Data-Based Predictive Control for Networked Nonlinear Systems with Network-Induced Delay and Packet Dropout

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***Abstract*—This paper addresses the data-based networked control problem for a class of nonlinear systems. Network communication constraints, such as network-induced delay, packet disorder, and packet dropout in both the feedback and forward channels, are considered and further treated as the round-trip time (RTT) delay that is redefined. By using the packet-based transmission mechanism and the model-free adaptive control algorithm, a data-based networked predictive control method is proposed to actively compensate for the random RTT delay. The proposed method does not require any information on the plant model and depends only on the input and output data of the plant. A simple and explicit sufficient condition, which is related to the upper bound of the RTT delays, is derived for the stability of the closed-loop system. Additionally, a zero steady-state output tracking error can be achieved for a step reference input. The effectiveness of the proposed method is demonstrated via simulation and experimental results.**

***Index Terms*—Networked control systems (NCSs), nonlinear systems, data-based control, predictive control, network-induced delay, packet dropout, stability analysis.**

I. 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, energy systems, and power grids [1], [2]. This is because the utilization of communication networks brings many appealing advantages such as increasing flexibility and mobility of control systems, and low installation and maintenance costs. However, it also inevitably causes some communication constraints such as network-induced delay, packet disorder, and packet dropout, which may deteriorate the system performance or even destabilize the system. Therefore, during the past two decades, various approaches have been developed to cope with them, for instance, stochastic control approach [3], time delay system approach [4], switched system approach [5], robust control approach [6], and so on.

Another typical approach to effectively deal with the above communication constraints is networked (network-based) predictive control (NPC) methods in [7]-[25], to name a few, which take full advantage of the feature of NCSs such as the packet-based transmission mechanism, as well as smart sensors and actuators [1]. However, most of the available NPC methods are focused on linear plants, for example, [7]-[20], and very limited results are concerned with nonlinear plants, for instance, [21]-[25]. Furthermore, these NPC methods are generally designed based on the accurate model or the appropriate uncertainty description of the plant, which thus are called model-based NPC methods.

It is well known that the nonlinearity commonly exists in practical systems, and unmodeled dynamics are also inevitable due to the impossibility of exactly modeling. Thus, without accurate models, most results of the above NPC methods cannot be guaranteed in practical applications. As a complementary approach, data-based control methods have received a great deal of attention in recent years [26]-[33]. However, most of them are developed for the traditional point-to-point systems, and quite few results are available for NCSs. Three typical data-based methods for NCSs are reviewed as follows. In [34], a data-driven predictive control scheme was proposed for linear NCSs by using the subspace matrices technique, but it is difficult to analyze the stability and performance. In [35], a model-free adaptive control (MFAC) algorithm described in [26] was directly applied to nonlinear systems with data dropouts. However, the system performance will become poor with the increase of data dropout rate. To mitigate the adverse effect of data dropouts, a modified MFAC algorithm was designed in [36]. However, the two methods in [35] and [36] only considered the data dropouts in the feedback channel.

To the best of our knowledge, the data-based control issue of networked nonlinear systems with network-induced delay, packet disorder, and packet dropout in both the feedback

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and forward channels has not been investigated. Therefore, the present study is an attempt to address this issue. The 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 redefined in this paper. The main contributions of this paper include the following three aspects: 1) to actively compensate for the RTT delay, a data-based NPC (DBNPC) method is proposed, which is free with the plant model and only based on the input and output (I/O) data of the plant; 2) a simple and explicit sufficient condition is derived to guarantee the closed-loop stability and a zero steady-state output tracking error for a step reference input; and 3) both simulation and experimental results are provided to illustrate the applicability and effectiveness of the proposed method.

This paper is organized as follows. In Section II, an MFAC algorithm is introduced and the data-based networked control problem for nonlinear systems is formulated. Section III focuses on the design of DBNPC scheme. The stability and convergence are analyzed in Section IV. The performance of the proposed method is evaluated via simulation and experimental results in Section V. Section VI draws conclusions.

Notation: The notation used here is fairly standard. $\Delta x(k)$ is defined as $\Delta x(k) = x(k) - x(k-1)$. $|x|$ means the absolute value of the scalar x. $\text{sign}(\cdot)$ represents the signum function. $x(k+i|k)$ refers to the ith-step-ahead predictive value of $x(k)$ based on the data up to time k.

II. Problem Formulation

Consider a single-input single-output discrete-time nonlinear system described by

$$y(k+1) = f\big(y(k), \cdots, y(k-n_y), u(k), \cdots, u(k-n_u)\big) \quad (1)$$

where $y(k)$ and $u(k)$ are the system output and control input at time k, respectively, $f(\cdot)$ is an unknown nonlinear function, and n_y and n_u are unknown orders.

For nonlinear system (1), the following two assumptions are first made [35], [36].

Assumption 1: The partial derivative of $f(\cdot)$ with respect to $u(k)$ is continuous.

Assumption 2: System (1) is generalized Lipschitz, i.e., $|\Delta y(k+1)| \leq b|\Delta u(k)|$ for any k and $\Delta u(k) \neq 0$, where b is a positive constant.

Remark 1: The generalized Lipschitz condition in Assumption 2 imposes an upper bound on the change rate of the system output driven by the change of the control input. From an energy viewpoint, it means that the energy change inside a practical system cannot go to infinity if the energy change of the control input is at a finite level [35], [36]. In practical applications, many control systems satisfy such a property, for example, flow control system, liquid level control system, temperature control system, speed control system, and so on.

If Assumptions 1 and 2 are satisfied, system (1) can be converted into the following equivalent dynamic linearization data model [26]

$$\Delta y(k+1) = \phi(k)\Delta u(k) \quad (2)$$

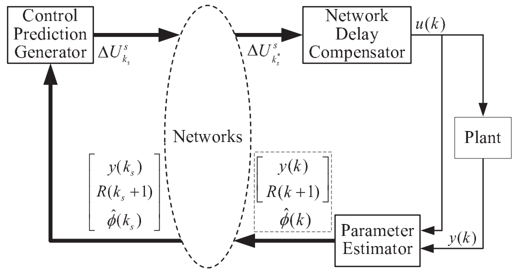


Fig. 1. DBNPC scheme.

where $|\phi(k)| \leq b$.

For the local control of system (1), where the controller is directly connected to the plant by dedicated hardwired links, an incremental controller is designed by using the MFAC algorithm in [26] as follows:

$$\hat{\phi}(k) = \hat{\phi}(k-1) + \frac{\eta \Delta u(k-1)}{\mu + \Delta u(k-1)^2}\big(\Delta y(k) - \hat{\phi}(k-1)\Delta u(k-1)\big) \quad (3)$$

$$\hat{\phi}(k) = \hat{\phi}(0), \quad \text{if } |\hat{\phi}(k)| \leq \varepsilon, \text{or } |\Delta u(k-1)| \leq \varepsilon, \text{ or } \text{sign}\big(\hat{\phi}(k)\big) \neq \text{sign}\big(\hat{\phi}(0)\big) \quad (4)$$

$$\Delta u(k) = \frac{\rho \hat{\phi}(k)}{\lambda + \hat{\phi}(k)^2}\big(r(k+1) - y(k)\big) \quad (5)$$

where $\hat{\phi}(k)$ is the estimation of $\phi(k)$ with the initial value $\hat{\phi}(0)$, $r(k+1)$ is a reference signal, $\mu > 0$, $\eta \in (0,1]$, $\lambda > 0$, $\rho \in (0,1]$, and ε is a small positive constant.

For the networked control of system (1), it is assumed that there exist the network-induced delay, packet disorder, and packet dropout in both the feedback and forward channels. Our task is to design a networked control scheme for system (1) based on the MFAC algorithm in (3)-(5) such that under all the communication constraints above, the resulting closed-loop system is stable and also achieves a zero steady-state output tracking error for a step reference input.

III. DBNPC Scheme

The DBNPC scheme is shown in Fig. 1, which includes three parts: a parameter estimator (PE) and a network delay compensator (NDC) on the plant side, and a control prediction generator (CPG) on the controller side. The design of each part will be discussed in subsequent subsections.

Assumption 3: The sensor and actuator are time-driven and synchronous, whereas the controller is event-driven.

Assumption 4: The RTT delay τ_k is random but bounded by $\bar{\tau}$, i.e.,

$$0 \leq \tau_k \leq \bar{\tau}. \quad (6)$$

Remark 2: It is worth noting that for the proposed DBNPC scheme in Fig. 1, if the sensor, controller, and actuator are time-driven and synchronous, the reference signal $r(k)$ can be generated on the controller side, which does not affect the design of DBNPC scheme. In practical applications, however, the precise clock synchronization between them is not easy to realize due to the influence of various network-induced limitations. Therefore, Assumption 3 is made in this paper, and thus the reference signal sequence $R(k+1)$ is generated on the plant side rather than on the controller side (see Fig. 1), which avoids the requirement for clock synchronization between the controller and the sensor/actuator.

Remark 3: In the context of computer networks, 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. Under this definition, the lost packet and the disordered packet also have their own RTT delays. The RTT delay of the former is infinite, and the RTT delay of the latter would be larger than that of in-order packets. Thus, the RTT delay would not have an upper bound. On the other hand, for the purpose of real-time control, the disordered packet is generally discarded. In other words, we just need to focus on the packets arriving at the actuator *in order*. Therefore, the RTT delay τ_k 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 (14)). As a result, the RTT delay will have an upper bound as long as the networks are not broken. Moreover, it represents the joint effect of the network-induced delay, packet disorder, and packet dropout in both the feedback and forward channels.

A. Design of PE

To obtain $\hat{\phi}(k)$ for the networked control of system (1), the parameter estimation algorithm in (3) and (4) is performed online by the PE in the sensor. At each sampling instant, the sensor sends the following feedback data together with the timestamp k in one packet to the controller:

$$D_k = \Big[y(k)\ \hat{\phi}(k)\ R(k+1)^T\Big]^T \tag{7}$$

where $R(k+1) = [r(k+1)\ r(k+2)\cdots r(k+\bar{\tau}+1)]^T$.

B. Design of CPG

Since the controller is event-driven, when receiving a feedback packet from the sensor, it calculates the following control increment by using the control law in (5):

$$\Delta u(k_s|k_s) = \alpha(k_s)\big(r(k_s+1) - y(k_s)\big) \tag{8}$$

where $\alpha(k_s) = \rho\hat{\phi}(k_s)/(\lambda + \hat{\phi}(k_s)^2)$, and $k_s \le k$ is the timestamp of the feedback packet. The control increment predictions up to time $k_s+\bar{\tau}$ can be calculated by the iteration of (2) and (8) as follows:

$$\Delta y(k_s+i|k_s) = \hat{\phi}(k_s)\Delta u(k_s+i-1|k_s) \tag{9}$$

$$y(k_s+i|k_s) = y(k_s+i-1|k_s) + \Delta y(k_s+i|k_s) \tag{10}$$

$$\Delta u(k_s+i|k_s) = \alpha(k_s)\big(r(k_s+i+1) - y(k_s+i|k_s)\big) \tag{11}$$

for $i = 1, 2, \cdots, \bar{\tau}$, where $y(k_s|k_s) = y(k_s)$. Then from (8) and (11), the sums of control increment predictions are obtained as

$$\Delta u_s(k_s+i|k_s) = \Delta u_s(k_s+i-1|k_s) + \Delta u(k_s+i|k_s) \tag{12}$$

for $i = 1, 2, \cdots, \bar{\tau}$, where $\Delta u_s(k_s|k_s) = \Delta u(k_s|k_s)$. Clearly, we can obtain the following prediction sequence:

$$\Delta U^s_{k_s} = [\Delta u_s(k_s|k_s)\ \Delta u_s(k_s+1|k_s)\cdots\Delta u_s(k_s+\bar{\tau}|k_s)]^T \tag{13}$$

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

C. Design of NDC

Due to the presence of the 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 control packets arrive at the actuator during one sampling interval. Suppose that at time k, the latest prediction sequence available in the actuator is $\Delta U^s_{k^*_s} = [\Delta u_s(k^*_s|k^*_s)\ \Delta u_s(k^*_s+1|k^*_s)\cdots\Delta u_s(k^*_s+\bar{\tau}|k^*_s)]^T$, where $k^*_s \le k_s$ is its timestamp. Then the real-time RTT delay τ_k can be calculated as

$$\tau_k = k - k^*_s. \tag{14}$$

To compensate for the random RTT delay, the NDC selects the following control signal for system (1):

$$u(k) = u(k^*_s - 1) + \Delta u_s(k|k^*_s) \tag{15}$$

which is equivalent to the case that the following control increment is applied to system (2):

$$\Delta u(k) = \Delta u(k|k^*_s). \tag{16}$$

Remark 4: From the aforementioned design procedure, it is easy to find that the proposed DBNPC scheme only involves the I/O data of the plant. Neither the dynamic model nor the structure information of the plant is needed. In other words, the proposed method is a pure data-based control method for networked nonlinear systems.

Remark 5: In the DBNPC scheme, there are six parameters to be determined, i.e., η and μ in (3), $\hat{\phi}(0)$ and ε in (4), as well as ρ and λ in (8) and (11). All these parameters have their individual physical significance. The parameters η and ρ are introduced respectively to make the parameter estimation algorithm in (3) and the control algorithm in (8) and (11) more general and more flexible, whose values can be set to be 1 in general applications. The parameter μ is a weighting factor to limit the change rate of $\hat{\phi}(k)$. Since $\phi(k)$ is a slowly time-varying parameter for nonlinear system (1) [26], its value has less effect on the system performance, and thus, it can take a value more than 0. $\hat{\phi}(0)$ is the initial value of $\hat{\phi}(k)$, which can be determined by the historical I/O data of the controlled plant. The parameter ε is a small positive constant, which is used in the resetting mechanism (4) to endow the parameter estimation algorithm (3) with a strong tracking ability. The parameter λ is a penalty factor on the change of the control increment $\Delta u(k)$, which is an important adjustable parameter for the implementation of the DBNPC scheme. Theoretical analysis as well as simulation and experimental results in following sections will show that a proper selection of λ can guarantee the closed-loop stability and a desirable output tracking performance.

IV. Stability Analysis

For the stability analysis, it is assumed that $\phi(k) > 0$ (or $\phi(k) < 0$) for all time k. Note that this assumption is not strong, which is similar to the requirement on the control direction in model-based control methods. Without loss of generality, suppose that $\phi(k) > 0$ for all time k. Thus, it is clear from (4) that $\hat{\phi}(k) > \varepsilon > 0$.

Before proceeding to the stability analysis for the resulting DBNPC system (DBNPCS), the following two lemmas are presented.

Lemma 1 [37]: For any constant $m > 0$, integers $l_1 \leq l_2$, and scalar function $\omega(\cdot)$ such that the sums in the following are well defined, then

$$-(l_2 - l_1 + 1)\sum_{i=l_1}^{l_2} m\omega(i)^2 \leq -m\Big(\sum_{i=l_1}^{l_2}\omega(i)\Big)^2 \tag{17}$$

Lemma 2: Consider the following discrete-time scalar linear system:

$$\begin{aligned} x(k+1) &= x(k) - a(k)x(k-\tau_k) \\ x(k) &= \psi(k), k = -\bar{\tau}, -\bar{\tau}+1, \cdots, 0 \end{aligned} \tag{18}$$

where $x(k)$ is the scalar state, $a(k)$ is the time-varying parameter, and $\psi(k)$ is the initial condition. System (18) with τ_k in (6) is asymptotically stable if $0 < a(k) < 2/(2\bar{\tau}+1)$.

Proof: Choose the following candidate Lyapunov functional:

$$V(k) = V_1(k) + V_2(k) \tag{19}$$

with

$$V_1(k) = px(k)^2$$

$$V_2(k) = \bar{\tau}\sum_{i=-\bar{\tau}}^{-1}\sum_{j=k+i}^{k-1} q\eta(j)^2$$

where $p > 0$ and $q > 0$ are scalars, and $\eta(k) = x(k+1) - x(k) = -a(k)x(k-\tau_k)$. Define $\delta V(k) = V(k+1) - V(k)$ and $X(k) = [x(k) \;\; x(k-\tau_k)]^T$. Along the trajectory of (18), with $0 \leq \tau_k \leq \bar{\tau}$, we have

$$\begin{aligned} \delta V_1(k) &= px(k+1)^2 - px(k)^2 \\ &= p\big(x(k) - a(k)x(k-\tau_k)\big)^2 - px(k)^2 \end{aligned} \tag{20}$$

$$\begin{aligned} \delta V_2(k) =& \bar{\tau}\sum_{i=-\bar{\tau}}^{-1}\Big(\sum_{j=k+1+i}^{k} q\eta(j)^2 - \sum_{j=k+i}^{k-1} q\eta(j)^2\Big) \\ =& \bar{\tau}\sum_{i=-\bar{\tau}}^{-1}\Big(q\eta(k)^2 - q\eta(k+i)^2\Big) \\ =& \bar{\tau}^2 q\eta(k)^2 - \bar{\tau}\sum_{i=k-\bar{\tau}}^{k-1} q\eta(i)^2 \\ \leq& \bar{\tau}^2 q\eta(k)^2 - \tau_k\sum_{i=k-\tau_k}^{k-1} q\eta(i)^2 \\ \leq& \bar{\tau}^2 q\eta(k)^2 - q\Big(\sum_{i=k-\tau_k}^{k-1}\eta(i)\Big)^2 \\ =& \bar{\tau}^2 q\big(a(k)x(k-\tau_k)\big)^2 - q\big(x(k) - x(k-\tau_k)\big)^2 \end{aligned} \tag{21}$$

where Lemma 1 is used. Then we obtain

$$\delta V(k) = X^T(k)\Psi X(k) \tag{22}$$

where

$$\Psi = \begin{bmatrix} -q & -pa(k)+q \\ -pa(k)+q & (p+q\bar{\tau}^2)a(k)^2 - q \end{bmatrix}$$

with the determinant

$$\det(\Psi) = -(pq + p^2 + q^2\bar{\tau}^2)a(k)^2 + 2pqa(k). \tag{23}$$

Note that the function $\det(\Psi) > 0$ with respect to $a(k)$ when

$$0 < a(k) < \frac{2pq}{pq + p^2 + q^2\bar{\tau}^2} \leq \frac{2pq}{pq + 2pq\bar{\tau}} = \frac{2}{2\bar{\tau}+1}. \tag{24}$$

Then with $-q < 0$ and $\det(\Psi) > 0$, it is obtained from (22) that $\Psi < 0$, and thus $\delta V(k) < 0$. That is, system (18) is asymptotically stable. This completes the proof. ■

Now, we present the results of stability and convergence for the DBNPCS.

Theorem 1: If λ is chosen as $\lambda \geq (2\bar{\tau}+1)^2\rho^2 b^2/16$, the closed-loop DBNPCS, i.e., system (1) with (15), is not only stable but also guarantees a zero steady-state tracking error for the step reference input $r(\cdot) = r^*$, where r^* is a constant.

Proof: Define the output tracking error as

$$e(k) = r^* - y(k). \tag{25}$$

In view of the design of CPG in (8)-(11) with (14), we have

$$\begin{aligned} e(k|k-\tau_k) =& r^* - y(k|k-\tau_k) \\ =& r^* - y(k-1|k-\tau_k) \\ &- \hat{\phi}(k-\tau_k)\Delta u(k-1|k-\tau_k) \\ =& r^* - y(k-1|k-\tau_k) \\ &- \hat{\phi}(k-\tau_k)\alpha(k-\tau_k)\big(r^* - y(k-1|k-\tau_k)\big) \\ =& c(k-\tau_k)e(k-1|k-\tau_k) \\ =& c(k-\tau_k)^{\tau_k}e(k-\tau_k) \end{aligned} \tag{26}$$

where

$$c(k-\tau_k) = 1 - \frac{\rho\hat{\phi}(k-\tau_k)^2}{\lambda + \hat{\phi}(k-\tau_k)^2}.$$

According to the compensation strategy in (16), as well as (11) and (26), it is obtained that

$$\Delta u(k) = \Delta u(k|k-\tau_k) = \alpha(k-\tau_k)c(k-\tau_k)^{\tau_k}e(k-\tau_k). \tag{27}$$

Thus, from (25), (2), and (27), we obtain the following closed-loop system:

$$\begin{aligned} e(k+1) &= e(k) - \Delta y(k+1) \\ &= e(k) - \phi(k)\Delta u(k) \\ &= e(k) - \beta(k)e(k-\tau_k) \end{aligned} \tag{28}$$

where

$$\beta(k) = \phi(k)\alpha(k-\tau_k)c(k-\tau_k)^{\tau_k}.$$

With $\lambda > 0$, $\rho \in (0, 1]$, and $\hat{\phi}(k-\tau_k) > 0$, we have

$$\begin{aligned} 0 < \alpha(k-\tau_k) = \frac{\rho\hat{\phi}(k-\tau_k)}{\lambda + \hat{\phi}(k-\tau_k)^2} &\leq \frac{\rho\hat{\phi}(k-\tau_k)}{2\sqrt{\lambda}\hat{\phi}(k-\tau_k)} \\ &= \frac{\rho}{2\sqrt{\lambda}} \end{aligned} \tag{29}$$

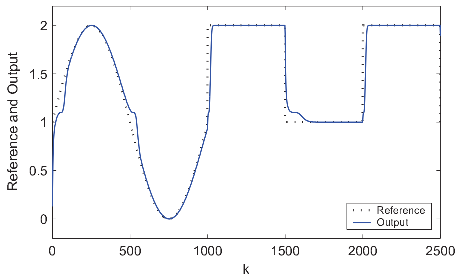


Fig. 2. Performance of LCS (simulation).

$$0 < 1-\frac{\hat{\phi}(k-\tau_k)^2}{\lambda+\hat{\phi}(k-\tau_k)^2} \le c(k-\tau_k) = 1-\frac{\rho\hat{\phi}(k-\tau_k)^2}{\lambda+\hat{\phi}(k-\tau_k)^2} < 1. \tag{30}$$

Then with $0 < \phi(k) \le b$, it is obtained from (28)-(30) that

$$0 < \beta(k) < \frac{\rho\phi(k)}{2\sqrt{\lambda}} \le \frac{\rho b}{2\sqrt{\lambda}}. \tag{31}$$

According to Lemma 2, it is clear that system (28) is stable if

$$0 < \beta(k) < \frac{\rho b}{2\sqrt{\lambda}} \le \frac{2}{2\bar{\tau}+1}. \tag{32}$$

That is, $\lambda \ge (2\bar{\tau}+1)^2\rho^2 b^2/16$. Also, it can be concluded from (28) that a zero steady-state output tracking error can be achieved. The proof is completed. ■

Remark 6: It is easy to see that Theorem 1 gives a simple and explicit stability condition for the closed-loop DBNPCS. In general, for nonlinear system (1), the parameter $\phi(k)$ is time-varying and related to the dynamics of the controlled plant, the operation point of the closed-loop system, control input signal, and so on. Thus, $\phi(k)$ and its upper bound b cannot be known beforehand. In this case, to guarantee the stability of the closed-loop control system, λ should be chosen large enough to ensure the condition in Theorem 1. On the other hand, to obtain a better control performance, one possible way is to define a performance index and then optimize λ online, which is our on-going research topic.

V. Simulation and Experiment

A. Numerical Simulation

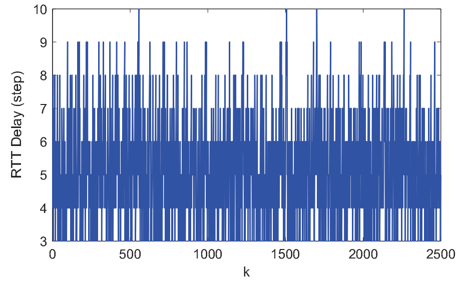
To assess the performance of the proposed DBNPC method, the following nonlinear plant is considered [30], [38]:

$$\begin{aligned} x(k) &= 1.5u(k) - 1.5u(k)^2 + 0.5u(k)^3 \\ y(k+1) &= 0.6y(k) - 0.1y(k-1) + 1.2x(k) - 0.1x(k-1). \end{aligned} \tag{33}$$

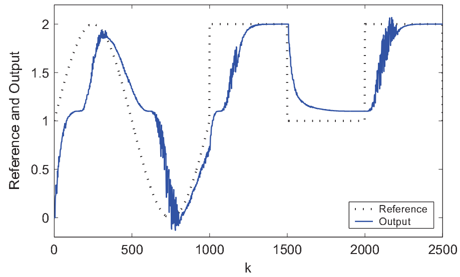
The estimator and controller parameters are set to be $\eta = 1$, $\mu = 1$, $\hat{\phi}(0) = 1$, $\varepsilon = 10^{-5}$, $\rho = 1$, and $\lambda = 12$.

Firstly, suppose that there exists no network between the controller and the plant. The MFAC algorithm in (3)-(5) is directly applied to system (33). The simulation result of the local control system (LCS) is shown in Fig. 2, which indicates that the output tracking performance is well achieved.

Secondly, the performance of NCS without compensation is tested, where the random RTT delays shown in Fig. 3(a) are considered. For the NCS, when no control packets arrive at the actuator at time k, the applied control input is chosen as $u(k) = u(k-1)$. The output response is shown in Fig. 3(b), which indicates that, compared with the LCS, the tracking performance of the NCS becomes much worse.



(a) Random RTT delays



(b) Output response

Fig. 3. Performance of NCS without compensation (simulation).

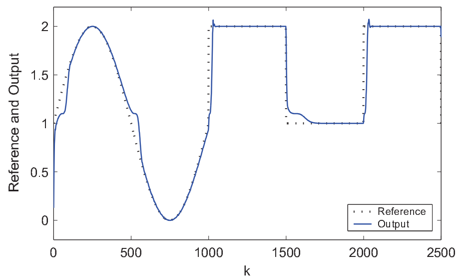
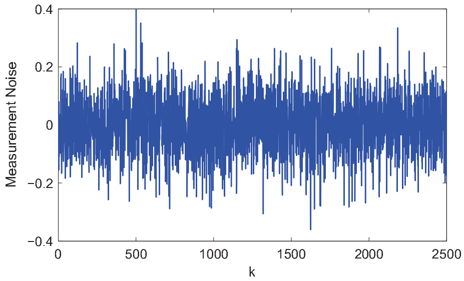


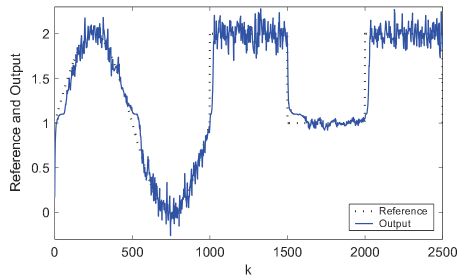
Fig. 4. Performance of DBNPCS (simulation).

Thirdly, with the random RTT delays in Fig. 3(a), the simulation result of the DBNPCS is given in Fig. 4, which indicates that the tracking performance is similar with that of the LCS, and is much better than that of the NCS without compensation. To quantitatively evaluate the system performance, a output tracking error index $E = \sum_{k=0}^{2500} |e(k)|$ is defined. It is obtained from Fig. 2, Fig. 3(b), and Fig. 4 that $E_{\mathrm{LCS}} = 104.9988$, $E_{\mathrm{NCS}} = 736.4561$, and $E_{\mathrm{DBNPCS}} = 107.4949$, respectively.

Finally, to illustrate the capability of the DBNPC method in handling measurement noise, a zero-mean Gaussian white noise with variance $\sigma_v^2 = 0.01$ shown in Fig. 5(a) is added to system (33). With the random RTT delays in Fig. 3(a), the simulation result is shown in Fig. 5(b), which indicates that the tracking performance is acceptable. In addition, to further assess the applicability of the DBNPC method, more general scenarios with different measurement noises and different values of λ are considered. The simulation results for the unit step reference input are provided in Table I, where σ_v^2 and



(a) Measurement noise



(b) Output response

Fig. 5. Performance of DBNPCS with measurement noise (simulation).

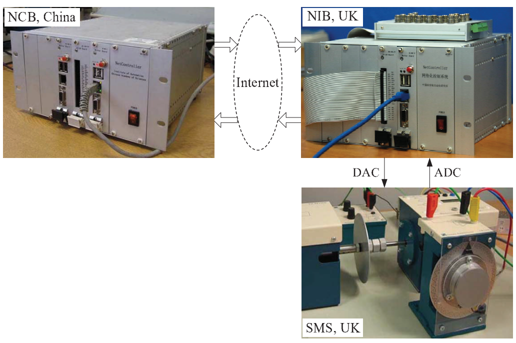


Fig. 6. Internet-based SMS.

σ_e^2 denote the variances of zero-mean Gaussian white noises and output tracking errors, respectively. It can be concluded that under a certain level of measurement noise, a suitably large value of λ can guarantee the stability of the closed-loop DBNPCS.

TABLE I
VARIANCES OF OUTPUT TRACKING ERRORS OF DBNPCS FOR DIFFERENT MEASUREMENT NOISES AND DIFFERENT VALUES OF λ

σ_e^2 \ σ_υ^2 / λ	0.1	1	10	100
1	0.4426	∞	∞	∞
10	0.0067	0.3761	∞	∞
100	0.0023	0.0087	0.4328	44.2104
1000	0.0156	0.0126	0.0157	0.7463

B. Practical Experiment

To further verify the DBNPC method in practice, an Internet-based servo motor system (SMS) test rig has been built as shown in Fig. 6, which consists of an SMS, a networked implementation board (NIB), and a networked controller board (NCB). The SMS and the NIB are located in the University of South Wales, Pontypridd, UK, and the NCB is placed in the Tsinghua University, Beijing, China. The SMS is a nonlinear system in nature, which is used here as the object of speed control (-10V$\sim$$+10$V) driven by the input voltage from -10V to $+10$V. The NIB is responsible for the implementation of the PE and NDC, and the NCB is employed for the realization of the CPG. The two boards are connected through the Internet, and the UDP/IP protocol is adopted between them for real-time control.

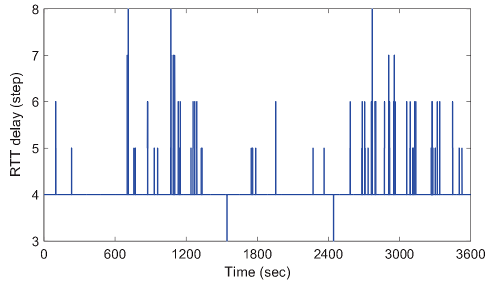


Fig. 7. RTT delays between the NCB (China) and NIB (UK).

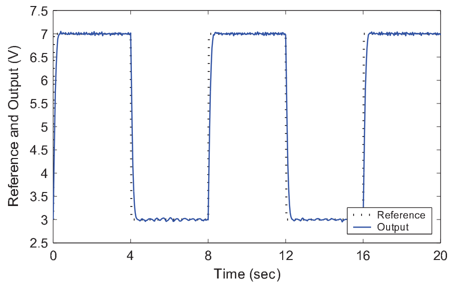


Fig. 8. Performance of LCS (experiment).

In practical experiments, the sampling period is set to be 0.04s. The estimator and controller parameters are chosen as $\eta = 1$, $\mu = 1$, $\hat{\phi}(0) = 1$, $\varepsilon = 10^{-5}$, $\rho = 1$, and $\lambda = 1.5$. Before performing control experiments, the RTT delays of the Internet between the NCB and the NIB are tested. Fig. 7 gives a real-time record of RTT delays in an hour, which indicates that the RTT delays are bounded by 3 and 8 steps.

The experimental results of the LCS, NCS without compensation, and DBNPCS are shown in Fig. 8, Fig. 9, and

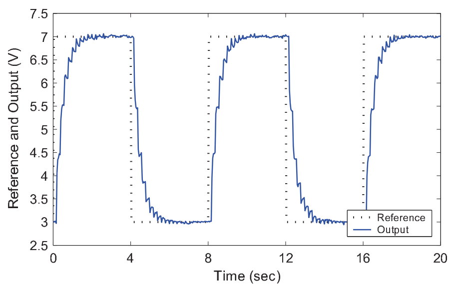


Fig. 9. Performance of NCS without compensation (experiment).

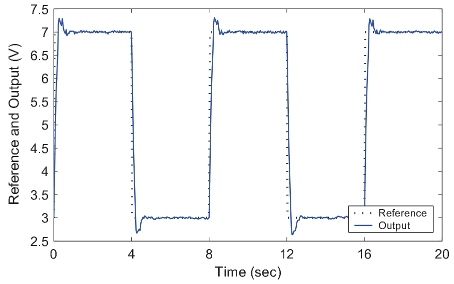


Fig. 10. Performance of DBNPCS (experiment).

Fig. 10, respectively. It can be seen that the output tracking performance is well achieved for the LCS. Due to the presence of random RTT delays, the NCS without compensation gives a poor output tracking performance. When the DBNPC method is applied to the SMS, the output tracking performance is greatly improved compared with the NCS without compensation. The tracking performance indexes $E = \sum_{t=0}^{20} |e(t)|$ of the above three control systems are $E_{\rm LCS} = 43.4302$, $E_{\rm NCS} = 238.2448$, and $E_{\rm DBNPCS} = 52.9261$, respectively. It should be noted that the overshoot of the DBNPCS occurring at each change of operation points can be reduced or eliminated by increasing the value of λ.

VI. Conclusion

This paper has investigated a data-based output tracking control method for a class of networked nonlinear systems subject to the network-induced delay, packet disorder, and packet dropout in the feedback and forward channels. A predictive control strategy based on the MFAC algorithm has been employed to generate control signals such that the above communication constraints can be effectively compensated. A simple and explicit condition has been established to guarantee the stability and convergence of the closed-loop system. Furthermore, both the simulation and experimental results have confirmed the effectiveness of the proposed method.

Future research efforts will be devoted to extending the proposed method to more general nonlinear systems. Moreover, in practical NCSs, there also exist some other network-induced constraints such as data quantization, time-varying sampling, and even network scheduling [1], [39], which should be considered simultaneously in a unified framework. Finally, it is worth mentioning that a new and typical application of NCSs can be found in modern industrial systems with network-based two-layer architecture [40], [41]. It would be interesting to extend the proposed method to deal with the local tracking control problem at the device layer and the network-based setpoints compensation problem at the operation layer in our future research.

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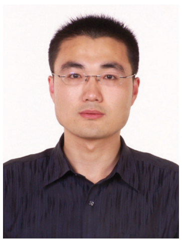

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