Design and Performance Analysis of Networked Predictive Control Systems Based on Input-Output Difference Equation Model

Zhong-Hua Pang*, Guo-Ping Liu, Donghua Zhou, and Dehui Sun

Abstract: This paper is concerned with the design and performance analysis of networked control systems, where random network-induced delay, packet disorder, and packet dropout in the feedback and forward channels are considered simultaneously and further treated as the round-trip time (RTT) delay. To actively compensate for the RTT delay, a networked predictive control scheme is designed based on the input-output difference equation model. For time-varying reference signals, the resulting closed-loop system can achieve the same output tracking performance and closed-loop stability as the corresponding local control system. Specifically, for the step reference input, it can provide a zero steady-state output tracking error. The controller design problem is solved by using the augmented state-space model as well as the static output feedback strategy. In addition, the stability of the closed-loop system is also discussed for the plant subject to bounded disturbances and modelling errors. Finally, simulation and experimental results are given to demonstrate the effectiveness of the proposed method.

Keywords: Networked control systems (NCSs), input-output model, predictive control, round-trip time delay, stability analysis, performance analysis.

1. INTRODUCTION

In recent years, networked control systems (NCSs) have been finding more and more applications in various fields such as process control, vehicle industry, teleoperation, transportation systems, and power grids, owing to their appealing features such as low installation and maintenance costs, high reliability, increased system flexibility, and decreased wiring. However, the utilization of communication network in control systems inevitably brings some communication constraints such as network-induced delay, packet disorder, and packet dropout, which may deteriorate the system performance or even destabilize the system. To overcome the adverse effect of these communication constraints, various approaches have been developed [1–5], among which a representative one is networked (or network-based) predictive control (NPC).

The existing NPC methods [6–20], to mention a few, can be divided into two classes. One is the NPC methods based on the state space model [6–13], where state feedback strategies or output feedback strategies are used in the controller design. The other is the NPC methods based on input-output difference equation model, in which model predictive control (MPC) algorithms or PID algorithms are used in the controller design [14–20]. Although the effectiveness of the aforementioned NPC methods has been confirmed by simulation or/and experimental results, they still have two drawbacks that 1) most of closed-loop stability conditions are only sufficient, and 2) the performance analysis for the closed-loop system is not clearly presented, which motivate the present study.

In this paper, the design and performance analysis of

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NCSs is investigated based on the input-output difference equation model. The network-induced delay, packet disorder, and packet dropout in the feedback and forward channels are considered, and further treated as the random but bounded round-trip time (RTT) delay. To actively compensate for the RTT delay, a model-based networked predictive control (MBNPC) scheme is designed. The main contributions of this paper include: 1) a static output feedback integral control law is proposed to construct control predictions based on the input-output difference equation model, 2) the performance and stability analysis is presented, and 3) the controller design method is introduced based on the corresponding augmented state-space model. Finally, both simulation and experimental results are provided to show the effectiveness of the proposed method.

Notation: Throughout the paper, Δ is the difference operator defined by $\Delta x(k) = x(k) - x(k-1)$, and $\mathrm{He}(M) = M + M^T$ denotes the Hermitian part of a square matrix M.

2. PROBLEM FORMULATION

Consider a plant described by the following input-output difference equation model:

$$a(z^{-1})y(k) = b(z^{-1})u(k-1), \tag{1}$$

where $y(k) \in \mathbb{R}$ and $u(k) \in \mathbb{R}$ are the output and input, respectively; and $a(z^{-1})$ and $b(z^{-1})$ are the polynomials with the orders of n_a and n_b, respectively, as follows:

$$a(z^{-1}) = 1 + a_1 z^{-1} + \cdots + a_{n_a} z^{-n_a},$$
$$b(z^{-1}) = b_0 + b_1 z^{-1} + \cdots + b_{n_b} z^{-n_b}.$$

Our purpose is to design a controller such that the system output $y(k)$ tracks a time-varying reference input $r(k)$. Define the output tracking error as

$$e(k) = r(k) - y(k). \tag{2}$$

For the local control (LC) of system (1), a controller is designed as

$$u(k) = K_1 y(k) + K_2 \sum_{i=0}^{k} e(i), \tag{3}$$

where K_1 and K_2 are the parameters to be determined. The control law in (3) is static output feedback control plus an integral control, which is thus named as static output feedback integral control (SOFIC). Its incremental form is

$$\Delta u(k) = K_1 \Delta y(k) + K_2 e(k). \tag{4}$$

For the networked control of system (1), the random network-induced delay, packet disorder, and packet dropout in the feedback (sensor-to-controller) and forward (controller-to-actuator) channels are considered simultaneously. The goal of this paper is to design a networked control scheme based on the SOFIC strategy in (4) such that the resulting closed-loop NCS is stable.

3. MBNPC SCHEME VIA SOFIC

The MBNPC scheme via SOFIC is shown in Fig. 1, which will be introduced in detail in the subsequent subsections. For the design of the MBNPC scheme, the following assumptions are first made.

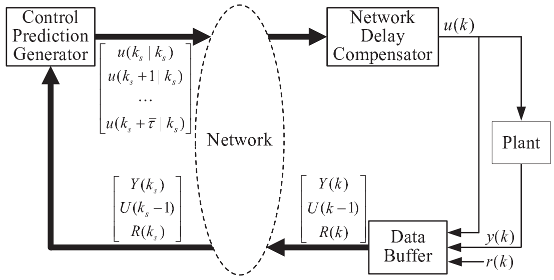

Fig. 1. MBNPC scheme.

Assumption 1: The sensor and the actuator are time-driven and synchronous, whereas the controller is event-driven.

Assumption 2: The RTT delay τ_k is bounded by $\bar{\tau}$, i.e., $\tau_k \leq \bar{\tau}$.

Remark 1: It is worth noting that, in the context of computer network, the RTT delay denotes the length of time it takes for a packet to be sent plus the length of time it takes for an acknowledgment of that packet to be received. It is obvious that the definition of the RTT delay is made for *each packet*. That is, the lost packet and the disordered packet also have their own RTT delay. The RTT delay of the former is infinite, and the RTT delay of the latter would be larger than that of in-order packets. As a result, the RTT delay would not have an upper bound. However, in general, the lost packet and the disordered packet are not used in NCSs for the purpose of real-time control. Therefore, the RTT delay is redefined in this paper, which is equal to the difference between the timestamp of the latest packet available in the actuator and the current time of the actuator at each time instant (see (13)). It is obvious that the new definition of the RTT delay is made for *each sampling instant* of the actuator, not for each packet. That is, no matter whether a packet is received or not, the actuator always calculates a real-time RTT delay by using the above new definition. As a consequence, the RTT delay will have an upper bound as long as the network are not broken. Furthermore, it can represent the joint effect of the network-induced delay, packet disorder, and packet dropout in both the feedback and forward channels.

3.1. Design of Data Buffer

At each sampling instant, the data buffer sends the following data with the timestamp k to the controller:

$$D_k = \left[Y(k)^T \; U(k-1)^T \; R(k)^T \right]^T, \tag{5}$$

where

$$Y(k) = [y(k)\ y(k-1)\cdots y(k-n_a)]^T,$$
$$U(k-1) = [u(k-1)\ u(k-2)\cdots u(k-1-n_b)]^T,$$
$$R(k) = [r(k)\ r(k+1)\cdots r(k+\bar{\tau})]^T.$$

3.2. Design of Control Prediction Generator

For clarity, the following operations are defined:

$$y(k+i|k) = y(k+i), \quad \text{if } i \le 0, \tag{6}$$
$$u(k+i|k) = u(k+i), \quad \text{if } i < 0, \tag{7}$$

where i is an integer.

When the feedback data in (5) arrive at the controller, the control signal is calculated based on the following SOFIC law:

$$u(k_s|k_s) = u(k_s-1) + K_1\Delta y(k_s) + K_2 e(k_s). \tag{8}$$

Then, the predictions of system output and control input up to time $k_s+\bar{\tau}$ can be obtained by the iteration of (1) and (8) as follows:

$$y(k_s+i|k_s) = a_1(z^{-1})y(k_s+i|k_s) + b(z^{-1})u(k_s+i-1|k_s), \tag{9}$$

$$\begin{aligned} u(k_s+i|k_s) = \ & u(k_s+i-1|k_s) + K_1\Delta y(k_s+i|k_s) \\ & + K_2 e(k_s+i|k_s), \end{aligned} \tag{10}$$

for $i = 1, 2, \cdots, \bar{\tau}$, where $a_1(z^{-1}) = 1 - a(z^{-1})$, and

$$\Delta y(k_s+i|k_s) = y(k_s+i|k_s) - y(k_s+i-1|k_s),$$
$$e(k_s+i|k_s) = r(k_s+i) - y(k_s+i|k_s).$$

It is clear from (8) and (10) that the following control prediction sequence is generated:

$$U_{k_s} = [u(k_s|k_s)\ u(k_s+1|k_s)\cdots u(k_s+\bar{\tau}|k_s)]^T, \tag{11}$$

which is lumped into one packet with the timestamp k_s and then transmitted to the actuator.

3.3. Design of Network Delay Compensator

Due to the presence of random network-induced delay, packet disorder, and packet dropout in the feedback and forward channels, it probably happens that one, more than one, or no packets arrive at the actuator during one sampling interval. Suppose that at time k, the latest control prediction sequence in the actuator is $U_{k_s^*}$ described by

$$U_{k_s^*} = [u(k_s^*|k_s^*)\ u(k_s^*+1|k_s^*)\cdots u(k_s^*+\bar{\tau}|k_s^*)]^T, \tag{12}$$

which is buffered in the network delay compensator (NDC), where k_s^* is its timestamp. At each execution instant k, the RTT delay can be obtained as follows:

$$\tau_k = k - k_s^*, \tag{13}$$

and to compensate for it, the NDC applies the following control signal to the plant:

$$u(k) = U_{k_s^*}(\tau_k) = u(k|k-\tau_k). \tag{14}$$

4. PERFORMANCE ANALYSIS AND CONTROLLER DESIGN

4.1. Performance Analysis

Theorem 1: For time-varying reference signals $r(k)$ with $r(k) = y_0$ for $k < \bar{\tau}$, where $y_0 \in \mathbb{R}$ is a steady-state value of the output $y(k)$, the MBNPC system can achieve the same output tracking performance as the corresponding local control system (LCS).

Proof: Without loss of generality, suppose that the steady-state control input $u(k-1) = u_0 \in \mathbb{R}$ for $k \le 0$. For the MBNPC system, it is obtained from (9) and (10) that

$$Y(k+1|k_s^*) = AY(k|k_s^*) + BU(k|k_s^*), \tag{15}$$

$$U(k|k_s^*) = CU(k-1|k_s^*) + DY(k|k_s^*) + Er(k), \tag{16}$$

where

$$Y(k|k_s^*) = [y(k|k_s^*)\ \ y(k-1|k_s^*)\ \ \cdots\ \ y(k-n_a|k_s^*)]^T,$$

$$U(k|k_s^*) = [u(k|k_s^*)\ \ u(k-1|k_s^*)\ \ \cdots\ \ u(k-n_b|k_s^*)]^T,$$

$$A = \begin{bmatrix} -a_1 & -a_2 & \cdots & -a_{n_a} & 0 \\ & & I_{n_a} & & 0_{n_a\times 1} \end{bmatrix},$$

$$B = \begin{bmatrix} b_0 & b_1 & \cdots & b_{n_b} \\ & 0_{n_a\times(n_b+1)} & & \end{bmatrix},\ C = \begin{bmatrix} 1 & 0_{1\times n_b} \\ I_{n_b} & 0_{n_b\times 1} \end{bmatrix},$$

$$D = \begin{bmatrix} K_1-K_2 & -K_1 & 0_{1\times(n_a-1)} \\ & 0_{n_b\times(n_a+1)} & \end{bmatrix},\ E = \begin{bmatrix} K_2 \\ 0_{n_b\times 1} \end{bmatrix},$$

and $k \ge k_s^* \ge 0$. Replacing $U(k|k_s^*)$ in (15) with (16) gives

$$Y(k+1|k_s^*) = (A+BD)Y(k|k_s^*) + BCU(k-1|k_s^*) + BEr(k). \tag{17}$$

Combining (16) and (17), we have

$$X(k+1|k_s^*) = \Lambda X(k|k_s^*) + \Gamma r(k), \tag{18}$$

where

$$X(k|k_s^*) = \left[Y(k|k_s^*)^T\ \ U(k-1|k_s^*)^T\right]^T,$$

$$\Lambda = \begin{bmatrix} A+BD & BC \\ D & C \end{bmatrix},\ \Gamma = \begin{bmatrix} BE \\ E \end{bmatrix}.$$

It is clear from (14) and (18) that

$$u(k) = I_u X(k+1|k_s^*), \tag{19}$$

where $I_u = \left[0_{1\times(n_a+1)}\ \ 1\ \ 0_{1\times n_b}\right]$.

Similarly for the LCS, it is obtained from (1) and (4) that

$$Y(k+1) = AY(k) + BU(k), \tag{20}$$

$$U(k) = CU(k-1) + DY(k) + Er(k), \tag{21}$$

and thus, the closed-loop LCS can be described by

$$X_L(k+1) = \Lambda X_L(k) + \Gamma r(k), \tag{22}$$

where $X_L(k)=[Y(k)^T\ U(k-1)^T]^T$ with $Y(k)$ and $U(k-1)$ defined in (5), and the subscript "L" denotes the variable corresponding to the LCS (the same below).

Then, it follows from (18) and (22) that

$$\begin{aligned} X(k+1|k_s^*) &= \Lambda^{\tau_k+1}X(k_s^*|k_s^*)+\sum_{j=0}^{\tau_k}\Lambda^j\Gamma r(k-j) \\ &= \Lambda^{\tau_k+1}X(k_s^*)+\sum_{j=0}^{\tau_k}\Lambda^j\Gamma r(k-j), \end{aligned} \tag{23}$$

$$X_L(k+1)=\Lambda^{\tau_k+1}X_L(k_s^*)+\sum_{j=0}^{\tau_k}\Lambda^j\Gamma r(k-j), \tag{24}$$

where $X(k_s^*)=\left[Y(k_s^*)^T\ U(k_s^*-1)^T\right]^T$.

With $y(k)=y_0$ and $u(k-1)=u_0$ satisfying (1) for $k\leq 0$, as well as the initial reference signal $r(k)=y_0$ for $k<\bar{\tau}$, it is obtained for the LCS from (4) and (1) that

$$u_L(k-1)=u_0, \tag{25}$$

$$X_L(k)=X_L(0), \tag{26}$$

for $k=0,1,2,\cdots,\bar{\tau}$.

Then, for the MBNPC system, from (9), (10), (23), (19), and (14), it can be calculated that

$$u(k_s^*-1)=u_0, \tag{27}$$

$$X(k_s^*)=X(0)=X_L(0), \tag{28}$$

$$X(k_s^*+i+1|k_s^*)=\begin{cases} X(0), & \text{if } k_s^*+i<\bar{\tau} \\ \Lambda_s^{k_s^*+i-\bar{\tau}}, & \text{if } k_s^*+i\geq\bar{\tau}, \end{cases} \tag{29}$$

$$U_{k_s^*}=\left[u_0\ u_0\ \cdots\ u_0\ I_u\Lambda_s^0\ I_u\Lambda_s^1\cdots I_u\Lambda_s^{k_s^*}\right]^T, \tag{30}$$

$$u(k_s^*)=U_{k_s^*-\tau_{k_s^*}}(\tau_{k_s^*}), \tag{31}$$

for $k_s^*=0,1,2,\cdots,\bar{\tau}$, where $i\geq 0$ is an integer, and

$$\Lambda_s^i=\Lambda^{i+1}X(0)+\sum_{j=0}^{i}\Lambda^j\Gamma r(\bar{\tau}+i-j).$$

Then, from (26), (28), and (29), we have

$$X(k)=X(k|k_s^*)=X_L(k), \tag{32}$$

for $k\leq\bar{\tau}$.

At time $k\geq\bar{\tau}$, due to the upper bound $\bar{\tau}$ of the RTT delay, at least one control prediction sequence (12) is available in the actuator. As a result, with the initial state in (32) and the same reference singals, it can be obtained from (23) and (24) that

$$X(k+1|k_s^*)=X_L(k+1), \tag{33}$$

for $k\geq\bar{\tau}$. Furthermore, by using the similar procedure in (27)-(31), we obtain

$$X(k+1)=X(k+1|k_s^*), \tag{34}$$

for $k\geq\bar{\tau}$. Thus, from (32)-(34), we have

$$X(k+1)=X_L(k+1), \tag{35}$$

for all $k\geq 0$. That is, the outputs and inputs of the MBNPC system are always equal to those of the corresponding LCS. The proof is completed. □

The stability condition of the MBNPC system is given by the following corollary:

Corollary 1: The MBNPC system is stable if and only if the eigenvalues of the matrix Λ are within the unit circle.

Proof: From (22) and (35), it is obtained that the MBNPC system is equivalent to the following form:

$$X(k+1)=\Lambda X(k)+\Gamma r(k). \tag{36}$$

Clearly, the MBNPC system is stable if and only if the eigenvalues of the matrix Λ are within the unit circle. □

Remark 2: It is worth noting that, compared with the stability conditions in [6–20] that are only sufficient, Corollary 1 gives a necessary and sufficient condition for the stability of the MBNPC system. Furthermore, the condition is not related to random RTT delays, which is significant for the design of MBNPC systems.

Next, we will analyze the output tracking performance of the MBNPC system for the step reference input.

Theorem 2: If the eigenvalues of matrix Λ are within the unit circle and $K_2\sum_{j=0}^{n_b}b_j\neq 0$, the MBNPC system can achieve a zero steady-state output tracking error for the following step reference input:

$$r(k)=\begin{cases} y_0, & k<\bar{\tau}, \\ \bar{r}, & k\geq\bar{\tau}, \end{cases} \tag{37}$$

where $\bar{r}\in\mathbb{R}$ is a constant.

Proof: It is obtained from (28), (34), and (37) that

$$\begin{aligned} X(k) &= \Lambda^{k-\bar{\tau}}X(\bar{\tau})+\sum_{j=0}^{k-\bar{\tau}-1}\Lambda^j\Gamma r(k-1-j) \\ &= \Lambda^{k-\bar{\tau}}X(0)+\sum_{j=0}^{k-\bar{\tau}-1}\Lambda^j\Gamma\bar{r}, \end{aligned} \tag{38}$$

for $k>\bar{\tau}$. With $y(k)=I_yX(k)$, $I_y=\left[1\ \ 0_{1\times(n_a+n_b+1)}\right]$, the steady-state output is obtained from (38) as

$$\begin{aligned} y_\infty &= \lim_{k\to\infty}I_y\Lambda^{k-\bar{\tau}}X(0)+\lim_{k\to\infty}I_y\sum_{j=0}^{k-\bar{\tau}-1}\Lambda^j\Gamma\bar{r} \\ &= 0+I_y(I-\Lambda)^{-1}\Gamma\bar{r}=\bar{r}, \end{aligned} \tag{39}$$

since the eigenvalues of the matrix Λ are within the unit circle. The proof of the equation $I_y(I-\Lambda)^{-1}\Gamma\bar{r}=\bar{r}$ in (39) is presented in the Appendix A. Therefore, it can be seen from (39) that the MBNPC system achieves a zero steady-state output tracking error for the step reference signal in (37). The proof is completed. □

Remark 3: It should be pointed out that, in the previous literature on NPC methods [6–20], the performance analysis was generally not involved. To evaluate the performance of NPC methods, only some tentative judgments were usually given by numerical or/and experimental results, for instance, “satisfactory", “desired", and “good", as well as “similar" and “almost the same" (compared with the LCS), and “superior" and “improved" (compared with the NCS without compensation). However, in this paper, it is *theoretically* established in Theorem 1 that the MBNPC system can achieve the same output tracking performance as the corresponding LCS. Specifically for the step reference input, it is derived that the MBNPC system can achieve a zero steady-state output tracking error.

4.2. Controller Design

Since the stability of the MBNPC system is not related to the RTT delay, the design of the SOFIC parameters, K_1 and K_2, can follow the design procedure of the LCS. As an example, System (1) can be written in the following state-space form:

$$\begin{aligned} x(k+1) &= \tilde{A}x(k) + \tilde{B}u(k), \\ y(k) &= \tilde{C}x(k), \end{aligned} \tag{40}$$

where $x(k) \in \mathbb{R}^{n_a}$ is the system state, and $\tilde{A}$, $\tilde{B}$, and $\tilde{C}$ are matrices with appropriate dimensions. System (1) can be further written into an incremental form:

$$\begin{aligned} \Delta x(k+1) &= \tilde{A}\Delta x(k) + \tilde{B}\Delta u(k), \\ \Delta y(k) &= \tilde{C}\Delta x(k). \end{aligned} \tag{41}$$

From (2) and (41), it learns that

$$e(k+1) = e(k) - \tilde{C}\tilde{A}\Delta x(k) - \tilde{C}\tilde{B}\Delta u(k) + \Delta r(k+1). \tag{42}$$

Then, from (41) and (42), we obtain the following augmented system:

$$\begin{aligned} x_e(k+1) &= A_e x_e(k) + B_e \Delta u(k) + E_e \Delta r(k+1), \\ y_e(k) &= C_e x_e(k), \end{aligned} \tag{43}$$

where

$$x_e(k) = \begin{bmatrix} \Delta x(k) \\ e(k) \end{bmatrix} \in \mathbb{R}^{n_a+1}, \; y_e(k) = \begin{bmatrix} \Delta y(k) \\ e(k) \end{bmatrix} \in \mathbb{R}^2,$$

$$A_e = \begin{bmatrix} \tilde{A} & 0_{n_a \times 1} \\ -\tilde{C}\tilde{A} & 1 \end{bmatrix}, B_e = \begin{bmatrix} \tilde{B} \\ -\tilde{C}\tilde{B} \end{bmatrix},$$

$$E_e = \begin{bmatrix} 0_{n_a \times 1} \\ 1 \end{bmatrix}, C_e = \begin{bmatrix} \tilde{C} & 0 \\ 0_{1 \times n_a} & 1 \end{bmatrix}.$$

Thus, the SOFIC law in (4) is equivalent to a static output feedback (SOF) law for augmented system (43), i.e.,

$$\Delta u(k) = K y_e(k), \tag{44}$$

where $K = [K_1 \;\; K_2]$ is the control gain. Then, the closed-loop system with $\Delta r(k+1) = 0$ is

$$x_e(k+1) = (A_e + B_e K C_e) x_e(k). \tag{45}$$

Various convex sufficient conditions for designing the SOF controller (44) have been proposed in recent years (see [21] and references therein). Among these existing works, LMI approaches are more popular due to the simplicity and efficiency, for example, in [22, 23]. In this paper, the controller design methods in [23] are used to compute the gain K, which are described in the following two cases. In addition, they are also modified to reduce the conservatism (see Remark 4).

1) C_e with full row-rank: The output matrix C_e is of full row-rank, which means that a non-singular matrix T_c can be found such that $C_e T_c = [I \;\; 0]$.

Theorem 3: If there exist a symmetric positive matrix P_c, and matrices G_c, F_c, L_c with the following structure

$$G_c = \begin{bmatrix} G_{c11} & 0 \\ G_{c21} & G_{c22} \end{bmatrix}, F_c = \begin{bmatrix} \lambda_c G_{c11} & 0 \\ F_{c21} & F_{c22} \end{bmatrix}, L_c = \begin{bmatrix} L_{c1} & 0 \end{bmatrix}, \tag{46}$$

satisfying the following LMI

$$\begin{bmatrix} P_c - \mathrm{He}(\bar{G}_c) & * \\ A_e\bar{G}_c + B_e\bar{L}_c - \bar{F}_c^T & \mathrm{He}(A_e\bar{F}_c + \lambda_c B_e \bar{L}_c) - P_c \end{bmatrix} < 0, \tag{47}$$

where $\lambda_c \in \mathbb{R}$, $\bar{G}_c = T_c G_c S_c$, $\bar{F}_c = T_c F_c S_c$, $\bar{L}_c = L_c S_c$, and $S_c = I$ or $S_c = T_c^T$. Then the SOF controller (44) with $K = L_{c1} G_{c11}^{-1}$ renders the closed-loop system (45) stable.

2) B_e with full column-rank: When the input matrix B_e is of full column-rank, there exists a non-singular matrix T_b such that $T_b B_e = [I \;\; 0]^T$.

Theorem 4: If there exist a symmetric positive matrix P_b, and matrices G_b, F_b, L_b with the following structure

$$G_b = \begin{bmatrix} G_{b11} & G_{b12} \\ 0 & G_{b22} \end{bmatrix}, F_b = \begin{bmatrix} \lambda_b G_{b11} & F_{b12} \\ 0 & F_{b22} \end{bmatrix}, L_b = \begin{bmatrix} L_{b1} \\ 0 \end{bmatrix}, \tag{48}$$

satisfying the following LMI

$$\begin{bmatrix} P_b - \mathrm{He}(\bar{G}_b) & \bar{G}_b A_e + \bar{L}_b C_e - \bar{F}_b^T \\ * & \mathrm{He}(\bar{F}_b A_e + \lambda_b \bar{L}_b C_e) - P_b \end{bmatrix} < 0, \tag{49}$$

where $\lambda_b \in \mathbb{R}$, $\bar{G}_b = S_b G_b T_b$, $\bar{F}_b = S_b F_b T_b$, $\bar{L}_b = S_b L_b$, and $S_b = I$ or $S_b = T_b^T$. Then the SOF controller (44) with $K = G_{b11}^{-1} L_{b1}$ makes the closed-loop system (45) stable.

Remark 4: It should be noted that matrices S_c and S_b actually play an important role in the above LMI conditions. S_c=I or T_c^T and S_b=I or T_b^T are set in Theorems 3 and 4, respectively, which obviously gives rise to a certain conservatism. In order to reduce the conservatism, S_c and S_b can be chosen as arbitrary invertible matrices. Hence, the improved LMI conditions for designing the SOF controller are generalized sufficiently to cover the cases of Theorems 3 and 4. At the same time, the invertibility of S_c and S_b, as well as the triangular structure of G_c and G_b, guarantees the invertibility of G_{c11} and G_{b11}.

Remark 5: It is noted that, in the above derivation, the disturbances and modelling errors are not considered, similar to [6–12] and [15–19]. However, in practice, unknown disturbances and modelling errors are usually inevitable. Thus, the plant is generally described by

$$a(z^{-1})y(k) = b(z^{-1})u(k-1) + \upsilon(k), \tag{50}$$

where $\upsilon(k) \in \mathbb{R}$ is the bounded random noise. In addition, without loss of generality, the following model is available for system (1) due to the presence of modelling errors:

$$\hat{a}(z^{-1})y(k) = \hat{b}(z^{-1})u(k-1), \tag{51}$$

with

$$\begin{cases} \hat{a}(z^{-1}) = 1 + \hat{a}_1 z^{-1} + \cdots + \hat{a}_{n_a} z^{-n_a}, \\ \hat{b}(z^{-1}) = \hat{b}_0 + \hat{b}_1 z^{-1} + \cdots + \hat{b}_{n_b} z^{-n_b}. \end{cases}$$

In this case, the system output predictions are calculated in the controller by using the following equation:

$$y(k_s+i|k_s) = \hat{a}_1(z^{-1})y(k_s+i|k_s) + \hat{b}(z^{-1})u(k_s+i-1|k_s), \tag{52}$$

where $\hat{a}_1(z^{-1}) = 1 - \hat{a}(z^{-1})$. The corresponding stability analysis for the MBNPC scheme is presented as follows.

Let the reference signal $r(k) = 0$, and similar to the derivation of (18), it is obtained from (52) and (10) that

$$X(k+1|k-\tau_k) = \hat{\Lambda}X(k|k-\tau_k) = \hat{\Lambda}^{\tau_k+1}X(k-\tau_k), \tag{53}$$

where

$$\hat{\Lambda} = \begin{bmatrix} \hat{A}+\hat{B}D & \hat{B}C \\ D & C \end{bmatrix}, \hat{B} = \begin{bmatrix} \hat{b}_0 & \hat{b}_1 & \cdots & \hat{b}_{n_b} \\ & 0_{n_a\times(n_b+1)} & & \end{bmatrix},$$

$$\hat{A} = \begin{bmatrix} -\hat{a}_1 & -\hat{a}_2 & \cdots & -\hat{a}_{n_a} & 0 \\ & I_{n_a} & & & 0_{n_a\times 1} \end{bmatrix}.$$

From (19) and (53), we have

$$u(k) = I_u X(k+1|k-\tau_k) = F_{\tau_k} X(k-\tau_k), \tag{54}$$

where $F_{\tau_k} = I_u \hat{\Lambda}^{\tau_k+1} = [f_{\tau_k,1}\ f_{\tau_k,2} \cdots f_{\tau_k,\bar{n}}]$ with $\bar{n} = n_a + n_b + 2$. Then, Equations (50) and (54) can be rewritten as

$$\bar{Y}(k+1) = \bar{A}\bar{Y}(k) + \bar{B}\bar{U}(k) + \bar{E}\upsilon(k+1), \tag{55}$$

$$\bar{U}(k) = \bar{C}_{\tau_k}\bar{U}(k-1) + \bar{D}_{\tau_k}\bar{Y}(k), \tag{56}$$

where

$$\bar{Y}(k) = [y(k)\ \ y(k-1)\ \cdots\ y(k-\bar{\tau}-n_a)]^T,$$

$$\bar{U}(k) = [u(k)\ \ u(k-1)\ \cdots\ u(k-\bar{\tau}-n_b)]^T,$$

$$\bar{A} = \begin{bmatrix} -a_1 & -a_2 & \cdots & -a_{n_a} & 0_{1\times(\bar{\tau}+1)} \\ & I_{n_a+\bar{\tau}} & & & 0_{(n_a+\bar{\tau})\times 1} \end{bmatrix},$$

$$\bar{B} = \begin{bmatrix} b_0 & b_1 & \cdots & b_{n_b} & 0_{1\times\bar{\tau}} \\ & 0_{(n_a+\bar{\tau})\times(n_b+\bar{\tau}+1)} & & & \end{bmatrix}, \bar{E} = \begin{bmatrix} 1 \\ 0_{(n_a+\bar{\tau})\times 1} \end{bmatrix},$$

$$\bar{C}_{\tau_k} = \begin{bmatrix} 0_{1\times\tau_k} & f_{\tau_k,n_a+2} & \cdots & f_{\tau_k,\bar{n}} & 0_{1\times(\bar{\tau}-\tau_k)} \\ & I_{n_b+\bar{\tau}} & & & 0_{(n_b+\bar{\tau})\times 1} \end{bmatrix},$$

$$\bar{D}_{\tau_k} = \begin{bmatrix} 0_{1\times\tau_k} & f_{\tau_k,1} & \cdots & f_{\tau_k,n_a+1} & 0_{1\times(\bar{\tau}-\tau_k)} \\ & & 0_{(n_b+\bar{\tau})\times(n_a+1+\bar{\tau})} & & \end{bmatrix}.$$

Combining (55) and (56) yields the following closed-loop system:

$$\bar{X}(k+1) = \bar{\Lambda}(\tau_k)\bar{X}(k) + \bar{\Gamma}\upsilon(k+1), \tag{57}$$

where

$$\bar{X}(k) = [\bar{Y}(k)^T\ \ \bar{U}(k-1)^T]^T,$$

$$\bar{\Lambda}(\tau_k) = \begin{bmatrix} \bar{A}+\bar{B}\bar{D}_{\tau_k} & \bar{B}\bar{C}_{\tau_k} \\ \bar{D}_{\tau_k} & \bar{C}_{\tau_k} \end{bmatrix}, \bar{\Gamma} = \begin{bmatrix} \bar{E} \\ 0_{(n_b+1+\bar{\tau})\times 1} \end{bmatrix}.$$

It is clear from (57) that the stability of the MBNPC system is not related to the bounded noise $\upsilon(k)$. Furthermore, the following stability condition can be obtained.

Theorem 5: For system (50) with the model in (51), the closed-loop MBNPC system (57) is stable if there exist $\bar{\tau}+1$ positive definite matrices $P(\tau_k)$ satisfying

$$\bar{\Lambda}^T(\tau_k)P(\tau_{k+1})\bar{\Lambda}(\tau_k) - P(\tau_k) < 0. \tag{58}$$

Proof: The proof can refer to [18], and thus is omitted here. □

5. SIMULATION RESULTS

To illustrate the effectiveness of the proposed MBNPC method, a servo motor system (SMS) shown in Fig. 5 is considered. For the sampling period 0.04s, its model is

$$\frac{b(z^{-1})}{a(z^{-1})} = \frac{3.5629z^{-1} + 2.7739z^{-2} + 1.0121z^{-3}}{1 - 1.2998z^{-1} + 0.4341z^{-2} - 0.1343z^{-3}}, \tag{59}$$

which can be written in the form of (40) with

$$\tilde{A} = \begin{bmatrix} 1.2998 & -0.4341 & 0.1343 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}, \tilde{B} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix},$$

$$\tilde{C} = \begin{bmatrix} 3.5629 & 2.7739 & 1.0121 \end{bmatrix}.$$

Theorems 3 and 4 can be used to calculate the gain K. Note that different methods may give different solvability. The solvability results for system (59) are listed in Table 1. Then using Theorem 3 with $\lambda_c = 0.1221$ and the following invertible matrix

$$S_c = \begin{bmatrix} -0.1890 & -0.5038 & -0.3549 & 1.9114 \\ -0.6509 & -0.7878 & 0.8059 & -2.2413 \\ 0.7085 & -0.1315 & 1.4301 & -0.2528 \\ 0.5223 & 1.1787 & 0.6622 & 0.6948 \end{bmatrix},$$

the gain K is calculated to be

$$K = \begin{bmatrix} -0.0519 & 0.0138 \end{bmatrix}, \tag{60}$$

which gives a stable closed-loop system with the closed-loop poles $\{0.6144 \pm 0.4221i,\ 0.5856,\ 0.2513\}$.

Table 1. Solvability of different methods in Theorems 3 and 4

Theorem	Method	Solvability
3	$S_c = I$	Yes
	$S_c = T_c^T$	Yes
	$S_c = \mathrm{IM}^1$	Yes
4	$S_b = I$	Yes
	$S_b = T_b^T$	No
	$S_b = \mathrm{IM}^1$	Yes

[1] IM denotes a given invertible matrix, as stated in Remark 4.

5.1. NCS without Compensation

When RTT delays are randomly chosen to be 4$\sim$7 steps, the output response of the NCS without network delay compensation is shown in Fig. 2, from which it can be seen that the closed-loop NCS without compensation becomes unstable.

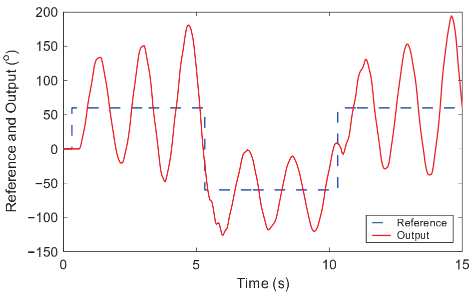

Fig. 2. Performance of NCS without compensation (simulation case).

5.2. MBNPC System

With the same 4$\sim$7 RTT delays, the simulation result of the MBNPC method is given in Fig. 3, which indicates that the closed-loop system is stable. Moreover, the performance of the MBNPC system (red solid line) is the same as that of the LCS (black dotted line) with zero steady-state output tracking errors, which coincides with the results of performance analysis in Section 4.1.

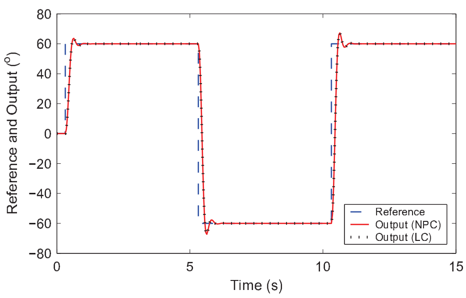

Fig. 3. Performance of MBNPC system (simulation case).

Then, the capability of the MBNPC method in handling measurement noise and modelling errors is tested. Suppose that, the following model polynomials are available for the SMS in (59):

$$\begin{cases} \hat{a}(z^{-1}) = 1 + 0.9a_1 z^{-1} + 0.8a_2 z^{-2} + 1.1a_3 z^{-3}, \\ \hat{b}(z^{-1}) = 0.7b(z^{-1}). \end{cases} \tag{61}$$

With the controller gain in (60), the positive definite matrices $P(\tau_k)$ for τ_k=4,5,6,7 can be obtained by solving the LMIs in (58), of which the dimension is 21 and thus their values are omitted here. Hence, it is clear from Theorem 5 that, with the model mismatch between (59) and (61), the closed-loop MBNPC system is stable. Furthermore, a zero-mean Gaussian white noise $\xi(k)$ with variance 6.0 is added to the output of the SMS, where $\xi(k) = \upsilon(k)/a(z^{-1})$. The simulation result is shown in Fig. 4, which indicates that, with the model in (61) and the measurement noise $\xi(k)$, the closed-loop MBNPC system is still stable.

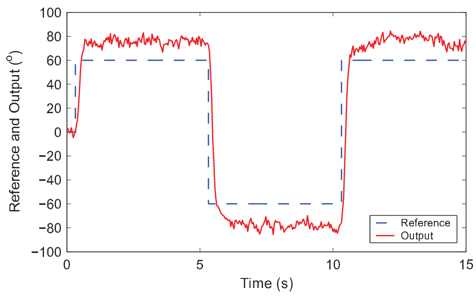

Fig. 4. Performance of MBNPC system with measurement noise and modelling errors (simulation case).

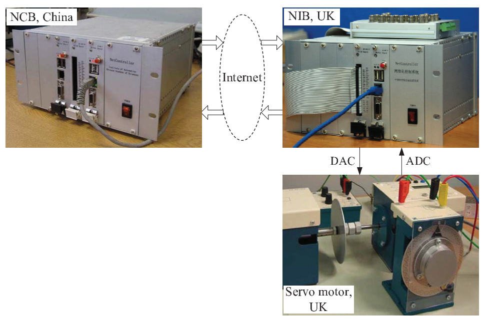

Fig. 5. Internet-based SMS.

6. EXPERIMENTAL RESULTS

6.1. Internet-Based SMS

To further test the MBNPC method in practice, an Internet-based SMS is built, as shown in Fig. 5. It consists of an SMS, a networked implementation board (NIB), and a networked controller board (NCB). The SMS is located in the University of South Wales, Pontypridd, UK, whose input and output are the control voltage (-10V $\sim$ 10V) and the angle position ($-120°$ $\sim$ $120°$), respectively. The NIB is directly connected to the SMS through wires. The NCB is placed in the Tsinghua University, Beijing, China, which is connected with the NIB through the Internet. With the sampling period 0.04s, the RTT delays of the Internet vary from 4 to 7 steps, as shown in Fig. 6.

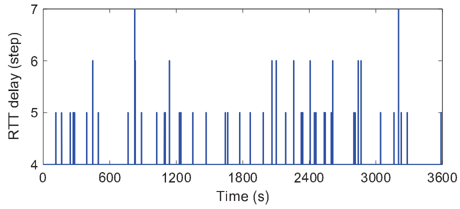

Fig. 6. RTT delays between NCB (China) and NIB (UK).

6.2. Practical Experiments

Although the SMS in Fig. 5 is actually nonlinear in nature, a simple linear model in (59) is used here. The SOFIC gain K is chosen to be the same as that in the simulation, as shown in (60). The output responses of the NCS without compensation and MBNPC system are shown in Figs. 7 and 8, respectively. It can be seen that, with the random RTT delays shown in Fig. 6, the NCS without compensation becomes unstable, and the MBNPC system is stable with a good performance (thick red line). In addition, for comparison, the NPC method in [18] is applied to the SMS, and the experimental result is also shown in Fig. 8 (thin black line). It can be seen that the NPC method in [18] produces large overshoots at each step change of the reference input due to large control actions.

It should be noted that, due to the mismatch between the model in (59) and the SMS, the MBNPC method yields a certain steady-state output tracking error, as shown in Fig. 8. To improve the performance of the MBNPC method, an online parameter estimator is designed in the controller to make the identified model close to the real plant. The experimental result is shown in Fig. 9 (thick red line). It can seen that the output response is superior to that of the MBNPC system with the fixed model in (59), and is comparable to that of the corresponding LCS (thin black line).

7. CONCLUSIONS

This paper has investigated the design and performance analysis of NCSs. Based on the input-output difference equation model, a networked predictive control scheme via a static output feedback integral controller has been presented to actively compensate for the network-induced delay, packet disorder, and packet dropout in the feedback and forward channels. The resulting closed-loop system can guarantee the stability and also achieve the desired output tracking performance.

Compared with the existing works on NPC methods, for example, [6–20], the main merits of this paper are twofold. First, it has been proved that, for time-varying reference signals, the MBNPC system can achieve the same output tracking performance as the corresponding LCS. Especially, it can guarantee a zero steady-state output tracking error for the step reference input. Second, a necessary and sufficient condition has been derived for the stability of the MBNPC system. Furthermore, the condition is not related to the RTT delay, and thus the controller design procedure of the MBNPC system can follow that of the LCS. The above merits have been also confirmed by the simulation and experimental results given in this paper.

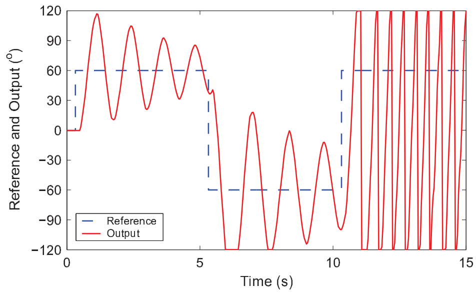

Fig. 7. Performance of NCS without compensation (experimental case).

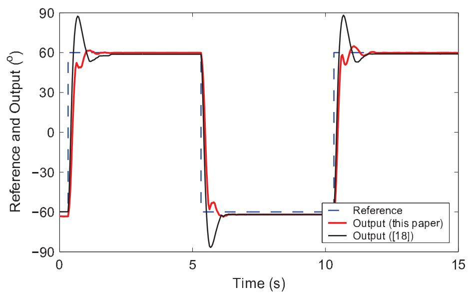

Fig. 8. Performance of MBNPC system (experimental case).

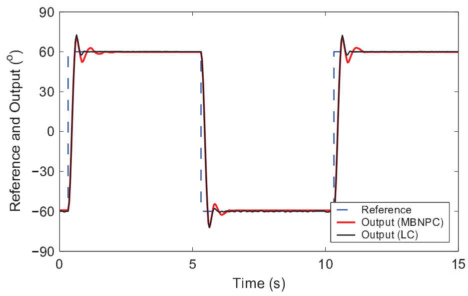

Fig. 9. Performance of MBNPC system with online estimator (experimental case).

APPENDIX A

1. Proof of Equation (39)

It is obtained from (18) that

$$\bar{\Lambda} = I - \Lambda = \begin{bmatrix} \bar{\Lambda}_{11} & \bar{\Lambda}_{12} \\ \bar{\Lambda}_{21} & \bar{\Lambda}_{22} \end{bmatrix} \tag{A,1}$$

where

$$\bar{\Lambda}_{11} = \begin{bmatrix} \bar{\lambda}_1 & \bar{\lambda}_2 & a_3 & \cdots & a_{n_a} & 0 & -b_0 - b_1 \\ -1 & 1 & 0 & \cdots & 0 & 0 & 0 \\ 0 & -1 & 1 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & -1 & 1 & 0 \\ K_2 - K_1 & K_1 & 0 & \cdots & 0 & 0 & 0 \end{bmatrix} \in \mathbb{R}^{(n_a+2)\times(n_a+2)}$$

$$\bar{\Lambda}_{12} = \begin{bmatrix} -b_2 & -b_3 & \cdots & -b_{n_b} & 0 \\ & & 0_{(n_a+1)\times n_b} & & \end{bmatrix} \in \mathbb{R}^{(n_a+2)\times n_b}$$

$$\bar{\Lambda}_{21} = \begin{bmatrix} 0 & 0 & \cdots & 0 & -1 \\ & & 0_{(n_b-1)\times(n_a+2)} & & \end{bmatrix} \in \mathbb{R}^{n_b\times(n_a+2)}$$

$$\bar{\Lambda}_{22} = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 \\ -1 & 1 & 0 & \cdots & 0 & 0 \\ 0 & -1 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & 0 \\ 0 & 0 & 0 & \cdots & -1 & 1 \end{bmatrix} \in \mathbb{R}^{n_b\times n_b}$$

$\bar{\lambda}_1 = 1 + a_1 - b_0(K_1 - K_2)$, and $\bar{\lambda}_2 = a_2 + b_0 K_1$.

Then, the Schur complement of $\bar{\Lambda}_{22}$ is

$$S_{\bar{\Lambda}_{22}} = \bar{\Lambda}_{11} - \bar{\Lambda}_{12}(\bar{\Lambda}_{22})^{-1}\bar{\Lambda}_{21} = \begin{bmatrix} \bar{\lambda}_1 & \bar{\lambda}_2 & a_3 & \cdots & a_{n_a} & 0 & -\sum_{j=0}^{n_b} b_j \\ -1 & 1 & 0 & \cdots & 0 & 0 & 0 \\ 0 & -1 & 1 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & -1 & 1 & 0 \\ K_2 - K_1 & K_1 & 0 & \cdots & 0 & 0 & 0 \end{bmatrix}. \tag{A,2}$$

Since $|\bar{\Lambda}_{22}| \neq 0$ and $|S_{\bar{\Lambda}_{22}}| = K_2 \sum_{j=0}^{n_b} b_j \neq 0$, from [24], we have

$$\bar{\Lambda}^{-1} = \begin{bmatrix} S_{\bar{\Lambda}_{22}}^{-1} & -S_{\bar{\Lambda}_{22}}^{-1}\bar{\Lambda}_{12}\bar{\Lambda}_{22}^{-1} \\ -\bar{\Lambda}_{22}^{-1}\bar{\Lambda}_{21}S_{\bar{\Lambda}_{22}}^{-1} & \bar{\Lambda}_{22}^{-1}\bar{\Lambda}_{21}S_{\bar{\Lambda}_{22}}^{-1}\bar{\Lambda}_{12}\bar{\Lambda}_{22}^{-1} + \bar{\Lambda}_{22}^{-1} \end{bmatrix} \tag{A,3}$$

with $S_{\bar{\Lambda}_{22}}^{-1}(1,1)=0$, $S_{\bar{\Lambda}_{22}}^{-1}(1,n_a+2)=1/K_2$, where $S_{\bar{\Lambda}_{22}}^{-1}(i,j)$ denotes the element of $S_{\bar{\Lambda}_{22}}^{-1}$ in the ith row and jth column.

With $\Gamma = \begin{bmatrix} b_0K_2 & 0_{1\times n_a} & K_2 & 0_{1\times n_b} \end{bmatrix}^T$ in (18), it is obtained from (39) and (A,3) that

$$y_\infty = I_y \bar{\Lambda}^{-1}\Gamma\bar{r} = \bar{r}. \tag{A,4}$$

Thus, Equation (39) is proved.

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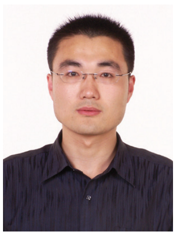

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