

PID control strategy for sensor random packet dropouts in networked control system

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Abstract— In this paper the control strategy for networked control systems is proposed that is able to deal with the problem of data packet dropout at the sensor-controller link. The PID control structure implemented in Simatic S7-200 programmable logical controller is considered. The control design is based on the generalized predictive control (GPC) where the sequence of future control inputs sequence up to a given horizon is calculated at each sampling instant which can be stored and used at next sampling instants in case the current output value is not available. The PID controller tuning rules are obtained by equating the PID control law with the pole-placement control structure of GPC given some conditions on the plant model orders. The proposed control strategy is implemented as switched control system where two or more control laws are switched arbitrarily often. The closed loop stability is investigated using the concept of quadratic stability.

Keywords— networked control system, PID controller, model predictive control, data dropout

I. INTRODUCTION

Networked control systems (NCS) where spatially distributed control loop components (sensor, actuator, controller) are connected by means of a shared communication medium (as shown in Fig. 1) gained increasing attention in recent years due to its cost effective and flexible applications.

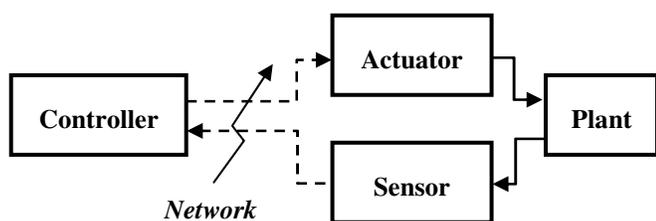


Fig.1 Network control system

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 system diagnosis and maintenance and offers modularity and flexibility in control system design.

On the other hand, integration of communication real-time networks into feedback control loops leads to many specific control issues giving rise to important research topics. The NCS design has to deal with the dynamics introduced by network, which may include communication disruptions such as communication channel noise, data packet dropouts, time-varying delays, bandwidth limitations and data quantization. These phenomena may degrade the performance of the control system or even drive the system to instability.

In the past two decades the problems of NCS design and analysis have been extensively studied. An overview of NCS control methodologies and description of network delays is in [1]. Intensive research attention has been paid to stability analysis and stabilization of networked control systems subject to data loss and time-varying transmission delays [2 – 6]. Several control design approaches have been used to NCS design: for instance, fuzzy logic [7], gain scheduling [8], prediction and model predictive control [9, 10], optimal control [11], robust control [12], adaptive control [13].

In this paper, we focus on the NCS design and analysis subject to data losses at the sensor-controller link. If the controller does not receive new feedback data, the plant is regulated in an open-loop and the control input is usually set 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 control systems with asynchronous measurement, where the samplings are not received at fixed time instants due to the difficulties of measuring. The performance of real-time NCS with data dropouts was discussed in [14]. In [14], stabilizing optimal control of linear time-invariant systems over unreliable communication links was studied. Predictive control for nonlinear systems with guaranteed stability in the presence of data losses was designed in [14]. 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 [5, 17].

Despite the wide development of advanced control methods, the industrial processes are often controlled by means of programmable logic controllers (PLC), where hardware and software are specifically adapted to industrial environment.

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This type of controllers usually offers only simple control structures, such as on-off control or PID control loops implemented in its digital form. The PID controller is the most dominating form of feedback in use recently; more than 90% of all control loops are PID [18]. The calculation of PID controller tuning constants can be performed using various methods using different performance criteria: analytical methods, empirical or simply trial and error ones. Advanced control design approaches can also be used for PID control design, for instance the model predictive control [19].

An increasing research attention has recently been paid to the PID control design for NCS. In [20] the optimization technique was used to find the best PID controller parameters, when the system has time-varying or stochastic delays. A new tool with graphical user interface for discrete-time PID controller tuning in networked control systems with time-varying delays has been described in [21]. A delay-dependent gain-scheduling approach for PID controllers in dual-rate implementations has been proposed in [22]. In [23, 24], fuzzy PID controllers have been used to deal with random delays in NCS. The guaranteed cost PID controller design for NCS with time-delay and polytopic uncertainties has been addressed in [25]. The robust H_∞ PID control for NCS such that load and reference disturbances can be attenuated with a prescribed level has been developed in [26].

The paper addresses the PID control design and implementation based on the model predictive control (MPC) approach that is able to deal with data dropouts in the control system. MPC represents a family of advanced control methods which make explicit use of plant model to predict its future behavior and to calculate the future control sequence minimizing an objective function [27]. 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 developed considerably and became popular both within the research control community and in industry [28]. MPC has also proved its effectiveness in NCS especially in the context of distributed and hierarchical control [29]. 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 [30].

In this paper the MPC approach is employed to treat the issue of data losses. As the future control inputs sequence 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 the next terms of the control sequence in case the sensor data at next sampling times is 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. This control strategy has been proposed in [31] and in this paper it is used for the PID control implemented by means of PLC.

The fundamental property of the control system is its stability. To analyze the stability of control loop with a switched controller, it is not sufficient to check whether the closed loop system with each applied control law is stable, but it is necessary to take into account also a dynamics induced by control law switching which can occur arbitrarily often. The analysis and synthesis of switched control systems is frequently based on the concept of quadratic stability [32, 33]. Using this concept, the stability of the proposed control strategy has been investigated and resulting stability condition has been derived in the form of linear matrix inequalities, which can be efficiently solved by many available software tools.

The paper is organized as follows. In section 2 standard model predictive control design procedure is briefly reminded. Section 3 describes the predictive-based PID control design. In section 4 the control strategy for the case of data dropout in the sensor-controller link is proposed and the stability of resulting switched control system is investigated. The effectiveness of the proposed control scheme is evaluated by the real-time control of a simple laboratory plant in section 5. Finally, some conclusions are given.

II. MODEL PREDICTIVE CONTROL

A. Plant Model

Consider that the SISO plant operation around the particular setpoint can be described by the following CARIMA model

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

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

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.

B. Control Design

Generalized predictive control (GPC) developed in [34] 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 following cost function is minimized

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

$$\text{subject to } D(z^{-1})u(t+i) = 0 \quad \text{for } ch \leq i \leq ph \quad (4)$$

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.

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

$$D(z^{-1})u(t) = - \sum_{j=sh}^{ph} \gamma_{1j} (y_0(t+j/t) - w(t+j)) = u(t) - u(t-1) \quad (5)$$

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

$$D(z^{-1})u(t+i) = - \sum_{j=sh}^{ph} \gamma_{(i+1)j} (y_0(t+j/t) - w(t+j)) \quad (6)$$

for $i = 1, \dots, ch-1$.

In (5) and (6), γ_{ij} for $i = 1, \dots, ch-1$, $j = sh, \dots, ph$, are the coefficients of i -th line of the matrix K

$$K = [G_1^T G_1 + \rho I_{ch}]^{-1} G_1^T \quad (7)$$

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

$$y_0(t+j/t) = H_{j-d}(z^{-1})D(z^{-1})u(t-1) + F_j(z^{-1})y(t) \quad (8)$$

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

The control laws (5)-(6) may also be implemented using the standard pole-placement control structure (shown in Fig. 1)

$$S_i(z^{-1})D(z^{-1})u(t+i-1) + R_i(z^{-1})y(t) = T_i(z^{-1})w(t) \quad (9)$$

for $i = 1, \dots, ch-1$

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

$$R_i(z^{-1}) = \sum_{j=sh}^{ph} \gamma_{ij} F_j(z^{-1}) = r_{i,0} + r_{i,1}z^{-1} + \dots + r_{i,nt}z^{-nt} \quad (10)$$

$$S_i(z^{-1}) = 1 + \sum_{j=sh}^{ph} \gamma_{ij} z^{-1-i} H_{j-d}(z^{-1}) = 1 + s_{i,1}z^{-1} + \dots + s_{i,ns}z^{-ns} \quad (11)$$

$$T_i(z^{-1}) = \sum_{j=sh}^{ph} \gamma_{ij} z^{-ph+j} = t_{i,0} + t_{i,1}z^{-1} + \dots + t_{i,nt}z^{-nt} \quad (12)$$

III. PREDICTIVE PID CONTROL

In this paper we employ the PID algorithm to do the model predictive control without the necessity of the specialized software. More specifically, the PID control structure implemented on PLC SIMATIC S7-200 has been considered [35]. The Siemens SIMATIC S7-200 series is a line of micro-programmable logic controllers that can control a variety of small applications. The PID control law implemented on this PLC is of the form

$$u(t) = M_p(t) + M_i(t) + M_d(t) \quad (13)$$

where

$$M_p(t) = K_c e(t) \quad (14)$$

$$M_i(t) = K_c \frac{T_s}{T_i} e(t) + M_x \quad (15)$$

$$M_d(t) = K_c \frac{T_d}{T_s} (y(t-1) - y(t)) \quad (16)$$

where $e(t) = w(t) - y(t)$ is the control error and the bias M_x is the running sum of all previous values of the integral term. T_s is the sample time, K_c , T_i and T_d are the loop gain, derivative and integral time constants, respectively.

To avoid step changes or bumps in the output due to derivative action on setpoint changes, this equation is modified to assume that the setpoint is a constant ($w(t) = w(t-1)$). This results in the calculation of the change in the plant output instead of the change in the error

$$M_d(t) = K_c \frac{T_d}{T_s} (w(t) - y(t) - w(t) + y(t-1)) = K_c \frac{T_d}{T_s} (y(t-1) - y(t)) \quad (17)$$

The aim is to implement the predictive control algorithm by means of the above described PID control structure. To obtain the tuning rules for the PID controller parameters, the pole-placement control structure (9) has to be compared to the incremental form of the PID control law [36]

$$\begin{aligned}
 D(z^{-1})u(t) &= u(t) - u(t-1) = \\
 &= \left(K_c + K_c \frac{T_s}{T_i} \right) w(t) - K_c w(t-1) + \\
 &+ \left(-K_c - K_c \frac{T_s}{T_i} - K_c \frac{T_d}{T_s} \right) y(t) + \\
 &+ \left(K_c + 2K_c \frac{T_d}{T_s} \right) y(t-1) - K_c \frac{T_d}{T_s} y(t-2) = \\
 &= P_w(z^{-1})w(t) - P_y(z^{-1})y(t)
 \end{aligned} \tag{18}$$

where

$$P_w(z^{-1}) = \left(K_c + K_c \frac{T_s}{T_i} \right) - K_c z^{-1} \tag{19}$$

$$\begin{aligned}
 P_y(z^{-1}) &= \left(K_c + K_c \frac{T_s}{T_i} + K_c \frac{T_d}{T_s} \right) + \\
 &+ \left(-K_c - 2K_c \frac{T_d}{T_s} \right) z^{-1} + K_c \frac{T_d}{T_s} z^{-2}
 \end{aligned} \tag{20}$$

and in case of PI control law

$$P_y(z^{-1}) = \left(K_c + K_c \frac{T_s}{T_i} \right) - K_c z^{-1}. \tag{21}$$

From the comparison of both control laws it yields that

$$S_i(z^{-1}) = 1 \tag{22}$$

$$R_i(z^{-1}) = P_y(z^{-1}) \tag{23}$$

$$T_i(z^{-1}) = P_w(z^{-1}) \tag{24}$$

i.e. the pole placement and the PID control laws are equivalent if $T_i(z^{-1})$ is the first order polynomial and $R_i(z^{-1})$ is the second order polynomial. In case of PI control law $R_i(z^{-1})$ has to be the first order polynomial. These conditions can be satisfied by the proper choice of the plant model structure (1)-(2), namely the second order plant model ($na=2, nb=0$) leads to PID control and the first order plant model ($na=1, nb=0$) to PI control, respectively [19]. On the other hand, there is no restriction on the choice of GPC tuning parameters so that the advantages of model predictive control can fully be exploited.

The PID tuning constants K_c , T_i and T_d can be derived from equation (23)

$$K_c = -r_{i,1} - 2r_{i,2} \tag{25}$$

$$T_i = -\frac{r_{i,1} + 2r_{i,2}}{r_{i,0} + r_{i,1} + r_{i,2}} T_s \tag{26}$$

$$T_d = \frac{-r_{i,2}}{r_{i,1} + 2r_{i,2}} T_s \tag{27}$$

As it can be seen from the equations (25) – (27), the PID tuning constants depend only on the parameters of the $R_i(z^{-1})$ polynomial. According to (10), the calculation of these parameters necessitates the knowledge of matrix G_i and $F_j(z^{-1})$ $j = sh, \dots, ph$ polynomials.

The matrix G_i has the following form

$$G_i = \begin{bmatrix} g_{sh-d-1} & \dots & g_0 & 0 & 0 & 0 \\ g_{sh-d} & \dots & \dots & g_0 & 0 & 0 \\ \vdots & \dots & \dots & \dots & \ddots & \vdots \\ g_{ch-1} & \dots & \dots & \dots & \dots & g_0 \\ \vdots & \dots & \dots & \dots & \dots & \vdots \\ g_{ph-d-1} & \dots & \dots & \dots & \dots & g_{ph-ch-d} \end{bmatrix} \tag{28}$$

and its coefficients can be obtained from the samples of plant step response, i.e. for the unit input step

$$\{u(0), u(1), u(2), \dots\} = \{1, 1, 1, \dots\} \tag{29}$$

the plant output signal is of the form

$$\{y(0), y(1), y(2), y(3), \dots\} = \{0, g_0, g_1, g_2, \dots\} \tag{30}$$

The $F_j(z^{-1})$ $j = sh, \dots, ph$ polynomials are solutions of the following Diophantine equations

$$1 = A(z^{-1})D(z^{-1})E_j(z^{-1}) + z^{-j}F_j(z^{-1}) \tag{31}$$

$$E_j(z^{-1})B(z^{-1}) = G_{j-d}(z^{-1}) + z^{-j+d}H_{j-d}(z^{-1}) \tag{32}$$

where

$$E_j(z^{-1}) = e_0 + e_1 z^{-1} + \dots + e_{j-1} z^{-j+1} \tag{33}$$

$$F_j(z^{-1}) = f_0^j + f_1^j z^{-1} + \dots + f_{na}^j z^{-na}$$

and they can be calculated recursively as follows

$$E_1(z^{-1}) = 1 \tag{34}$$

$$F_1(z^{-1}) = z(1 - A(z^{-1})D(z^{-1})) \tag{35}$$

$$\begin{aligned}
 E_j(z^{-1}) &= E_{j-1}(z^{-1}) + f_0^{j-1} z^{-j+1} \\
 F_j(z^{-1}) &= z^j(1 - E_j(z^{-1})A(z^{-1})D(z^{-1})) \quad \text{for } j = 2, \dots, ph.
 \end{aligned} \tag{36}$$

IV. PREDICTIVE PID CONTROL SUBJECT TO SENSOR DATA DROPOUT

In standard operation, predictive control is implemented using the receding horizon strategy, i.e. the control input is

calculated at each sampling instant using the current measured value of the plant output according to the control law

$$S_1(z^{-1})D(z^{-1})u(t) + R_1(z^{-1})y(t) = T_1(z^{-1})w(t) \quad (37)$$

However, if the current output value is not available due to the sensor data dropout, the control law (37) can not be evaluated and the control input is usually set to zero or to the last implemented value.

As it has been stated above, if the control horizon is greater than one, not only current value of control input $u(t)$ is calculated, but also the future values of control input $u(t+i)$, $i=1, \dots, ch-1$, which can be stored and used 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, i.e. the control law takes the following form

$$S_2(z^{-1})D(z^{-1})u(t) + R_2(z^{-1})y(t-1) = T_2(z^{-1})w(t-1) \quad (38)$$

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

A. Stability Analysis

The above described control strategy can be implemented by switching between the control laws (37) and (38) (or the other ones if needed). 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 introduces behavior in the overall system that is not present in any of the composite subsystems.

Switched systems have a long history of interest in the control community and they have attracted increasing interest in recent years due to their importance both in the control theory and applications [37, 38]. They represent a special class of hybrid dynamical systems which comprise a collection of subsystems described by linear dynamics (in the form of differential or difference equations), together with a switching rule that specifies the switching between the subsystems. 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.

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

$$\dot{x}(t) = A(t)x(t), \quad A(t) \in \Omega \quad (39)$$

where $\Omega \subseteq R^{n \times n}$. A sufficient condition for the stability of LDI (39) is the existence of a quadratic function

$$V(\zeta) = \zeta^T P \zeta, \quad P > 0 \quad (40)$$

that decreases along every nonzero trajectory of (39). 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

$$\dot{x}(t) = \sum_{i=1}^N \alpha_i A_{ci} x(t) \quad (41)$$

or in the discrete-time case

$$x(t+1) = \sum_{i=1}^N \alpha_i A_{ci} x(t) \quad (42)$$

where

$$\sum_{i=1}^N \alpha_i = 1, \quad \alpha_i \in (0,1), \quad i = 1,2,3,\dots,N \quad (43)$$

Lemma 1

The polytopic system (42)-(43) is quadratically stable if and only if there exists a positive definite matrix $P = P' > 0$ such that

$$A_{ci}^T P A_{ci} - P \leq 0 \quad \text{for } i = 1,2,3,\dots,N \quad (44)$$

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) [39, 40]. The resulting optimization problems can be solved numerically very efficiently using recently developed interior-point methods.

Using Schur complement the Ljapunov equation (44) can be rewritten to the LMI (linear matrix inequality) form

$$\begin{bmatrix} -P & A_{ci}^T P \\ P A_{ci} & -P \end{bmatrix} < 0 \quad \text{for } i = 1,2,3,\dots,N \quad (45)$$

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 (45) where N is the number of lost output samples and A_{ci} , $i = 1,2,3,\dots,N$ are the discrete state matrices of the closed loop system with the corresponding control law.

V. EXPERIMENTAL EVALUATION

The effectiveness of the proposed control approach has been evaluated by real-time control of a laboratory heating system depicted in Fig. 2. This system is a heat insulated box divided into two independent heated parts. The air is blown into the box by fan controlled by voltage U_v . Inside the box, two coil heating elements and four temperature sensors are installed. In our experiments, the controlled variable is the temperature T_3 and the control input is the coil heater voltage U_s . Fan voltage U_v has been used to generate a disturbance. The range of the fan and coil heaters as well as the range of the temperature sensors are 0 – 10 V.

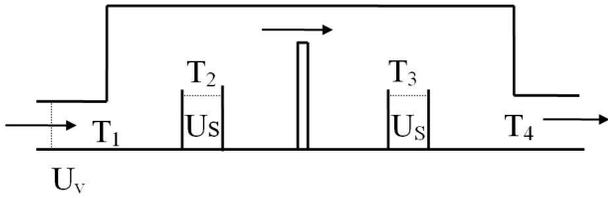


Fig. 2 Heating system

First the second order model of the temperature dynamics has been identified with the sampling period $T_s = 1$ s

$$G(z^{-1}) = \frac{-0.003319z^{-1} + 0.01731z^{-2}}{1 - 1.073z^{-1} + 0.09509z^{-2}} \quad (46)$$

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

$$sh = 1, \quad ph = 30, \quad \rho = 10 \quad (47)$$

As the output sensor data dropouts lasting one sampling period have been expected, the control horizon 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 has been stored and used at the next sampling instant only in case of the measured output dropout. The satisfaction of closed loop stability sufficient condition (45) has been verified, where $N=2$ and the closed loop matrices are as follows

$$A_{c1} = \begin{pmatrix} 2.6880 & -2.0992 & 0.1024 & 0.3357 & -0.0226 & -0.0047 & 0.0004 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \quad (48)$$

$$A_{c2} = \begin{pmatrix} 2.6872 & -2.0953 & 0.0958 & 0.3409 & -0.0244 & -0.0045 & 0.0004 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \quad (49)$$

The solution $P = P' > 0$ of (45) exists; i.e. the closed loop system with two switched controllers is stable.

In order to evaluate the proposed switching control strategy the dropouts of 3 % of sensor data have been artificially generated in simulation, where the set point value has been set to 1. The plant output time response is in Fig. 3 and the time instants of data dropouts are in Fig. 4.

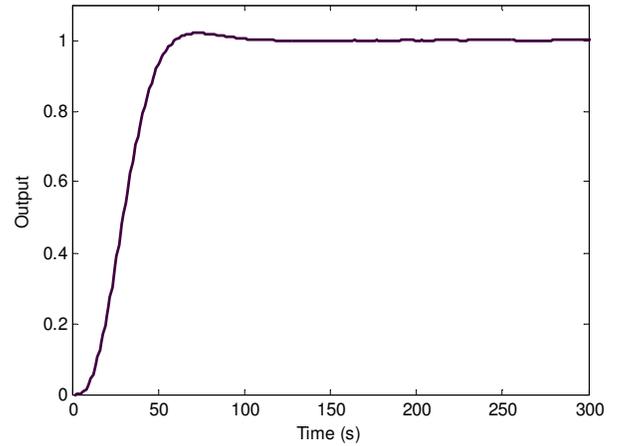


Fig. 3 Output time response

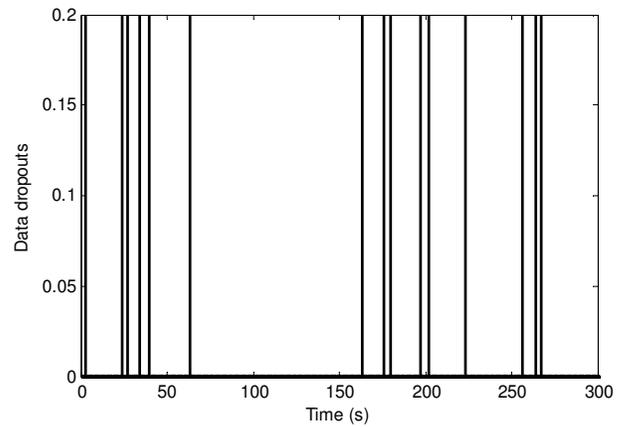


Fig. 4 Time instants of data dropouts

Next, the control horizon has been increased to 3, i.e. the dropout of two consecutive output sensor samples has been assumed. In this case the closed loop state matrices have the following form

$$A_{c1} = \begin{pmatrix} 2.6989 & -2.1300 & 0.1298 & 0.3304 & -0.0253 & -0.0041 & 0.0003 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \quad (50)$$

$$A_{c2} = \begin{pmatrix} 2.6971 & -2.1233 & 0.1204 & 0.3366 & -0.0271 & -0.0039 & 0.0003 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \quad (51)$$

$$A_{c3} = \begin{pmatrix} 2.6954 & -2.1168 & 0.1109 & 0.3429 & -0.0291 & -0.0037 & 0.0003 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \quad (52)$$

and the closed loop stability condition is satisfied.

In the simulation, 7.67 % of first samples and 1.67 % of second samples have been artificially lost. The simulation results are in Fig. 5 and Fig. 6. It can be seen that in both simulations the sensor data dropouts have not caused the deterioration of closed loop performances.

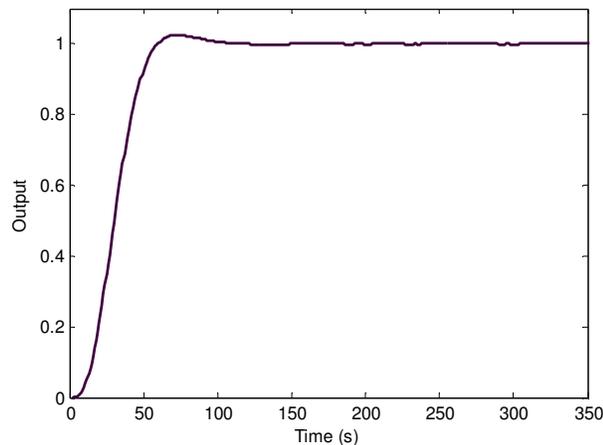


Fig. 5 Output time response

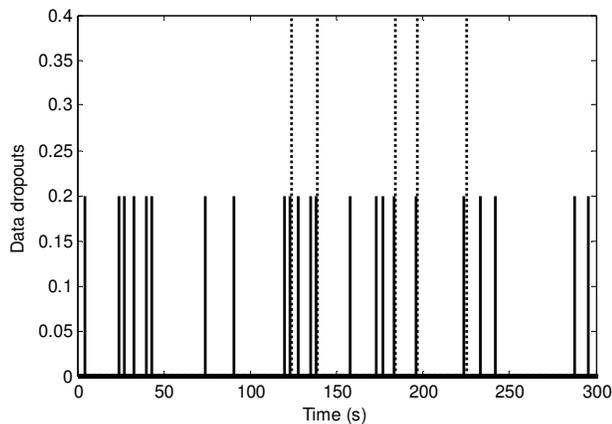


Fig. 6 Time instants of data dropouts

For the real-time temperature control the control horizon has been set to 2. The control inputs $u(t)$ and $u(t+1)$ have been generated by two PID control laws implemented in the PLC Simatic S7-200 with the following parameters

$$\begin{aligned} u(t): & \quad K_c = 6.6192, \quad T_i = 15.3529, \quad T_d = 0.1072, \\ u(t+1): & \quad K_c = 6.1179, \quad T_i = 15.3046, \quad T_d = 0.1072 \end{aligned} \quad (53)$$

Figures 7 and 8 show the control results of two experiments. In the first experiment the model predictive control with no data dropouts has been performed. In the second one, 2% data

dropouts have been artificially generated and the proposed control strategy has been implemented. The measured temperature together with its reference value is shown in Fig. 7. Fig. 8 shows the time plots of both control input (the coil heater voltage) and disturbance signal (the fan voltage).

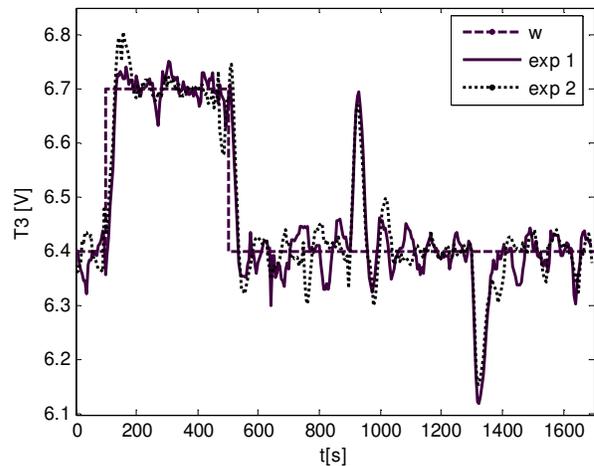


Fig. 7 Output and reference time responses

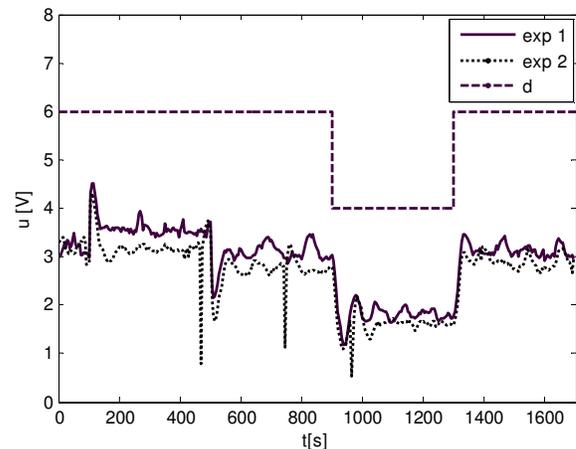


Fig. 8 Control input and disturbance time responses

As it can be seen from Fig. 7, control performances obtained in both experiments are comparables, i.e. the issue of data dropout has been successfully solved using the proposed control strategy. If more consecutive data dropouts are expected, then the control horizon can be increased and more future values of control input can be calculated. From the implementation point of view, each future value of the control input is calculated by separate control law, i.e. the resulting control scheme become more complicated. For example, in PLC Simatic S7-200 a maximum of eight PID control loops can be implemented.

VI. CONCLUSION

In the paper the PID control strategy for NCS that is able to deal with the data dropouts in the sensor – controller link has been presented. The PID control structure is the most

frequently used control structure which can be found also in simple industrial controllers. The PID controller design is based on the model predictive control design where the future values of control inputs up to a given control horizon are calculated. The proposed control strategy can be formulated as switching between two or more controllers. The stability analysis of the resulting control scheme has been based on the concept of quadratic stability and the sufficient stability condition has been expressed 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.

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