Model predictive control for networked control systems with random data dropouts

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***Abstract*—** In this paper, the model predictive control for the networked control systems is proposed. The problem of data dropouts in the sensor controller link when the controller does not receive new feedback data is treated. As in predictive control design the sequence of future control actions up to a given horizon is calculated at each sampling time, the natural idea is to use not only the first control action, but also other terms of the control sequence, in case the sensor data at next sampling times are not available. From the implementation point of view there are two or more control laws (depending on the number of lost output samples) which are switched arbitrarily fast. A sufficient stability condition for this switched control system is derived using the concept of quadratic stability. The effectiveness of the proposed control strategy is demonstrated by control of a simple laboratory plant.

***Keywords*—** data loss, model predictive control, networked control system, quadratic stability.

I. Introduction

Networked control systems (NCS) gained increasing attention in recent years due to its cost effective and flexible applications. The use of a data network in a control loop enables remote data transfers and data exchanges among users, reduces the complexity in wiring connections and the costs of medias, provides ease in maintenance and offers modularity and flexibility in control system design. Several network protocols for real-time remote industrial control purposes have been developed during last decades, for example Area Network (CAN) or Profibus. The computer networking technologies especially Ethernet have also progressed rapidly and are also appealing for use in control applications. Modern network solutions, like PROFINET or WLAN have been recently developed for industrial applications [1]. The wireless technologies, such as Bluetooth or Zigbee, received significant attention and can play an important role in networked control systems [2].

In the networked control system, several components of the system may communicate over the common network that connects them together, as illustrated in Fig. 1. This brings many specific control issues giving rise to important research topics. The networked control system design has to deal with the dynamics introduced by the communication network, which may include communication disruptions such as communication channel noise, data losses, bandwidth limitations, time-varying delays, and data quantization. The variable transmission delays can arise due to various reasons, and are of various characteristics and magnitudes - measurement delays, operator delays, computational delay from control or optimization algorithms and communication delays. All these phenomena in the control loop can lead to performance degradation and eventual instability in control systems.

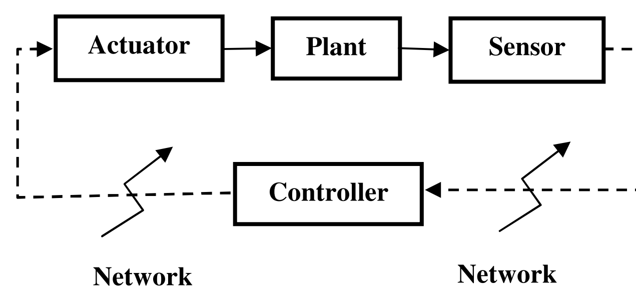

Fig. 1 Networked control scheme

Recent research efforts have led to important results on the design and stability analysis of networked control systems [3 – 5]. Various control design approaches have been used. A new tool for PID controller tuning in networked control systems with time-varying delays has been described in [6]. In [7] the gain scheduler middleware which modifies the controller output with respect to the current network traffic conditions has been presented. The remote fuzzy logic controller has been proposed in [8] to compensate the network-induced delay for a single-input–single-output plant. The model based predictive NCS architecture that runs under non-ideal network conditions where packet loss and random time delays occur has been presented in [9]. Implementation of optimal control techniques in NCS design has been investigated in [10, 11]. H∞ control for NCSs with the effects of both the network-induced delay and the input saturation has been designed in [12]. An adaptive algorithm to estimate and compensate random communication time delay in NCS has been proposed in [13].

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In this paper, we focus on design and analysis of network control systems subject to data losses at the sensor-controller link. In this case feedback is lost and the actuator must operate on its own, usually setting the control input to zero or to the last implemented value. The data packets may be lost due to the network congestion or due to the link failures caused by the unreliable nature of the links, such as in the case of wireless networks. The similar problem arises in the control systems with asynchronous measurement, where the samplings are not received at fixed time instants due to the difficulties of measuring.

Although an intensive research activity is devoted to the design and analysis of networked control system, only few papers deal with the issue of data losses. The stability and disturbance attenuation issues for a class of networked control systems under bounded uncertain access delay and packet dropout effects were investigated in [14]. The optimal control of linear time-invariant systems over unreliable communication links is studied and sufficient conditions for the existence of stabilizing control laws were derived in [15].

If the controller does not receive new feedback data, the plant is regulated in an open-loop system. The intuitive idea of using the plant model at the controller/actuator side to approximate the plant behavior during time periods when sensor data are not available was used in [4]. In [16] a novel timeout scheme and an autoregressive prediction model for delayed/lost sensor were used. In [17] the predictive control for nonlinear systems with guaranteed stability in the presence of data losses was designed.

In the present paper, we also use the model predictive control (MPC) approach to deal with data losses in the control system. MPC represents a family of advanced control methods which make explicit use of the model to predict the future plant behavior and to calculate the future control sequence minimizing an objective function [18]. The objective function is formulated as a combination of the set-point tracking performances and control effort. MPC belongs to the category of open-loop optimization techniques and its implementation is based on the receding horizon strategy, i.e. only the first term of the future control sequence is used at each sampling instant and the calculation is repeated in the next sampling time. This allows to incorporate a feedback into the control loop and to improve the control performances in the presence of disturbances and unmodelled dynamics.

First predictive control algorithms have been proposed at the end of the 1970s; they quickly became popular and developed considerably over the last three decades both within the research control community and in industry [19]. The popularity of MPC is mainly due to the fact, that it can be used to control a great variety of processes including time-delayed systems, the nonminimum phase systems or the unstable ones. The multivariable case can easily be dealt with as well. Another important feature of this control design approach is that constraints on the input/output variables can be systematically incorporated into the design procedure, which might improve the resulting control system performances and the process operation safety.

MPC has proved its effectiveness in the networked control systems especially in the context of distributed and hierarchical control. The review of decentralized, distributed and hierarchical control architectures based on MPC is in [20]. The problem of variable time delays in control loop has been addressed in [21] where the time-stamped MPC algorithm that uses a communication delay model along with time-stamping and buffering has been proposed.

In our paper the MPC approach is employed to treat the issue of data losses. As the sequence of future control actions up to a given horizon is calculated at each sampling time, the natural idea is to use not only the first control action, but also other terms of the control sequence in case the sensor data at next sampling times are not available. From the implementation point of view there are two or more control laws (depending on the number of lost output samples) which are switched arbitrarily fast.

Stability is one of the most important characteristics of control systems. To analyze stability of control loop with a switched controller, it is not sufficient to check whether each applied control law ensures the closed loop stability, but it is necessary to take into account also a dynamics induced by control law switching which can occur arbitrarily often. The stability analysis of the proposed control strategy will be based on the concept of quadratic stability which is frequently used for the analysis and synthesis of switched control systems [22, 23]. Resulting stability condition is reformulated to the linear matrix inequalities form, which can be efficiently solved by many available software tools.

The paper is organized as follows. First standard model predictive control design procedure is briefly described. Then a control strategy for the case of data loss in the sensor-controller link is proposed. In the fourth section the stability analysis of the switched control systems is presented. The effectiveness of the proposed control scheme is evaluated by simulations and real-time control of a simple laboratory plant. Finally, some conclusions are given.

II. Model Predictive Control

A. Plant Model

The plant model is the cornerstone of the predictive control design. It should be accurate enough to fully capture the plant dynamics and allow predictions to be calculated. We consider the plant model in the form of the ARMAX model

$$A\left(z^{-1}\right)y(t) = B\left(z^{-1}\right)u(t-d-1) + \frac{C\left(z^{-1}\right)}{D\left(z^{-1}\right)}\xi(t) \tag{1}$$

with

$$\begin{aligned}A(z^{-1}) &= 1 + a_1 z^{-1} + \ldots + a_{na} z^{-na} \\ B(z^{-1}) &= b_0 + b_1 z^{-1} + \ldots + b_{nb} z^{-nb} \\ C(z^{-1}) &= 1 + c_1 z^{-1} + \ldots + c_{nc} z^{-nc} \\ D(z^{-1}) &= 1 + d_1 z^{-1} + \ldots + d_{nd} z^{-nd}\end{aligned} \tag{2}$$

where $u(t)$ is the control variable, $y(t)$ the measured plant output, d denotes the minimum plant model time-delay in sampling periods, $v(t)$ represents the external disturbance and $\xi(t)$ is the stationary random process with zero mean value and finite variance. For simplicity in the following the $C(z^{-1})$ polynomial is chosen to be 1. Of practical importance, $D(z^{-1}) = 1 - z^{-1}$ allows incorporating an integral action into the control design.

B. Control Design

Generalized predictive control (GPC) developed in [24] belongs to the most popular predictive algorithms based on the parametric plant model. The control objective is to compute the future control sequence in such a way that the future plant output is driven close to the prescribed set point value; this is accomplished by minimizing the following cost function

$$\begin{aligned}J = E\Bigg\{&\sum_{j=sh}^{ph}\left(\hat{y}(t+j/t) - w(t+j)\right)^2 + \\ &+\rho\left(D\left(z^{-1}\right)u(t+j-sh)\right)^2\Bigg\}\end{aligned} \tag{3}$$

subject to

$$D\left(z^{-1}\right)u(t+i) = 0 \quad \text{for} \quad ch \le i \le ph \tag{4}$$

where sh, ph and ch are positive scalars defining the starting horizon, prediction horizon and control horizon, ρ is a nonnegative control weighting scalar. $\hat{y}(t+j/t)$ denotes the j-step ahead prediction of $y(t)$ based on the data available up to the time t and $w(t+j)$ is the future set point value at time $(t+j)$.

The cost function (3)-(4) may be rewritten in the suitable vector form

$$\begin{aligned}J = &\left(G_1 U(t+ch-1) + Y_0(t) - W(t+ph)\right)^T. \\ &.\left(G_1 U(t+ch-1) + Y_0(t) - W(t+ph)\right) + \\ &+\rho\, U(t+ch-1)^T U(t+ch-1)\end{aligned} \tag{5}$$

where

$$G_1 = \begin{bmatrix} g_{sh-d-1} & \cdots & g_0 & 0 & 0 & 0 \\ g_{sh-d} & \cdots & \cdots & g_0 & 0 & 0 \\ \vdots & \cdots & \cdots & \cdots & \ddots & \vdots \\ g_{ch-1} & \cdots & \cdots & \cdots & \cdots & g_0 \\ \vdots & \cdots & \cdots & \cdots & \cdots & \vdots \\ g_{ph-d-1} & \cdots & \cdots & \cdots & \cdots & g_{ph-ch-d} \end{bmatrix} \tag{6}$$

$$U(t+ch-1) = \left[D\left(z^{-1}\right)u(t), \ldots, D\left(z^{-1}\right)u(t+ch-1)\right]^T \tag{7}$$

$$W(t+ph) = \left[w(t+d+1), \ldots, w(t+ph)\right]^T \tag{8}$$

$$Y_0(t) = \left[y_0(t+d+1/t), \ldots, y_0(t+ph/t)\right]^T . \tag{9}$$

$y_0(t+j/t)$ denotes j-step ahead prediction of the plant free response calculated as follows

$$y_0(t+j/t) = H_{j-d}(z^{-1})D(z^{-1})u(t-1) + F_j(z^{-1})y(t) . \tag{10}$$

The polynomials $F_j\left(z^{-1}\right)$ and $H_{j-d}\left(z^{-1}\right)$ as well as the coefficients of matrix G_1 can be obtained by solving the following Diophantine equations

$$1 = A(z^{-1})D(z^{-1})E_j(z^{-1}) + z^{-j}F_j(z^{-1}) \tag{11}$$

$$E_j(z^{-1})B(z^{-1}) = G_{j-d}(z^{-1}) + z^{-j+d}H_{j-d}(z^{-1}) . \tag{12}$$

The future control sequence minimizing the cost function (5) is given by

$$U(t+ch-1) = -K\left(Y_0(t) - W(t+ph)\right) \tag{13}$$

where

$$K = \left[G_1^T G_1 + \rho I_{ch}\right]^{-1} G_1^T . \tag{14}$$

In standard GPC implementation only the first term of the calculated future control sequence

$$\begin{aligned}D\left(z^{-1}\right)u(t) &= -\sum_{j=sh}^{ph}\gamma_{1j}\left(y_0(t+j/t) - w(t+j)\right) = \\ &= u(t) - u(t-1)\end{aligned} \tag{15}$$

is used at each sampling time and the optimization process is repeated at the next sampling time. However, the further control increments can also be calculated and stored for potential use at next sampling times

$$D\left(z^{-1}\right)u(t+i) = -\sum_{j=sh}^{ph}\gamma_{(i+1)j}\left(y_0(t+j/t) - w(t+j)\right)$$
$$\text{for} \quad i = 1, \ldots, ch-1 . \tag{16}$$

In (15) and (16) the coefficients γ_{ij} for $i = 1, \ldots, ch-1$, $j = sh, \ldots, ph$ are the coefficients of i-th line of matrix K.

The control laws (15)-(16) may also be implemented using the standard pole-placement control structure

$$S_i\left(z^{-1}\right)D\left(z^{-1}\right)u(t+i-1) + R_i\left(z^{-1}\right)y(t) = T_i\left(z^{-1}\right)w(t)$$
$$\text{for} \quad i = 1, \ldots, ch-1 . \tag{17}$$

The $R_i(z^{-1})$, $S_i(z^{-1})$ and $T_i(z^{-1})$ polynomials depend on the plant model as well as on the choice of the tuning parameters *sh, ph*, *ch*, ρ and can be calculated as follows

$$R_i(z^{-1}) = \sum_{j=sh}^{ph} \gamma_{ij} F_j(z^{-1}) \tag{18}$$

$$S_i(z^{-1}) = 1 + \sum_{j=sh}^{ph} \gamma_{ij} z^{-1-i} H_{j-d}(z^{-1}) \tag{19}$$

$$T_i(z^{-1}) = \sum_{j=sh}^{ph} \gamma_{ij} z^{-ph+j} . \tag{20}$$

III. Model Predictive Control Subject to Sensor Data Loss

In standard predictive control operation the control input is calculated at each sampling instant according to the control law (shown in Fig. 2)

$$S_1(z^{-1})D(z^{-1})u(t) + R_1(z^{-1})y(t) = T_1(z^{-1})w(t) \tag{21}$$

using the measured value of the plant output.

In case the current output value is not available due to the sensor data loss, the control law (21) can not be evaluated. In this situation the control input is usually set to zero or to the last implemented value.

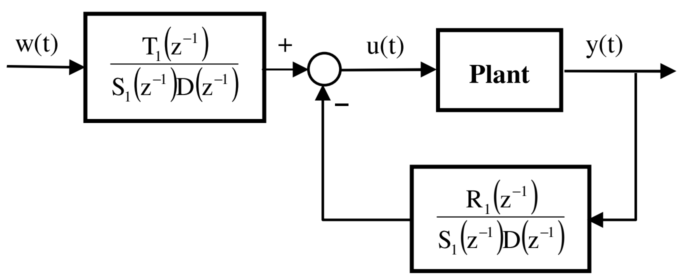

Fig. 2 Pole placement control structure

The model predictive control approach offers another possibility. As it has been stated above, at each sampling instant the sequence of future control inputs $u(t+i)$, $i = 1,\ldots,ch-1$ is calculated which can be stored and employed at next sampling instants. Thus in case of data dropout at time t the control input $u(t+1)$ calculated at previous sampling instant can be used instead, i.e. the control law takes the following form

$$S_2(z^{-1})D(z^{-1})u(t) + R_2(z^{-1})y(t-1) = T_2(z^{-1})w(t-1) . \tag{22}$$

If the data dropout continues at further sampling instants, another terms of future control input sequence can be used.

The above described control strategy can be implemented by switching between the control laws (21) and (22) (or the other ones if needed) as depicted in Fig. 3. At any given time only one of the controllers is active in the closed-loop and supplies the control signal.

The fundamental objective for the control design is the stability of the resulting closed-loop system. The stability analysis of switched control systems is by no means trivial. Even if each applied control law ensures the closed loop stability, it is necessary to prove the closed loop stability in case of switching between these control laws which can occur arbitrarily often. The switching action between controllers can induce a dynamical behavior that cannot be observed in any of the particular control systems.

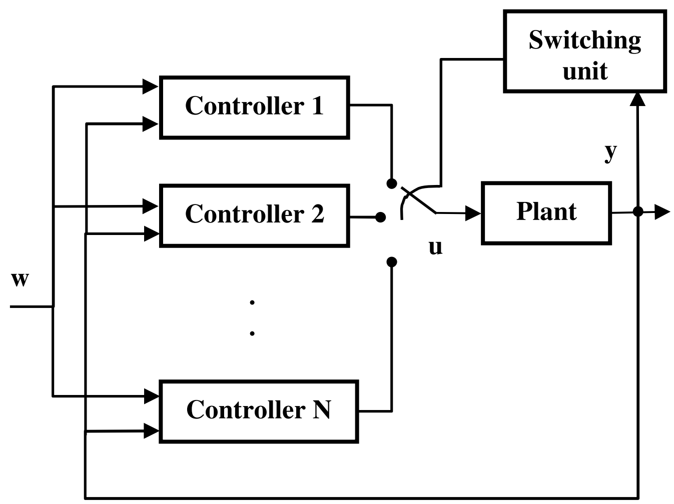

Fig. 3 Switched control system

IV. Stability Analysis of Linear Switched Systems

Switched systems are a special class of hybrid dynamical systems which consist of a family of subsystems and a switching law specifying the switching between the subsystems. The continuous dynamics of switched linear systems is described by a set of linear time-invariant differential equations which involve (at least partially) the same states. Each of these differential equations models the dynamics of a linear time-invariant (LTI) system.

The analysis and synthesis of switched systems has attracted increasing interest in recent years due to their importance both in the control theory and applications [25, 26]. Switching may be caused by the inherent multimodal nature of the process, or it may arise on the side of controller when the process is exposed to changing conditions, disturbances or constraints.

There are two possible alternatives in study of switched control systems. In the first one the objective is to find a switching law such that the switched control system is stable and satisfies the desired performance requirements. In the second case the switching law is defined and the closed loop stability has to be investigated.

Stability analysis of switched control systems is frequently based on the concept of quadratic stability. Consider uncertain time-varying linear system described by the linear differential inclusion (LDI) in the form

$$\dot{x}(t) = A(t)x(t), \qquad A(t) \in \Omega \tag{23}$$

where $\Omega \subseteq R^{nxn}$. A sufficient condition for the stability of LDI (23) is the existence of a quadratic function

$$V(\zeta) = \zeta^T P \zeta, \qquad P > 0 \tag{24}$$

that decreases along every nonzero trajectory of (23). If there exists such a matrix *P*, the LDI (23) is quadratically stable and $V(\zeta)$ is the corresponding quadratic Lyapunov function.

The switched linear system can be described as an uncertain system with a polytopic type uncertainty

$$\dot{x}(t) = \sum_{i=1}^{N} \alpha_i A_{ci} x(t) \tag{25}$$

or in the discrete-time case

$$x(t+1) = \sum_{i=1}^{N} \alpha_i A_{di} x(t) \tag{26}$$

where

$$\sum_{i=1}^{N} \alpha_i = 1 \qquad \alpha_i \in \langle 0,1 \rangle \qquad i = 1,2,3,...,N \, . \tag{27}$$

As the control strategy proposed in the previous section is formulated and implemented in discrete-time form, the stability condition for the linear discrete-time uncertain system (26)-(27) is of interest.

Lemma 1

The polytopic system (26)–(27) is quadratically stable if and only if there exists a positive definite matrix $P = P' > 0$ such that

$$A_{di}^T P A_{di} - P \le 0 \quad \text{for} \quad i = 1,2,3,...,N \, . \tag{28}$$

For $N = 1$ the quadratic stability means the satisfaction of necessary and sufficient conditions, while for $N > 1$ it implies only the satisfaction of sufficient conditions.

Wide variety of problems arising in control theory lead to convex or quasiconvex optimization problems which can be formulated as a set of linear matrix inequalities (LMI) [27, 28]. The resulting optimization problems can be solved numerically very efficiently using recently developed interior-point methods.

Using Schur complement the Ljapunov equation (28) can be rewritten to the following LMI form

$$\begin{bmatrix} -P & A_{di}^T P \\ P A_{di} & -P \end{bmatrix} < 0 \quad \text{for} \quad i = 1,2,3,...,N \tag{29}$$

which can be solved by many software packages, such as MATLAB LMI toolbox, software SEDUMI, etc.

According to the Lemma 1 the stability analysis of the control system with arbitrary switching of controllers necessitates solving the system of *N* linear matrix inequalities (29) where *N* is the number of lost output samples and A_{di} $i = 1,2,3,...,N$ are the discrete state matrices of the closed loop system with the corresponding control law. If the solution $P = P' > 0$ of (29) exists, the closed loop is stable, i.e. the controllers can be switched arbitrarily often.

V. Example

The effectiveness of the proposed control scheme has been evaluated by control of a cylindrical laboratory tank depicted in Fig. 4.

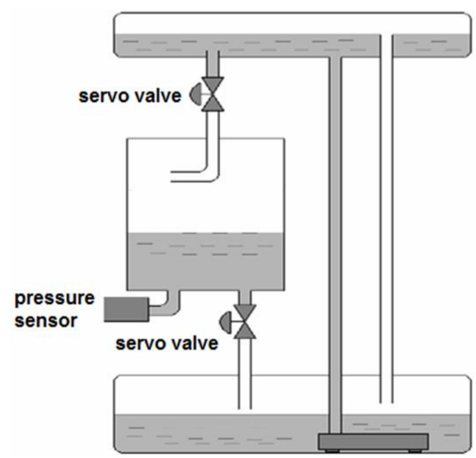

Fig. 4 Cylindrical laboratory tank

The plant output is the water height measured by a pressure sensor and the plant control input is the inflow servo valve opening. The tank has also the outflow servo valve which has been used to generate a disturbance. The servo valves are governed by voltage within the range 0 – 10 V. The pressure sensor range is 0 – 10 V, too.

The control signal has been calculated in PC and implemented using the programmable logical controller Simatic S7-200. For the communication between PC and PLC the OPC (OLE for Process Control) communication standard has been used.

The following second order model of the water height dynamics has been identified with the sampling period *Ts = 1 s*

$$G(z^{-1}) = \frac{-0.002254 + 0.003291z^{-1}}{1 - 1.916z^{-1} + 0.917z^{-2}} \, . \tag{30}$$

Based on this model the GPC controller has been designed using the following control design parameters

$$\mathrm{sh} = 1, \quad \mathrm{ph} = 30, \quad \rho = 10 \,. \tag{31}$$

First standard implementation of GPC has been tested using different values of control horizon $ch \in \{1,2,3,4,5\}$. The results of closed loop simulations are shown in Fig. 5. As it can be seen, the closed loop performances of all controllers are almost identical.

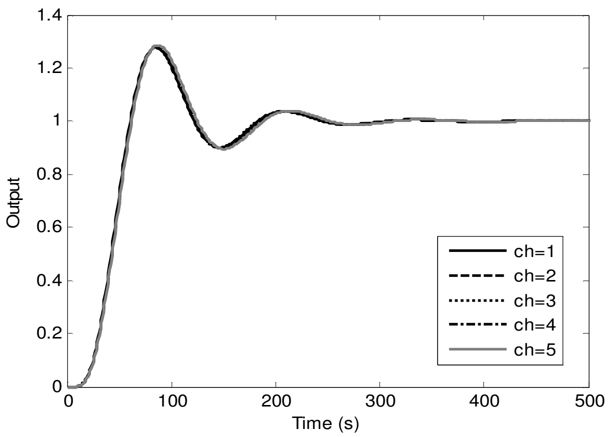

Fig. 5 Output time responses for different values of control horizon

Then data dropouts in the sensor controller link lasting one sampling period have been assumed. The control horizon has been set to 2 so that not only $u(t)$ but also the future value of control input $u(t+1)$ is available at each sampling instant. To analyze the closed loop stability, the LMI (29) has been solved, where $N = 2$ and the closed loop matrices have the following form

$$\mathrm{Ad}_1 = \begin{pmatrix} 3.8832 & -4.8594 & 0.6596 & 3.2698 & -2.4210 & 0.3924 & 0.0755 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \tag{32}$$

$$\mathrm{A}_{d2} = \begin{pmatrix} 3.8663 & -4.7736 & 0.4821 & 3.4601 & -2.5313 & 0.4244 & 0.0721 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \tag{33}$$

The solution $P = P' > 0$ of (29) exists; i.e. the closed loop system with two switched controllers is stable.

To evaluate the control system performances, two simulations have been performed. First, no data dropouts occur and then dropouts of 1.5% data have been artificially generated and the proposed control strategy has been implemented. The results of both experiments are compared in Fig. 6. It can be seen that the plant output time responses differ only slightly. Time instants of data dropouts are in Fig. 7.

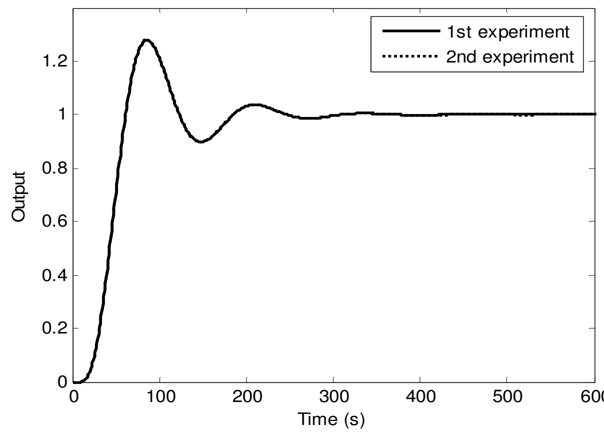

Fig. 6 Output time responses

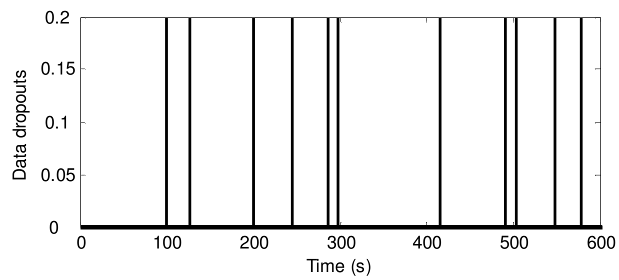

Fig. 7 Time instants of data dropouts

Next, loss of two consecutive output samples has been assumed. The control horizon has been increased to 3. The resulting closed loop matrices are as follows

$$\mathrm{A}_{d1} = \begin{pmatrix} 3.8864 & -4.8727 & 0.6797 & 3.2593 & -2.4246 & 0.3980 & 0.0739 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \tag{34}$$

$$\mathrm{A}_{d2} = \begin{pmatrix} 3.8688 & -4.7841 & 0.4972 & 3.4539 & -2.5364 & 0.4300 & 0.0706 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \tag{35}$$

$$\mathrm{A}_{d3} = \begin{pmatrix} 3.8503 & -4.6905 & 0.3045 & 3.6592 & -2.6541 & 0.4636 & 0.0671 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \tag{36}$$

The solution of LMI (29) with the closed loop matrices (34)–(36) exists, i.e. the sufficient condition for the closed loop stability is satisfied. The simulation results are shown in Fig. 8. As in the previous case, the no-dropouts case (first experiment) has been compared to the situation when the 9% of first samples and 3.5% of second samples have been lost (second experiment). It can be seen that even such significant loss of data does not cause the deterioration of the control system performances. Time instants of data dropouts can be seen in Fig. 9.

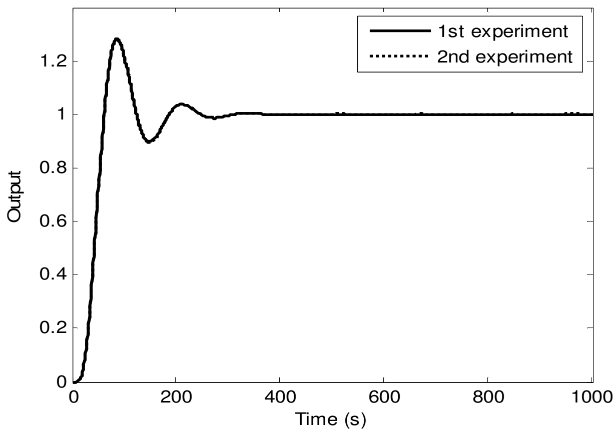

Fig. 8 Output time responses

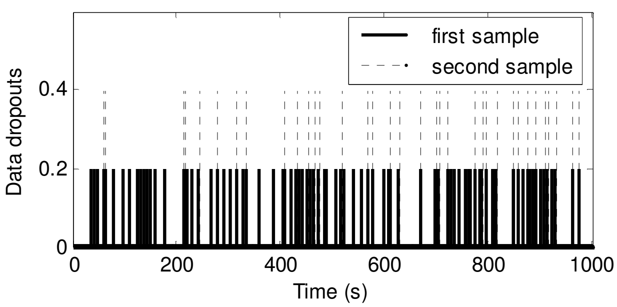

Fig. 9 Time instants of data dropouts

The effectiveness of the proposed control strategy has also been evaluated by real-time experiments. The control horizon ch has been set to 2, i.e. in addition to $u(t)$ also the future value of control input $u(t+1)$ has been calculated at each sampling instant, which would be used at the next sampling instant only in case of the output data dropout.

Figures 10 to 12 show the real-time control results of two experiments. In the first experiment the model predictive control with no data dropouts has been performed. In the second one, 1.5% data dropouts have been artificially generated and the proposed control strategy has been implemented. The measured water height together with its reference value is shown in Fig. 10. Fig. 11 shows the time plots of control input (inflow valve opening). The disturbance signal (outflow valve opening) and the time instants of data dropouts are in Fig. 12.

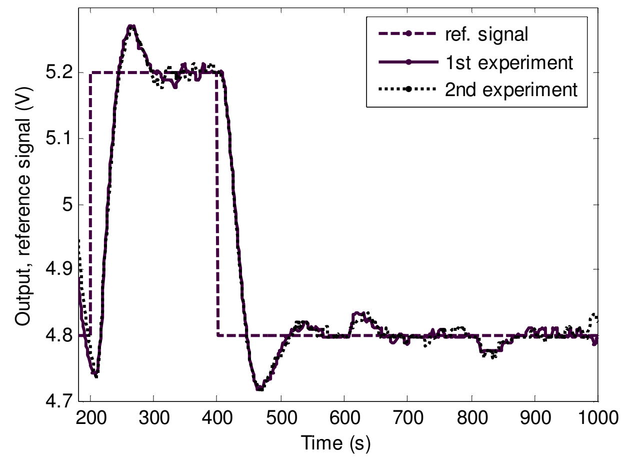

Fig. 10 Output and reference time responses

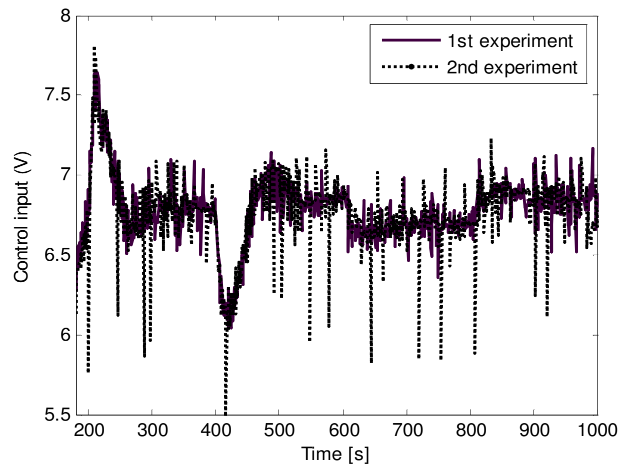

Fig. 11 Control input time responses

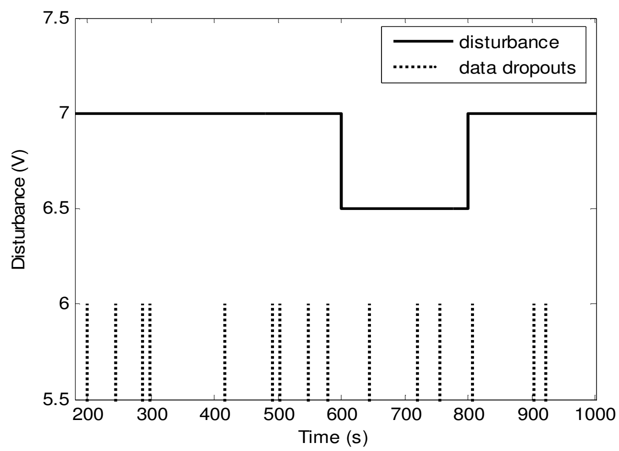

Fig. 12 Disturbance time response and data dropouts

As it can be seen from Fig. 10, control performances obtained in both experiments are comparables, i.e. the issue of data dropout has been successfully solved using the proposed control strategy.

VI. CONCLUSION

The paper has dealt with the data loss issue in networked control systems. The proposed control strategy is based on the model predictive control design where the future values of control inputs are calculated and used at next sampling instants in case of data losses at the sensor-controller link. To analyze the closed loop stability with the proposed control strategy, the concept of quadratic stability has been used. The sufficient stability condition has been derived in the form of linear matrix inequalities. The proposed control approach can be useful in network control system applications where data dropouts in the sensor-controller link are expected. In the presented example the control performances have not been significantly deteriorated even in case when two consecutive output samples have been lost.

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REFERENCES

[1] M. Blaho, L. Mrafko, M. Urban, J. Murgaš, “Networked control systems with PROFINET and IWLAN,” *Recent advances in manufacturing engineering - Proc. of the 4th International Conference on manufacturing engineering, quality and production systems*, Barcelona, Spain, 2011, pp. 219-223.

[2] M. Tabbara, D. Ne and A.R. Teelšic, “Stability of Wireless and Wireline Networked Control Systems,” *IEEE Transactions on Automatic Control*, vol. 52, pp. 1615–1630, 2007.

[3] Y. Tipsuwan and M. Chow, “Control Methodologies in Networked Control Systems,” *Control Engineering Practice*, vol. 11, pp. 1099–1111, 2003.

[4] L. A. Montestruque and P. J. Antsaklis, “On the Model-Based Control of Networked Systems,” *Automatica*, vol. 39, pp. 1837 – 1843, 2003.

[5] W. Zhang, M. S. Branicky and, S. M. Phillips, “Stability of Networked Control Systems,” *IEEE Control Systems Magazine*, pp. 84-99, February 2001.

[6] L. Eriksson, “A PID Tuning Tool for Networked Control Systems,” *Proc. of the 4th WSEAS International Conference on signal processing, robotics and automation*, Salzburg, Austria, 2005.

[7] Y. Tipsuwan and M.-Y. Chow, “Gain Scheduler Middleware: A Methodology to Enable Existing Controllers for Networked Control and Teleoperation—Part I: Networked Control,” *IEEE Transactions on Industrial Electronics*, vol. 51, No. 6, pp. 1218-1227, 2004.

[8] K. Ch. Lee, S. Lee and M. H. Lee, “Remote Fuzzy Logic Control of Networked Control System via Profibus-DP,” *IEEE Transactions on Industrial Electronics*, vol. 50, No. 4, 781-792, 2003.

[9] A. T. Naskali and A. Onat, “Random Network Delay in Model Based Predictive Networked, Control Systems,” *Proc of the 6th WSEAS International Conference on Applied Computer Science*, Tenerife, Canary Islands, Spain, 2006, pp. 199-206.

[10] M. Moayedi, Y. K. Foo and Y. C. Soh, “LQG Control for Networked Control Systems with Random Packet Delays and Dropouts via Multiple Predictive-Input Control Packets,” *Preprints of the 18th IFAC World Congress Milano (Italy)*, 2011, pp. 72-77.

[11] Z. Xiang and X. Jian, “Communication and Control Co-Design for Networked Control System in Optimal Control”, *Proc. of the 12th WSEAS International Conference on SYSTEMS*, Heraklion, Greece, 2008, pp. 698-703.

[12] S. H. Kim and P. Park, “Network-delay-dependent H-inf control of systems with input saturation,” *Proc. of the 2007 WSEAS International Conference on Computer Engineering and Applications*, Gold Coast, Australia, 2007, pp. 117-121.

[13] L. Chunmao, X. Jian, Z. Yue, “Stochastic Delay Estimation and Adaptive Control of Networked Control Systems,” *Proc. of the 6th WSEAS International Conference on Simulation, Modelling and Optimization*, Lisbon, Portugal, 2006, pp.72-76.

[14] H. Lin and P. J. Antsaklis, “Stability and Persistent Disturbance Attenuation Properties for a Class of Networked Control Systems: Switched System Approach,” *International Journal of Control*, vol. 78, No. 18, pp. 1447–1458, 2005.

[15] O. C. Imer, S. Yüksel and T. Basar, “Optimal Control of LTI Systems Over Unreliable Communication Links,” *Automatica*, vol. 42, pp. 1429 – 1439, 2006.

[16] W. Kim, K. Ji and A. Srivastava, “Network-Based Control with Real-Time Prediction of Delayed/Lost Sensor Data,” *IEEE Transactions on Control Systems Technology*, vol. 14, pp. 182-185, 2006.

[17] D. M. de la Peña and P, D. Christofides, “Lyapunov-Based Model Predictive Control of Nonlinear Systems Subject to Data Losses”, *IEEE Transactions on Automatic Control*, vol. 53, pp. 2076-2089, 2008.

[18] E.F. Camacho and C. Bordons, *Model Predictive Control*, Springer-Verlag, 2004.

[19] S.J. Qin and T.A. Badgwell, “A Survey of Industrial Model Predictive Control Technology,” *Control Engineering Practice*, vol. 11, pp. 733-764, 2003.

[20] R. Scattolini, “Architectures for Distributed and Hierarchical Model Predictive Control – A review,” *Journal of Process Control*, vol. 19, pp. 723–731, 2009.

[21] D. Srinivasagupta, H. Schättler and B. Joseph, “Time-Stamped Model Predictive Control: An Algorithm for Control of Processes with Random Delays,” *Computers and Chemical Engineering*, vol. 28, pp. 1337–1346, 2004.

[22] Y. Wang, Z. Zuo, “On quadratic stabilizability of linear switched systems with polytopic uncertainties”, *IEEE International Conference on Systems, Man and Cybernetics*, 2005, pp. 1640 - 1644 Vol. 2.

[23] G. Zhai, H. Lin and P.J. Antsaklis, "Quadratic stabilizability of switched linear systems with polytopic uncertainties", *Int. J. Control*, vol 76, pp. 747-753, 2003.

[24] D.W. Clarke, C. Mohtadi and P.S. Tuffs, “Generalized Predictive Control – Part I. The Basic Algorithm. Part II. Extensions and Interpretations,” *Automatica*, vol. 23, pp. 137-160, 1987.

[25] M.S. Branicky, "Multiple Lyapunov functions and other analysis tools for switched and hybrid systems", *IEEE Trans. Automat. Contr.*, vol 43, pp. 475-482, 1998.

[26] E. Skafidas, R.J. Evans, A.V. Savkin and I.R. Petersen, "Stability results for switched controller systems", *Automatica*, vol 35, pp. 553-564, 1999.

[27] D. Rosinová and V. Veselý, “Robust Static Output Feedback for Discrete-Time Systems: LMI Approach,” *Periodica Polytechnica Ser. El. Eng.*, vol. 48, No 3-4, 151-163, 2004.

[28] S. Boyd, L. El Ghaoui, E. Feron and V Balakrishnan, *Linear Matrix Inequalities in System and Control Theory*, Society for Industrial and Applied Mathematics, SIAM, Philadelphia, 1994.

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