinear system comprising Eqs. (1), (16), and (17) can be stabilized if and only if the eigenvalues of $A-BK$ are within the unit circle. The proof is completed.

Remark 4 It is clear from Theorem 1 that the stability of the closed-loop networked nonlinear predictive control system comprising Eqs. (1), (16), and (17) is not related to communication delays and data loss. By the MB-NPC scheme, a similar control performance can be provided as the one given by the local control system, therefore, the above design scheme largely simplifies the design procedure of the predictive controllers for networked nonlinear systems.

4. Simulated example

To illustrate the model-based networked predictive control scheme, the discrete-time model of the nonlinear system is described by

$$\begin{pmatrix} x_1(k+1) \\ x_2(k+1) \end{pmatrix} = \begin{pmatrix} x_1(k)\cos(x_2(k))+u(k) \\ 2x_1(k)+x_2^2(k) \end{pmatrix},$$

$$y(k) = x_2(k).$$

The initial conditions of the system states were chosen as $x_1(0) = -1.15$, $x_2(0) = 1.45$.

The implementation procedure of the model-based networked predictive controller is given in the following:

Step 1 Design the state observer. According to Eq. (7), it can be obtained that

$$\begin{pmatrix} \hat{x}_1(k) \\ \hat{x}_2(k) \end{pmatrix} = \begin{pmatrix} \chi_1(k)\cos(\chi_2(k))+u(k-1) \\ 2\chi_1(k)+\chi_2^2(k) \end{pmatrix},$$

where $\chi_1(k)$ and $\chi_2(k)$ can be calculated using Eq. (6)

$$\begin{pmatrix} \chi_1(k) \\ \chi_2(k) \end{pmatrix} = \begin{pmatrix} 0.5y(k)-0.5y^2(k-1) \\ y(k-1) \end{pmatrix}.$$

Step 2 Design the feedback linearizing controller. Construct a state-coordinate change Eq. (8)

$$\begin{aligned} z(k) &= \begin{pmatrix} z_1(k) \\ z_2(k) \end{pmatrix} = \begin{pmatrix} h(x(k)) \\ h^{\circ} f(x(k), u(k)) \end{pmatrix} \\ &= \begin{pmatrix} x_2(k) \\ 2x_1(k)+x_2^2(k) \end{pmatrix} \end{aligned}$$

and a feedback Eq. (9)

$$\begin{aligned} v(k) &= h^{\circ} f^2(x(k), u(k)) \\ &= (2x_1(k)+x_2^2(k))^2 + 2x_1(k)\cos(x_2(k)) + 2u(k), \end{aligned}$$

such that it yields the following linear system

$$\begin{aligned} \begin{pmatrix} z_1(k+1) \\ z_2(k+1) \end{pmatrix} &= \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} z_1(k) \\ z_2(k) \end{pmatrix} + \begin{pmatrix} 0 \\ 1 \end{pmatrix} v(k), \\ y(k) &= z_1(k). \end{aligned}$$

Considering local control, the desired poles of the linearized system are chosen to be $[0.53+0.21\mathrm{i}\ \ 0.53-0.21\mathrm{i}]$. Using the pole placement method, the control gain matrix K is designed to be $K = [k_1\ k_2] = [0.325\ \ -1.060]$. By Eq. (12), the local controller is obtained that $u(k) = -0.5k_1\hat{x}_2(k) - 0.5k_2(2\hat{x}_1(k) + \hat{x}_2^2(k)) - \hat{x}_1(k)\cos(\hat{x}_2(k)) - 0.5(2\hat{x}_1(k)+\hat{x}_2^2(k))^2$.

Step 3 Design the networked predictive controller. This can be achieved using the MB-NPC scheme in Subsection 2.2.

In this section, two cases are considered below.

Case 1 Networked control without MB-NPC scheme. In this case, the MB-NPC scheme is not employed, but a normal observer-based state-feedback control is used without taking into account network delay compensation. It is assumed that there exists a $\tau_{\rm f}$-step delay in the forward channel. Thus, the controller is given by $u(k) = -0.5k_1\hat{x}_2(k-\tau_{\rm f}) - 0.5k_2(2\hat{x}_1(k-\tau_{\rm f}) + \hat{x}_2^2(k-\tau_{\rm f})) - \hat{x}_1(k-\tau_{\rm f})\cos(\hat{x}_2(k-\tau_{\rm f})) - 0.5(2\hat{x}_1(k-\tau_{\rm f}) + \hat{x}_2^2(k-\tau_{\rm f}))^2$. The simulation results in Fig. 2 show that the closed-loop system is unstable.

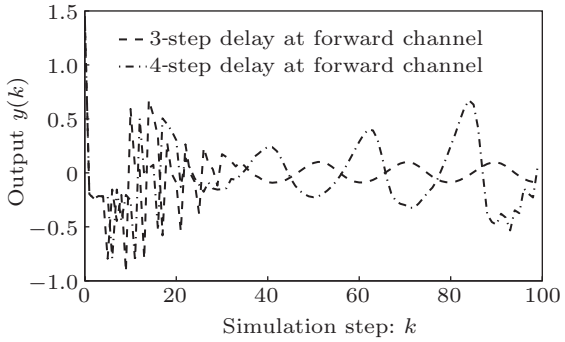


Fig. 2. Networked control without compensating for the communication delay.

Case 2 Networked predictive control. The model-based networked predictive control strategy is used to compensate for the network delay. The parameters of the networks in the forward and feedback channels are $\tau_f = 2$ and $\tau_b = 2$. The simulation results given in Fig. 3 demonstrate that the closed-loop system is asymptotic-stable when the designed controller parameters of the closed-loop MB-NPC system are the same as those of the local closed-loop system.

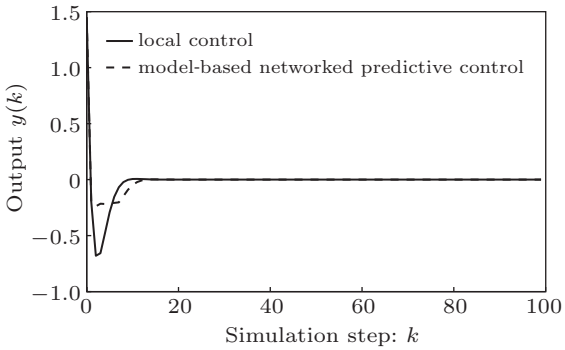


Fig. 3. Model-based networked predictive control.

5. Conclusion

This paper has addressed a design problem of NCSs with communication delay and data loss. The model-based networked predictive control scheme has been introduced to compensate for communication delay and data loss. An algorithm for designing a model-based predictive controller for networked systems has been proposed so that the closed-loop networked systems can achieve the desired poles and also guarantee the stability of the closed-loop system. Its feasibility and efficacy have been confirmed by the simulation results given in this paper.

Acknowledgment

The authors would like to thank Prof. Fu Yan-Ming and Dr. Ouyang Hua for their valuable discussion about stability analysis.

References

[1] Baillieul J 2004 *IEEE Trans. Autom. Control* **49** 1421
[2] An B R and Liu G P 2012 *Proceedings of the* 10*th World Congress on Intelligent Control and Automation*, July 6–8, 2012, Beijing, China, p. 831
[3] An B, Liu G and Chai S 2012 *Proceedings of the* 2012 *UKACC International Conference on Control*, September 3–5, 2012, Cardiff, United Kingdom, p. 834
[4] Garcia J, Palomo F R, Luque A, Aracil C, Quero J M, Carrion D, Gamiz F, Revilla P, Perez-Tinao J, Moreno M, Robles P and Franquelo L G 2004 *IEEE Trans. Ind. Electron.* **51** 1168
[5] Liu J, Munoz de la Pena D, Ohran B J, Christofides P D and Davis J F 2008 *Chem. Eng. Sci.* **63** 5394
[6] Wu J, Jia Q, Johansson K and Shi L 2013 *IEEE Trans. Autom. Control* **58** 1041
[7] Liu X and Kumar K D 2012 *IEEE Trans. Aero. Elec. Sys.* **48** 2302
[8] Bae J, Zhang W and Tomizuka M 2013 *IEEE Trans. Control Syst. Technol.* **21** 1980
[9] Goodwin G C, Haimovich H, Quevedo D E and Welsh J S 2004 *IEEE Trans. Autom. Control* **49** 1427
[10] Yang C X, Guan Z H and Huang J 2009 *J. Franklin Inst.* **346** 1006
[11] Mahmoud M S 2009 *Appl. Math. Comput.* **211** 33
[12] Chen J and Lau V 2012 *IEEE Trans. Signal Process.* **60** 443
[13] Zhang W A and Yu L 2010 *Acta Automatica Sinica* **36** 87
[14] Hu S and Zhu Q 2003 *Automatica* **39** 1877
[15] Yue D, Han Q L and Peng C 2004 *IEEE Trans. Circuits Syst. Express Briefs* **51** 640
[16] Yu Y B, Zhong Q S, Liao X F and Yu J B 2008 *Chin. Phys. B* **17** 842
[17] Hu W, Liu G P and Rees D 2007 *IEEE Trans. Ind. Electron.* **54** 1603
[18] Yu Y B, Bao J F, Zhang H B, Zhong Q S, Liao X F and Yu J B 2008 *Chin. Phys. B* **17** 2377
[19] Guan Z H, Yang S H and Yao J 2012 *Int. J. Robust Nonlinear Control* **22** 205
[20] Zhang Q L, Lu L and Zhang Y 2011 *Chin. Phys. B* **20** 090514
[21] Zhong P P, Zhang H N, Wang J D, Qin X J, Wei Z J, Chen S and Liu S H 2011 *Chin. Phys. B* **20** 050307
[22] Ciccarella G, Dalla Mora M and Germani A 1995 *Syst. Control Lett.* **24** 291
[23] Xiang Z R, Chen Q W and Hu W L 2001 *Kongzhi Lilun Yu Yingyong* **18** 80 (in Chinese)
[24] Aouaouda S, Chadli M, Shi P and Karimi H R 2013 *Int. J. Robust Nonlinear Control*
[25] Yang J, Li S, Sun C and Guo L 2013 *IEEE Trans. Aerosp. Electron. Syst.* **49** 1263
[26] Lee H G, Arapostathis A and Marcus S I 1987 *Int. J . Control* **45** 1803
[27] Monaco S and Normand-Cyrot D 1987 *Proceedings of the IEEE Conference on Decision and Control*, 1987, Los Angeles, CA, USA, p. 979
[28] Nijmeijer H and van der Schaft A J 1990 *Nonlinear Dynamical Control Systems* (New York: Springer)
[29] Kurtz M J and Henson M A 1998 *Int. J. Control* **70** 603
[30] Ouyang H, Liu G P, Rees D and Hu W 2007 *Proc. Inst. Mech. Eng. Part I J. Syst. Control Eng.* **221** 453