New Constrained Predictive PID controller for packet dropouts in Wireless Networked Control Systems ⋆

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Abstract: A new constrained predictive PID controller is presented to achieve stability and performance robustness in Wireless Networked Control Systems (WNCS), where the communication is subject to dropouts in both communication directions: sensor to control and control to actuator transmission. The control strategy is based on a new PID controller with similar properties to Model-Based Predictive Control (MBPC). A Kalman filter used for output prediction and a consecutive dropouts compensator have also been added to the control scheme. The purpose of this approach is to develop an estimation algorithm and a control system that maintain information of the sensor packets and the control actions. Several experiments using the TrueTime network simulator showed that the predictive PID controller performs as good as the MBPC scheme with the advantage of having a simple structure.

Keywords: Wireless Networked Control Systems, predictive PID.

WNCS are control systems where controllers, actuators and sensors are connected to a shared communication network. WNCS applications are increasing as a result of stronger industrial and academic interests in the potential benefits of these systems. The networked solution offers the possibility of decreased costs, simplify the installation and maintenance and increase system-wide monitoring and control capabilities. However, the inclusion of the network leads to significant technical barriers that limit the application of wireless technologies in process control. The main issue is the limited capacity of the shared channel that causes the degradation of WNCS control performance. In particular, the network may introduce large communication delays and loss of information, which greatly influence the controller stability and robustness. These problems motivated the development of control systems that address the complexity and intricate estimation of the WNCS, meanwhile, the simplicity and efficiency of the controller are preferred. Among these methods, the networked predictive control scheme is considerably effective, since it can actively compensate for the transmission delays and consecutive packet dropouts (Sun et al., 2014).

While there are numerous approaches that have been reviewed such as fuzzy, predictive, event-triggered and robust control, the Proportional Integral Derivative (PID) control has received the most attention in the history of process control. There are some networked PID control methods to compensate for delays and dropouts. For instance, Dasgupta et al. (2015) addressed the closed-loop stability of the system under time-varying delays and dropouts with a discrete PID controller. WNCS applications are cited by Abdullah et al. (2016); Blevins et al. (2014) and Hassan et al. (2017).

Motivated by the optimality of the predictive control solution and the simplicity and flexibility of the PID control, it is beneficial to apply the predictive approach to the PID control loops and adapt them to the network communication. Very few studies have been focused on predictive control algorithms with PID structures that can effectively compensate dropouts. For example, Miklovičová and Mrosko (2012) addressed the compensation of control dropouts using Generalised Predictive Control (GPC) and pole placement structure to design a PID controller. Hassan et al. (2016) presented a predictive WNCS to compensate variable delays and disturbance, where a Smith predictor is combined with PID control. A similar solution is postulated by Wu et al. (2016) to compensate random delays and dropouts.

In this paper, a new predictive PID controller with similar properties to MBPC is developed to compensate dropouts in WNCS. A quadratic programming problem optimises a MBPC cost function to find the optimal PID gains at every sampling time. The constraint handling is included to guarantee the loop stability to the controller limitations. The problem of the occurrence of dropouts from sensor to controller is compensated by combining the controller with a Kalman Filter (KF). The measured output $y(k)$ is replaced with the Kalman estimation $\hat{y}_e(k)$ allowing the controller to receive information of the process even in the presence of dropouts. To compensate consecutive dropouts from controller to actuator, predictions of the control signal are calculated and saved in the actuator for the next sampling instant.

In comparison with the above PID approaches, where the loss of information is generally assumed only in one direction, the new predictive PID controller has the advantage of compensating both communication ways. It also provides an innovative and reliable design for WNCS where stability robustness to

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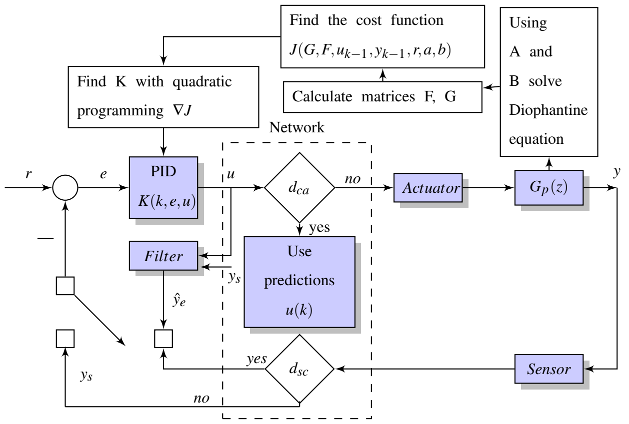

Figure 1. Diagram of predictive PID controller structure

variations of the system's gain and poles can be accomodated. Moreover, it compensates for a high incidence of dropouts and at the same time satisfies input constraints and rejects disturbance in WNCS, which have not yet been addressed in the revised literature.

This paper is structured as follows. Section 2 introduces the MBPC scheme. The predictive PID controller is derived in Section 3. A compensator of dropouts from controller to actuator is studied in Section 4. A Kalman filter and a compensator for consecutive sensor packet dropouts have been added to the control scheme in Section 5. Sections 6 and 7 include several experiments to show the performance and robustness of the controller. Finally, conclusions and future research work are presented in Section 8.

1. PRELIMINARIES

1.1 Predictive PID implementation

The proposed control scheme is presented by the block diagram depicted in Fig. 1. The controller signal is u, y stands for process output, e is the error and r is the reference signal. The controlled plant is $G_p(z)$. The proposed framework is for a class of linear, discrete-time, constrained process. A WNCS whose sensor and control information is transported over a wireless network is considered. The dropouts from sensor to controller and from controller to actuator are represented as d_{psc} and d_{pca}, respectively. A quadratic programming problem optimises a MBPC criterion to find the optimal PID gains at every sampling time. The constraint handling is presented to stop input saturation. The measured output y_s is switched to the Kalman filter estimation $\hat{y}_e$ allowing the controller to always have information of the process even in the presence of dropouts. Predictions of the control signal are calculated and applied accordingly to compensate consecutive dropouts from controller to actuator.

1.2 Network constraints

A Wireless Local Area Network (WLAN) is selected in this study. Due to collisions or congestion in the channel, the system has to tolerate dropouts. In this paper, the percentage of dropouts and delays are assumed to be bounded. Also, a maximum number of consecutive dropouts has been investigated γ_{max} as well as a different percentage of dropouts.

2. THE MBPC METHOD

The MBPC algorithm seeks a set of optimal control signals that minimises the following quadratic cost function Camacho and Bordons (2007):

$$J=\sum_{j=N_1}^{N}\left[\hat{y}(k+j)-r(k+j)\right]^2+\sum_{j=N_1}^{N_u}\lambda\left[\Delta u(k+j-1)\right]^2 \quad (1)$$

where N_1 and N are positive scalars indicating the initial and final predictive horizons. λ is a constant weight used to penalise the control effort. N_u is the control horizon. The future reference trajectory is $r(k+j)$ and has been assumed to be known. The control objective is to minimise the cost function to compute the future control signals that guaranties that the future process output $y(k+j)$ follows the future reference $r(k+j)$. Meantime it assures that the control signal is penalized as well.

To optimise the performance, appropriate horizons and an accurate model are required. To find the prediction of process output $\hat{y}(k+j)$, a linear SISO plant is described using the Controlled Auto Regressive and Integrated Moving-Average (CARIMA) model:

$$A(q^{-1})y(k)=q^{-d}B(q^{-1})u(k-1)+C(q^{-1})\xi(k)/\Delta \quad (2)$$

where $y(k)$ and $u(k)$ are the process output and the control input, respectively. The process delay is d. A discrete-time setting is assumed and the current time is labelled as time instant k. A, B and C are polynomials function of the backwards shift operator q^{-1} with order n_a, n_b and n_c, respectively; such that:

$$\begin{aligned}A(q^{-1})&=1+a_1q^{-1}+a_2q^{-2}+\cdots+a_{n_a}q^{-n_a}\\B(q^{-1})&=b_0+b_1q^{-1}+b_2q^{-2}+\cdots+b_{n_b}q^{-n_b}\\C(q^{-1})&=c_0+c_1q^{-1}+c_2q^{-2}+\cdots+c_{n_c}q^{-n_c}\end{aligned} \quad (3)$$

The model represents the uncertainty of random disturbances in the process. $\xi(k)$ is a zero mean white noise, and $\Delta=1-q^{-1}$ is a difference operator, indicating the difference between the current time point and the previous time point. The proposed model is more appropriate in industrial applications where disturbances are non-stationary. For simplicity, C is chosen as one in the following analysis. Next, a Diophantine equation is used to find the output predictions:

$$1=E_j(q^{-1})\Delta A(q^{-1})+q^{-j}F_j(q^{-1}) \quad (4)$$

where E_j and F_j are polynomials. Multiplying (2) by $\Delta E_j(q^{-1})q^j$ gives:

$$\Delta A(q^{-1})E_j(q^{-1})\hat{y}(k+j)=E_j(q^{-1})B(q^{-1})\Delta u(k+j-d-1)+E_j(q^{-1})\xi(k+j) \quad (5)$$

The best estimation of the future disturbance is achieved by selecting $\xi(t+k)=0$. Substituting $A(q^{-1})E_j(q^{-1})$ from (4) in (5), it results:

$$\left[1-q^{-j}F_j(q^{-1})\right]\hat{y}(k+j)=E_j(q^{-1})B(q^{-1})\Delta u(k+j-d-1) \quad (6)$$

Simplifying results in:

$$\hat{y}(k+j)=F_j(q^{-1})y(k)+E_j(q^{-1})B(q^{-1})\Delta u(k+j-d-1) \quad (7)$$

where

$$\begin{aligned}E_j(q^{-1})&=e_{d+j,0}+e_{d+j,1}q^{-1}+\cdots+e_{d+j,j-1}q^{-(d+j-1)}\\F_j(q^{-1})&=f_{d+j,0}+f_{d+j,1}q^{-1}+\cdots+f_{d+j,n_a}q^{-n_a}\end{aligned}$$

Define $G_j=E_j(q^{-1})B(q^{-1})$, then (7) can be expressed as:

$$\hat{y}(k+j)=F_j(q^{-1})y(k)+G_j(q^{-1})\Delta u(k+j-d-1) \quad (8)$$

Applying the last result to (1), the cost function J is formulated as the following quadratic problem:

$$J = (\mathbf{Gu} + \mathbf{Fy} - \mathbf{r})^{\mathbf{T}}(\mathbf{Gu} + \mathbf{Fy} - \mathbf{r}) + \lambda \boldsymbol{u}^{\mathbf{T}}\boldsymbol{u} \tag{9}$$

where

$$\boldsymbol{r} = [r(k+1) \quad r(k+2) \quad \cdots \quad r(k+N)]^T$$
$$\mathbf{y} = [\hat{y}(k+1) \quad \hat{y}(k+2) \quad \cdots \quad \hat{y}(k+N)]^T$$
$$\mathbf{u} = [\Delta u(k) \quad \Delta u(k+1) \quad \cdots \quad \Delta u(k+N_u-1)]^T$$
$$\boldsymbol{F}(q^{-1}) = \begin{bmatrix} F_{d+1}(q^{-1}) \\ F_{d+2}(q^{-1}) \\ \vdots \\ F_{d+N}(q^{-1}) \end{bmatrix}, \boldsymbol{G} = \begin{bmatrix} g_0 & 0 & \cdots & 0 \\ g_1 & g_0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ g_{N-1} & g_{N-2} & \cdots & g_0 \end{bmatrix}$$

For simplicity of notation, it is assumed that $d = 0$ in the equations above. The quadratic cost function is minimised by solving $\nabla J = 0$. Note that the optimal input solution $\Delta u(k+j-1) = 0$ for $j > 1$. The control horizon has been selected as one because the PID law only computes $\Delta u(k)$.

3. THE DESIGN OF THE PREDICTIVE PID CONTROLLER

3.1 The PID

The velocity form of the PID controller with sampling time t_s is considered:

$$\Delta u(k) = k_p[e(k) - e(k-1)] + k_i t_s e(k) + \frac{k_d}{t_s}[e(k) - 2e(k-1) + e(k-2)] \tag{10}$$

The matrix representation is:

$$\Delta u(k) = \mathbf{K}^T \mathbf{e}(k) \tag{11}$$

where $\mathbf{e}(k)$ is the vector of control errors:

$$\mathbf{e}(k) = [e(k) \quad e(k-1) \quad e(k-2)]^T \tag{12}$$

The vector of gains $\boldsymbol{K}$ is defined as:

$$\boldsymbol{K} = \left[k_p + k_i t_s + \frac{k_d}{t_s} \quad -k_p - 2\frac{k_d}{t_s} \quad \frac{k_d}{t_s} \right]^T = [k_1\ k_2\ k_3]^T \tag{13}$$

The PID controller gains must be positive scalars: $k_p > 0$, $k_i > 0$, $k_d > 0$. Therefore, it is easy to see that the vector of gains $\boldsymbol{K}$ must fulfil the linear inequality constraints:

$$k_1 + k_2 + k_3 > 0, \quad k_2 + 2k_3 < 0, \quad k_3 \geq 0 \tag{14}$$

3.2 The predictive PID controller

The PID predictive controller is obtained by combining the MBPC and PID control laws. The purpose of the design is to compute the PID gains in such a way that the control signal is as close as possible to the MBPC signal. First, by simplifying (9) yields:

$$J(K) = \mathbf{u}^{\mathbf{T}}(\mathbf{G}^{\mathbf{T}}\mathbf{G} + \lambda \boldsymbol{I})\mathbf{u} + \mathbf{u}^{\mathbf{T}}\mathbf{2G}^{\mathbf{T}}(\mathbf{Fy} - \mathbf{r}) \tag{15}$$

Replacing Δu from (11) leads to:

$$J(K) = [\mathbf{e}(\mathbf{k})^{\mathbf{T}}\boldsymbol{K}]^{\mathbf{T}}(\mathbf{G}^{\mathbf{T}}\mathbf{G} + \lambda \boldsymbol{I})\mathbf{e}(\mathbf{k})^{\mathbf{T}}\boldsymbol{K} + [\mathbf{e}(\mathbf{k})^{\mathbf{T}}\boldsymbol{K}]^{\mathbf{T}}\mathbf{2G}^{\mathbf{T}}(\mathbf{Fy} - \mathbf{r}) \tag{16}$$

This is equivalent to:

$$J(K) = \boldsymbol{K}^{\mathbf{T}}\, \mathbf{e}(\mathbf{k})\, (\mathbf{G}^{\mathbf{T}}\mathbf{G} + \lambda \boldsymbol{I})\mathbf{e}(\mathbf{k})^{\mathbf{T}}\, \boldsymbol{K} + \boldsymbol{K}^{\mathbf{T}}\, \mathbf{2}\,\mathbf{e}(\mathbf{k})\, \mathbf{G}^{\mathbf{T}}(\mathbf{Fy} - \mathbf{r}) \tag{17}$$

The new algorithm will be carried out by minimising the cost function respect to the PID controller gains K:

$$\Delta\mathbf{u_{cons}} = \min_{\boldsymbol{K}} J(\boldsymbol{K}, \mathbf{y}) \tag{18}$$

where Δu_{cons} is the constrained optimal input at time instant k. It follows directly from (17) that the PID gains can be found by solving the following quadratic program:

$$\begin{aligned} \min_{\boldsymbol{K}} \quad & \frac{1}{2}\boldsymbol{K}^{\mathrm{T}}\, \mathbf{H}\, \boldsymbol{K} + \mathbf{f}^{\mathrm{T}}\, \boldsymbol{K} \\ s.t. \quad & \boldsymbol{a}(k)\, \boldsymbol{K} \leq \boldsymbol{b}(k) \end{aligned} \tag{19}$$

where

$$\begin{aligned} \mathbf{H} &= \mathbf{2}(\mathbf{G}^{\mathbf{T}}\mathbf{G} + \lambda \boldsymbol{I})\mathbf{e}(\mathbf{k})\mathbf{e}(\mathbf{k})^{\mathbf{T}} \\ \mathbf{f} &= \mathbf{2G}^{\mathbf{T}}(\mathbf{Fy} - \mathbf{r})\mathbf{e}(\mathbf{k}) \end{aligned} \tag{20}$$

The constraints of (19) will guarantee the contributions of control input and rate input are applied according to the controller limitations. $\boldsymbol{a}(k)$ depends on the past values of the error and $\boldsymbol{b}(k)$ on the upper and lower limits on the control input and rate input. The design is provided in the next section. The control law can be rewritten from (11) as:

$$\Delta\mathbf{u}(\mathbf{k}) = \boldsymbol{K}(\mathbf{k})\mathbf{e}(\mathbf{k}) \tag{21}$$

The Optimisation Toolbox of Matlab is selected to solve the problem and find the PID gains. The optimisation problem has been set using the command $quadprog(H, f, a, b)$, where $\boldsymbol{H,f}$ have been stated in (20) and $\boldsymbol{a, b}$ are the constraint matrices of the linear inequality. The *interior-point-convex* algorithm is used. The solver tries to find the optimal point based on the Karush-Kuhn-Tucker (KKT) conditions, where the gradient must be zero at the minimum and take constraints into account.

It is important to stress that the vector of PID gains will change at every time instant k. As a consequence, the proposed predictive PID is time-varying and it will be optimised for a bounded percentage of dropouts. The advantage of the predictive PID is that it improves the traditional PID performance by equating its control signal with the MBPC control signal. Since the gains are varying every sampling time, the performance of the PID controller is as good as the MBPC controller. Moreover, the control signal along the input steps changes smoothly, as demonstrated in Section 6.

3.3 Constraints for the control input and control rate input

To introduce the constraint handling, the predictive PID control subject linear constraints is solved:

$$-\Delta u_{min} \leq \Delta u(k) \leq \Delta u_{max}, \quad -u_{min} \leq u(k) \leq u_{max} \tag{22}$$

Using (13) the predictive PID control law in equation (21) can be defined as:

$$\Delta u(k) = k_1\, e(k) + k_2\, e(k-1) + k_3\, e(k-2) \tag{23}$$

Hence, by noticing that $\Delta u = u(k) - u(k-1)$, the constraints can be written as:

$$\begin{aligned} &-\Delta u_{min} \leq k_1\, e(k) + k_2\, e(k-1) + k_3\, e(k-2) \leq \Delta u_{max} \\ &-u_{min} - u(k-1) \leq k_1\, e(k) + k_2\, e(k-1) + k_3\, e(k-2) \\ &\leq u_{max} - u(k-1) \end{aligned} \tag{24}$$

By combining (14) with the previous result, the final constraint matrix is found:

$$\begin{bmatrix} 0 & 1 & 2 \\ 0 & 0 & -1 \\ -1 & -1 & -1 \\ e(k) & e(k-1) & e(k-2) \\ -e(k) & -e(k-1) & -e(k-2) \\ e(k) & e(k-1) & e(k-2) \\ -e(k) & -e(k-1) & -e(k-2) \end{bmatrix} \begin{bmatrix} k_1 \\ k_2 \\ k_3 \end{bmatrix} \leq \begin{bmatrix} -\varepsilon \\ 0 \\ -\varepsilon \\ \Delta u_{max} \\ -\Delta u_{min} \\ u_{max} - u(k-1) \\ -u_{min} + u(k-1) \end{bmatrix} \tag{25}$$

where ε is a small positive scalar. The constraints should be fulfilled for every $\Delta u_j(k), for\ j = 1, \ldots, N-1$. The final constraint matrix in (25) has the form $\boldsymbol{a}(k)\,\boldsymbol{K} \leq \boldsymbol{b}(k)$ previously defined in the optimisation problem proposed in (19).

4. DROPOUTS FROM CONTROLLER TO ACTUATOR COMPENSATION

To compensate dropouts from controller to actuator, predictions of the control signal are calculated. First, from (20) the matrix G_1 is computed instead of G:

$$\mathbf{G1} = \mathbf{G}(\mathbf{1}:\mathbf{N},\mathbf{j}) \tag{26}$$

where j stands for columns of matrix $\boldsymbol{G}$ and $N_1 \leq j \leq N$. Therefore, the quadratic program computes N predictions of the control signal $\Delta u(k)$ using the coefficients of $j-th$ column of matrix $\boldsymbol{G}$. During a successful transmission from controller to actuator, the controller inputs are saved in the actuator for the next sampling instant. At time k, a dropouts detector at the actuator location indicates if the new control signal is not received and applies the next prediction $u_j(k)$ to compensate the dropout. If there is not saved predictions, the actuator arbitrarily applies the initial condition $u_0 = 0$. Note, that it has been assumed that some computational and buffering resources are available at the actuator.

Notably, in the proposed algorithm the controller has not knowledge of the control input that the actuator applies. However, this is not a limitation since it has been demonstrated that acknowledgements from the actuator to the controller do not improve the stability of the networked predictive control (see Gupta and Martins (2010) and the references therein).

In the case of consecutive dropouts, the maximum number of consecutive dropouts, γ_{max} is selected to match the prediction horizon N. Thus, the "smart" actuator can determine the occurrence of consecutive dropouts and apply the past predictions until either the condition is over or γ_{max} has been reached. For this end, a consecutive dropouts detector has been created. It consists of an index, m, that counts the number of consecutive dropouts and it is reset every time the information is available. To obtain γ_{max} the WNCS was implemented in the simulator and the number of consecutive dropouts was measured for variations of the percentages of dropouts from 25% to 80%. A maximum value of $\gamma_{max} = 30$ was selected since it covered the maximum number of consecutive dropouts.

5. DROPOUTS FROM SENSOR TO CONTROLLER COMPENSATION

The occurrence of dropouts during the transmission from the sensor to the controller results in an open-loop system which degrades the reliability of the WNCS. To solve this problem a KF is proposed to estimate $\hat{y}_e(k)$. In the presence of dropouts, only the traditional equations for estimation (prediction) of the KF are computed. Once the information is available the measurement (update) equations are calculated. The KF gives an estimation as follows:

$$\begin{aligned} \hat{x}(k+1) &= A\hat{x}(k) + Bu(k) + K_f(k)[y(k) - \hat{y}_e(k)] \\ \hat{y}_e(k) &= C\hat{x}(k) \end{aligned} \tag{27}$$

$K_f(k)$ represents the filter gain that is calculated using a set of recursive equations:

$$K_f(k) = P(k)C^T[CP(k)C^T + R]^{-1} \tag{28}$$

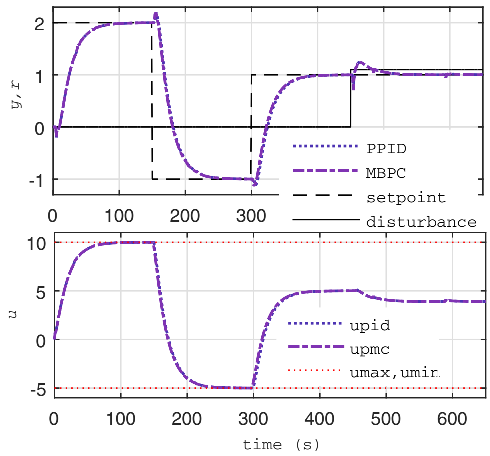

Figure 2. System outputs for predictive PID and MBPC

where R is the covariance of the measurement noise and $P(k)$ is the covariance of estimation error that is computed as follows:

$$P(k) = P(k) - P(k)C^T[CP(k)C^T + R]^{-1}CP(k) \tag{29}$$

and that can be updated as:

$$P(k+1) = AP(k)A^T + BQB^T \tag{30}$$

where Q is the covariance of the process noise.

The filter gain is computed by selecting appropriate values for Q and R.

6. SIMULATION STUDIES

6.1 Numerical example 1: Non-minimum phase process

Consider the following non-minimum phase process with dead time and sampling time $t_s = 1\,s$:

$$G_p(z) = \frac{-0.26785\,(z-1.292)\,z^{-3}}{(z-0.6065)(z-0.006738)} \tag{31}$$

The predictive algorithm is implemented and simulated using the TrueTime network configured for 802.11b Wireless Local Area Network (WLAN), with a data rate of 800000 bits/s. The minimum frame size has been selected as 272 bits (see Chacón-Vásquez (2017) for more details).

As explained before, the prediction horizon is $N = 30$ and the control horizon $N_u = 1$. The closed-loop stability is achieved by selecting $\lambda = 25$. Control input constraints have been assumed as $u_{max} = 10$, $u_{min} = -5$ and the rate input $\Delta u_{max} = 10$. A step disturbance of magnitude 1.1 is introduced at time $t = 450\,s$ to test the robustness of the design. The results have been compared with the solutions obtained by the classical MBPC with constraints. Fig. 2 shows the system outputs and constrained controller inputs of predictive PID and MBPC for step changes in reference signal (dashed line). The predictive PID shows almost the same behaviour than MBPC as it is expected. The reference tracking and the disturbance rejection are achieved. Note that the input constraints (dotted line) are satisfied. However, further tests shown this leads to a slower rising time compared to the case without constraints.

The percentage and occurrence of dropouts for the simulation are depicted in Fig. 3. A variable $d_p(k)\ \varepsilon\ [0,1]$ indicates if the packet containing the feedback signal $y(k)$ is received ($d_{psc}(k) = 0$) or if it is dropped ($d_{psc}(k) = 1$). Similarly,

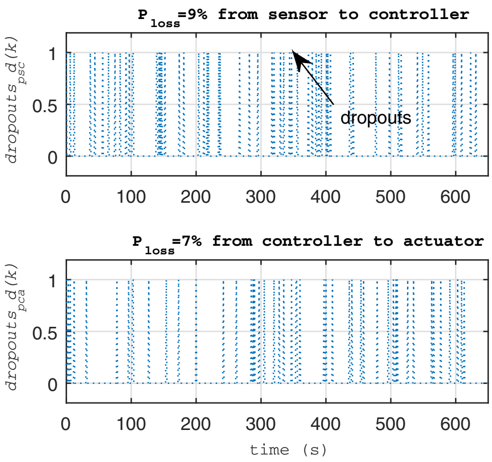

Figure 3. Time instant of data dropouts

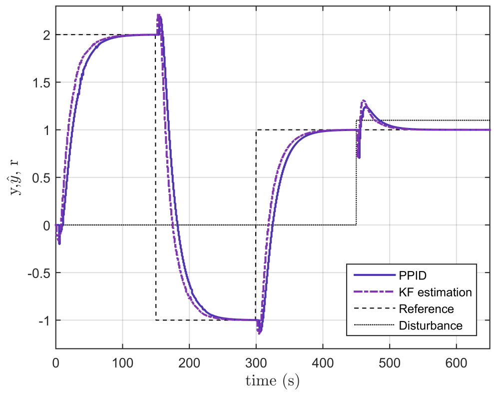

Figure 4. KF estimation for constrained predictive PID

dropouts from the controller to the actuator are represented as $(d_{pca}(k) = 1)$ and $(d_{pca}(k) = 0)$ if there is no dropouts. Fig. 4 shows that the KF output estimation is close to the process output. Therefore, when a dropout from sensor to controller occurs, the KF provides an accurate estimate of the process output.

The control system is stable and works within the requirements for the entire drop of sensor and controller packets. Further tests showed that the percentages of dropouts could be increased up to $P_{loss} = 84\%$ which is the threshold to ensure the closed-loop stability. The performance of predictive PID and MBPC responses for servo and regulatory responses has been assessed using the Integral of Absolute Error (IAE) criterion. The results are summary in the Table 1. The indexes values demonstrate that the predictive PID method performs as good as the MBPC scheme.

Table 1. IAE values for step responses

Controller	J_r	J_d
Predictive PID	211.8	7.988
MBPC	205	7.989

7. ROBUSTNESS RESULTS

Since the PID predictive controller is model based, the effects of model uncertainties and dropouts on NCS's stability require further examination. Therefore, the stability of the method is investigated here studying the closed-loop responses for variations of the process model parameters and the percentage of dropouts. The following process is selected for this analysis:

$$G_p(z) = \frac{0.06347z^{-1} + 0.04807z^{-2}}{1 - 1.323z^{-1} + 0.4346z^{-2}} \tag{32}$$

The controller settings are the same than the previous example. A step of magnitude one is selected. Control constraints have been chosen as $u_{max} = 1$, $u_{min} = 0$ and $\Delta u_{max} = 10$.

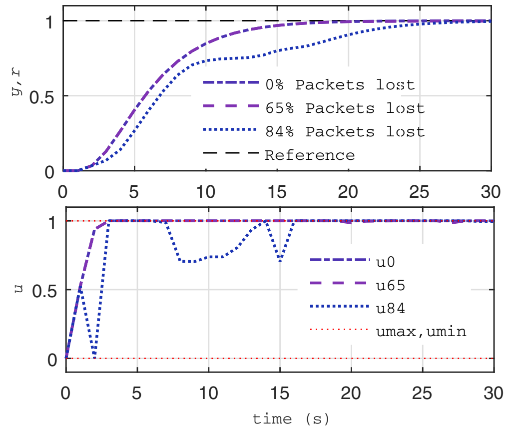

Figure 5. Comparison of step responses with dropouts variations

Study of stability for variations of percentage of dropouts The percentages of dropouts from sensor to controller and from controller to actuator are varied to demonstrate the robustness of the design. The step responses for different scenarios are shown in Fig. 5. The dashed lines show that when the probability of loss is increased from 0% to 65%, the responses are similar. Nevertheless, after 20 s, the control input for a 65% of packet loss presents small oscillations. If the probability keeps increasing, the oscillations continue to grow until the output is unstable. The dotted line shows that for a percentage of dropouts of 84%, the performance of the control system decreases considerably. Further validations report this percentage is the threshold to ensure the closed-loop stability.

Study of stability for variations of the gain

Fig. 6 shows that even with the constraints, the closed-loop system is stable if the gain is increased and reduced to $\pm 35\%$ of the model process gain. Although the process presented a small oscillation and slower rising time, zero steady error and a good tracking performance are accomplished when the process gain changes within the given percentages.

Study of stability for variations of the poles

Fig. 7 shows the closed-loop responses for variations in the non-dominant pole called p_1. Note that, the effect of varying the p_2 is similar since the poles are closer to each other. It is evident from the plot, that pole variations of $\pm 35\%$ are permitted without making the closed-loop system unstable.

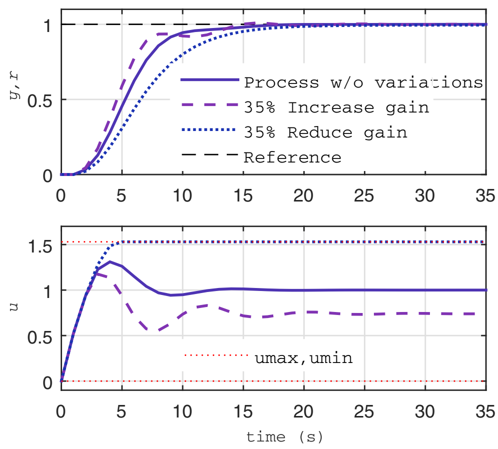

Figure 6. Comparison of step responses with gain process model variations

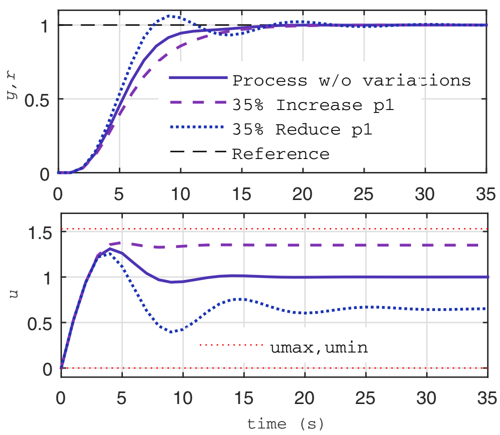

Figure 7. Comparison of step responses with pole 1 process model variations

7.1 Discussion

The performance stability of the control scheme is satisfactory for the selected prediction horizon. Further tests showed that a larger N deteriorate the performance because the errors in the prediction are bigger for long prediction horizon. The predictive PID controller and MBPC show similar performances; in some cases, the predictive PID controller performs better than the MBPC for higher percentages of dropouts. The constraint handling produces a reduction of the performance, but satisfactory results are still found. In most cases, a faster weight λ can improve the sluggish response of the control signal. However, there are scenarios where the control strategy can not stabilise faster responses with high percentages of dropouts. The new predictive PID controller offers a good performance to model uncertainty. Also, this methodology can compensate systems subject to dropouts within a large range of variations. The fact that the closed-loop system is robust to process and dropouts variations obeys to the optimisation tool used to obtain the predictive PID controller gains and the accurate estimation of the KF. The approach successfully minimises the error by changing the controller gains at every sampling time and allowing a maximum system parameters variation and percentage of dropouts.

8. CONCLUSIONS

A new predictive PID controller was presented to compensate dropouts in WNCS. The results showed that the approach successfully solved two main problems in the WNCS: missing sensor measurements and controller actions. The problem of dropouts from sensor to controller was compensated by combining the controller with a KF. The predictions of the control signal were calculated to compensate consecutive dropouts from controller to actuator. The proposed method dealt with long dropouts and high consecutive occurrence. The performance analysis showed that the predictive PID method performs as good as the MBPC scheme. Also, the control system meets the stability requirements in the presence of disturbance, model uncertainties and input constraints. In future works, this approach will be extended to complex WNCS with MIMO systems and decentralised control whose results can be tested in an industrial context.

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