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Stochastic MPC with applications to process control

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This paper presents a model predictive control formulation for Networked Control Systems subject to independent and identically distributed (i.i.d.) delays and packet dropouts. The design takes into account the presence of a communication network in the control loop, resorting to a buffer in the actuator to store and consistently apply delayed control sequences when fresh control inputs are not available. The proposed approach uses a statistical description of transmissions to optimize the expected future control performance conditioned upon previously calculated control packets and transmission acknowledgements. Its applicability to process control is illustrated via experimental studies using quadruple tank process.

Keywords: Packetized model predictive control, packet dropouts, time-delays, networked control systems.

1 Introduction

Networked Control Systems (NCSs) are spatially distributed systems wherein the communication between plants, sensors, actuators and controllers occurs through a communication network. This kind of systems and their characteristics are extensively described in J. P. Hespanha, P. Naghshtabrizi and Y. Xu (2007), W. Zhang, M. S. Branicky and S. M. Phillips (2001), R. A. Gupta (2010) and S. Zampieri (2008).

NCSs have become a very important field in the control community due to its cost-effective and flexible applications. Nowadays, there is a large number of applications for which the use of communication networks is necessary. For example, they are specially needed in systems where space and weight are limited, when the distances under consideration are large or in control applications where the wiring is not possible, see, for instance, coordination of UAV formations P. Millan, L. Orihuela, I. Jurado and F.R. Rubio (2013) or Wireless Sensor Networks J. Chen, K. H. Johansson, S. Olariu, I. Ch. Paschalidis and I. Stojmenovic (2011).

There are also some generic advantages when using digital communication networks:

(1) The complexity in point-to-point wiring connections are very reduced, as well as the costs of media. Therefore, installation costs can be also drastically reduced.
(2) In the case of wireless networks, the reduction of the wiring complexity makes easier the diagnosis and maintenance of the system, providing higher operation efficiency.
(3) NCSs are flexible and re-configurable.
(4) NCSs provide modularity, control decentralisation and integrated diagnostics.

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Nonetheless, NCS are tipically affected by time-varying delays, data losses and quantization effects, which may degrade system performance and even destabilize the system.

To overcome these problems, several authors have proposed to send control sequences from the controller side. This sequences, appropriately buffered and scheduled at the actuator end, become a safeguard in case of delays or eventual packet dropouts. This concept naturally fits the Model Predictive Control (MPC) paradigm, which makes it possible to calculate future model-based data and to use them to compute the control actions. Some examples of networked control, considering only dropouts, based on MPC for linear and non-linear systems can be found in P. Millan, I. Jurado, C. Vivas and F. R. Rubio (2008), D. Muñoz and P. D. Christofides (2008), D. Quevedo and D. Nešic (2011), for deterministic cases, and D. Quevedo, J. Østergaard and D. Nešić (2011), for stochastic cases. In D. Quevedo and I. Jurado (2013), delays and dropouts are considered together for the stability analysis of sequence-based control for non-linear systems.

In this paper, a new stochastic model predictive controller is presented to deal with different scenarios depending on the network statistics. A MPC for NCSs is proposed in P. L. Tang and C. W. de Silva (2007). The control strategy includes a buffering policy where the predicted control sequence at the actuator in anticipation of typical data transmission errors associated with NCS. Closed-loop stability in the sense of Lyapunov is guaranteed for the controller in the linear case.

The related work F. Weissel and Hanebeck (2008) presents a framework for stochastic nonlinear model predictive control (NMPC) that incorporates the noise influence on systems with continuous state spaces. Also, a NMPC is designed in F. Weissel, T. Schreiter, M. F. Huber and U. D. Hanebeck (2008) for systems for which the state is not directly accessible, but has to be estimated from observations. In D. Lyons, A. Hekler, M. Kuderer and U. D. Hanebeck (2010), it is designed a closed-loop NMPC for systems whose internal states are not completely accessible, incorporating the impact of possible future measurements into the planning process. A closed-loop control approach that considers the single future measurement that has the worst impact on the control objective is proposed.

In A. Hekler, J. Fischer and U. D. Hanebeck (2012), a problem sequence-based approach is proposed that extends a given controller designed without consideration of the network-induced disturbances. The idea is to model the unknown future control inputs by random variables, the so-called virtual control inputs, which are characterized by discrete probability density functions. Subject to this probabilistic description, a sequence-based control approach is proposed.

In this work, it is supposed that the statistics, but not the actual realizations, of the time delays and dropouts can be measured or estimated with enough precision, exploiting this fact to design a stochastic packetized MPC to improve the control performance.

The paper is organized as follows: Section 2 presents the problem statement. Section 3 describes the controller design method. Section 4 shows some experimental results. Section 5 draws conclusions.

2 Problem statement

This technique is focused on the design of a predictive control structure for a networked control system with packet dropouts and delays.

Systems to be considered are unconstrained discrete-time linear multiple-inputs plants, under the effect of disturbances as:

$$x(k+1) = Ax(k) + Bu(k) + B_w w(k) \tag{1}$$

with $k \in \mathbb{N}_0 \triangleq \mathbb{N} \cup \{0\}$ and

$$u(k) \in \mathbb{U} \subseteq \mathbb{R}^{m_1}, \quad x(k) \in \mathbb{X} \subseteq \mathbb{R}^n, \quad \forall k \in \mathbb{N}_0$$

In this setup, plant and controller are assumed to be linked through a communication network (see Figure 1). Our interest lies in clock-driven Ethernet-like networks linking controller outputs to plant inputs. Data are sent in large packets, so the relevant phenomena for control purposes are transmission delays and packet dropouts.

This approach assumes secured links in just one way, between plant output and controller input. That is, packets or delays can occur only in the controller to actuator path. Sensor to controller link dropouts can be included into the present framework by proceeding as in D. Quevedo and I. Jurado (2013).

Acknowledgments are assumed as part of the network protocol (TCP-like protocols), so that at any time instant k, the controller knows whether a control packet arrived at destination or not. Packets are also assumed to be time-stamped so they can be correctly sequenced at any point of the control loop.

To summarize, for the proposed control algorithm to work, all elements in the control loop are assumed to behave in a time-driven manner. Thus, the network model operates at the same sampling rate as the plant-controller model, with the following rules: time-driven sensors periodically sample plant outputs and states, a time-driven predictive controller computes a control sequence at each sampling time and a time-driven buffered actuator applies control signals at each sampling time.

3 Control Scheme

This section tackles the problem of designing a predictive packet-based control structure for a networked control system affected by random time-delays and packet dropouts. For the control strategy to work, it is assumed a prior study of the control network performance, in such a way that some given statistical properties of delays and dropouts can be determined. Based on this information, this work adopts a stochastic approach to improve the control performance in the presence of stringent network conditions.

3.1 *Controller formulation*

In order to achieve an appropriate performance level, it is proposed the use of a receding horizon predictive control framework.

In standard model predictive control formulations, the controller has access to the plant states $x(k)$, and computes at every time instant k a finite horizon optimal control sequence $U_k \in (\mathbb{U})^{N_u}$ of length N_u, such that the following functional is minimized

$$V(U(k),k) = \sum_{i=k}^{k+N_u-1} \ell(x'(i),u'(i)) + F(x'(k+N_u))$$

where $x'(\cdot)$ and $u'(\cdot)$ denote predicted plant states and control values respectively, $\ell(x'(i),u'(i)) = x'(i)^T Qx'(i) + u'(i)^T Ru(i)$ denotes the *stage cost* and $F(x'(k+N_u)) = x'(k+N_u)^T Px'(k+N_u)$ is the *terminal cost*, with Q, R and P being positive definite matrices.

Assuming this setup, it is shown next how an stochastic predictive control structure can be combined with an appropriate buffering and queuing strategy providing remarkable control performance and ro-

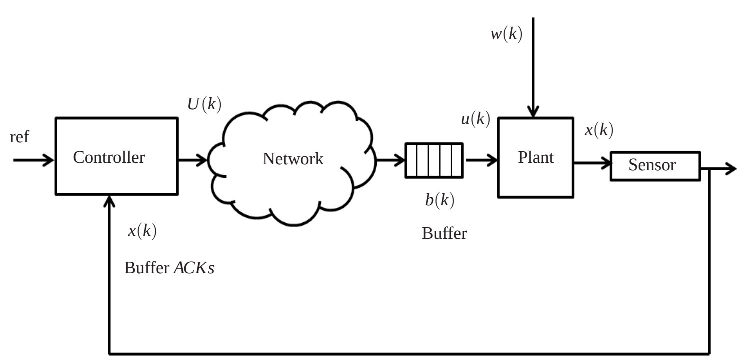

Figure 1.: Networked Control System

bustness with respect to packet dropouts and communication delays.

The relevant phenomena to consider in this section are transmission delays and packet dropouts, which can degrade the control performance or even destabilize the plant. The random nature of both effects in real-time communication networks motivates the stochastic approach taken in this work. Delays and dropouts are assumed to be stochastic i.i.d. processes with known statistical distributions.

To summarize, for the proposed control scheme to work, all elements in the control loop are assumed to behave in a time-driven manner, with the following elements:

(1) Sensors periodically sample the plant state $x(k)$ and send it to the controller.
(2) A stochastic predictive controller computes a control sequence $U(k) = [u(k|k)\ u(k+1|k) \ldots u(k+N_u|k)]$ at each sampling time and sends it through the network.
(3) At the actuator side, control inputs are applied to the plant according to a buffer policy to be explained in the next section.
(4) Network is affected by i.d.d. dropouts and i.d.d delays $\tau(k)$. Where

$$\tau(k) = \begin{cases} i & \text{if } U(k) \text{ is received at time } k+i \\ & \quad \text{at the actuator node,} \\ \infty & \text{if } U(k) \text{ is lost} \end{cases} \tag{2}$$

Assumption 1: The process $\{\tau(k)\}_{k\in\mathbb{N}_0}$ is i.i.d., with delay distribution,

$$\mathbf{Prob}\{\tau(k) = i\} = p_i, \quad i = \{0, 1, \ldots, \tau^{max}\}, \tag{3}$$

where τ^{max} is the maximum considered delay, and $\mathbf{Prob}\{\tau(k) = \infty\} = p_\infty$ is the dropout probability. In equation (3), τ^{max} is the maximum considered transmission delay. Packets received with a delay larger that τ^{max} are automatically rejected by the controller and treated as dropped papers.

Owing to the network effects, in our buffer-based implementation the controller does not know the buffer state. This way, the MPC formulation has to be modified in order to deal with the uncertainties in current and future control inputs. In order to maintain an appropriate performance level in the presence of stringent network condition, this work proposes the use of a stochastic predictive controller making use of the network statistics. More precisely, the controller will try to find $U(k)$ which minimizes the expected value of the following cost function:

$$V(x(k), \mathscr{U}_d(k), \mathscr{T}(k), U(k)) = \sum_{i=k}^{k+N_u-1} \ell(x'(i), u'(i)) + F(x'(k+N)), \tag{4}$$

where N_u is the prediction horizon, $x(k)$ is the measured state of the plant at time k, $\mathscr{U}_d(k)$ is the set of optimal control sequences sent between $k-1$ and $k-\tau^{max}$ and

$$\mathscr{T}(k) = \{\tau(k), \tau(k-1), \ldots, \tau(k-\tau^{max})\}$$

is the set of possible delays of those control sequences. For example, values $\tau(k-2) = 1$, $\tau(k-1) = \infty$ and $\tau(k) = 3$ mean that the control sequence computed by the controller at times $k-2$ reaches the buffer at time $k-1$, the control input computed at time k reaches the buffer at time $k+3$, and that computed at time $k-1$ is lost.

Also in (4), $U^*(k)$ is the new control sequence to be computed by the controller at time k. Moreover, $x'(i)$ and $u'(i)$ are state and control input open-loop predictions which take into account the buffer policy:

$$\text{Open loop predictions} \begin{cases} x'(k) = x(k), \\ x'(k+1) = Ax(k) + Bu'(k), \\ \quad \vdots \\ x'(k+N) = Ax'(k+N-1) + Bu'(k+N-1), \end{cases} \tag{5}$$

where $u'(k)$, ..., $u'(k+N-1)$... is the predicted control sequence.

When random time-varying delays and dropouts are taken into account, one of the main difficulties is the impossibility of predicting the system trajectory in a deterministic way. This is true even in the absence of disturbances and model uncertainties, as the inputs actually applied to the plant are unknown to the controller. Different approaches, including min-max or worst-case techniques can be taken to deal with this difficulty.

In this work it is exploited the fact that, for most of real networked system, it is not difficult to study and approximate the statistics of time delays and dropouts to improve the control performance. That way, open-loop predictions described above depend on future delay and dropout realizations, so that the control inputs applied to the plant can be predicted by explicit enumeration of the realizations.

The actual control inputs applied to the plant depends on the arrival of the control sequences sent by the controller and on the buffer policy.

3.2 *Buffer policy*

This section explains in detail the buffer operation and its model.

The buffer policy is based on consistently applying optimal control signals computed in the past and stored in the buffer. Aditionaly, when a control sequence arrives, the buffer is updated if that sequence has been calculated more recently than the one currently stored.

Let us represent the state of the buffer at a given time instant k as $b(k) \in \mathbb{R}^{m_1 N}$ and denote

$$\hat{k}(k,\tau(k)) = \max_{l}\{k-l : \tau(k-l) \leq l\},$$

where $\hat{k}(k,\tau(k))$ represents the time instant when the most recent control sequence received at the buffer time up to time k was computed.

It easy to see that $\tau(k-l) = l$ indicates that the optimal control sequence computed in $k-l$, that is $U(k-l)$, arrives at time k to the buffer. Then, the dynamics of the buffer can be expressed as the recursive rule:

$$b(k) = \alpha(\mathscr{T}(k))U(\hat{k}) + (1-\alpha(\mathscr{T}(k))\tilde{S}b(k-1) \qquad (6)$$

where $\tilde{S} \in \mathbb{R}^{m_1 N \times m_1 N}$ is a shift matrix defined as the block matrix:

$$\tilde{S} = \begin{bmatrix} 0_{m_1} & I_{m_1} & 0_{m_1} & \dots & 0_{m_1} & 0_{m_1} \\ 0_{m_1} & 0_{m_1} & I_{m_1} & \dots & 0_{m_1} & 0_{m_1} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0_{m_1} & 0_{m_1} & 0_{m_1} & \dots & 0_{m_1} & I_{m_1} \\ 0_{m_1} & 0_{m_1} & 0_{m_1} & \dots & 0_{m_1} & 0_{m_1} \end{bmatrix}$$

In (6), $\alpha(\mathscr{T}(k)) \in \{0,1\}$ is a signal accounting for reception of control sequences at the buffer computed by the controller subsequent to those received before, such that:

$$\alpha(\tau) = \begin{cases} 1 \text{ if } & \tau(\hat{k}) = l \\ 0 \text{ if } & \text{otherwise} \end{cases}$$

With this description the control action $u(k)$ provided by the buffer at instant k can be expressed as

$$u(k) = \begin{bmatrix} I_{m_1} \; 0_{m_1} \; \dots \; 0_{m_1} \end{bmatrix} b(k) \qquad (7)$$

From equations (1) and (7) one can easily see that the state of the buffer is involved in the state of the NCS. However, the controller does not have access to its state and this entails a non standard MPC problem. Every sampling time, the controller has access to the plant states $x(k)$ and finds a finite horizon optimal control sequence $U(k) \in \mathbb{R}^{m_1 N}$ by solving the following optimization problem:

$$\min_{U(k)\in\mathbb{R}^{m_1 N}} \mathbb{E}\left\{V(x(k),\mathscr{U}_d(k),\mathscr{T}(k),U(k)|x(k),\mathscr{U}_d(k),\mathscr{T}(k))\right\} \tag{8}$$

where expectation is taken with respect to the discrete distribution of $\mathscr{T}(k)$ and $\mathscr{U}_d(k)$ is the set of optimal control sequences sent between $k-1$ and $k-\tau^{max}$. This can be done by explicit enumeration of the realization of $\mathscr{T}$ weighting all these realization with the corresponding probability.

As a consequence of *Assumption 1*, the minimization problem becomes:

$$\min_{U(k)\in\mathbb{R}_1^m} \sum_{i\in\mathbb{N}_0}^{\infty} p_i V(x(k),\mathscr{U}_d(k-i),i,U(k)) \tag{9}$$

Next, it will be shown how this stochastic predictive controller combined with a buffer operation provides robustness to packet delays and dropouts.

4 Experimental results

This section presents an application of the proposed scheme to test its performance in a laboratory-scale experimental setup.

4.1 *System description*

The plant is a variant of the quadruple-tank process, originally proposed in Johansson (2000), see Instruments (2012). A picture of the platform is given in Figure 2. This educational plant is a model of a fragment of a chemical plant and is intended to test different control strategies. It is composed of four water tanks, each one equipped with a pressure sensor to measure the water level. The couplings between the tanks can be modified using seven manual valves thereby changing the dynamics of the system. Water is delivered to the tanks by two independently controlled, submerged pumps. Drain flow rates can be modified using easy-to-change orifice caps

The coupled tanks are controlled using Simulink and an Advanced PCI1711 Interface Card. The system is highly configurable, due to the numerous available valves. For the experiments, the following configuration is chosen (see Figure 2):

- Input water is delivered to the upper tanks. Pump 1 feeds tank 1 and pump 2 feeds tank 3.
- Tanks 1 and 3 are coupled by opening the corresponding valve.

Figure 2 shows a block diagram of the whole system.

The tanks are equiped with sesors that transmit the water level to the predictive controller. The control objective is to track references for the water levels of the lower tanks by regulating voltage applied to pumps 1 and 2.

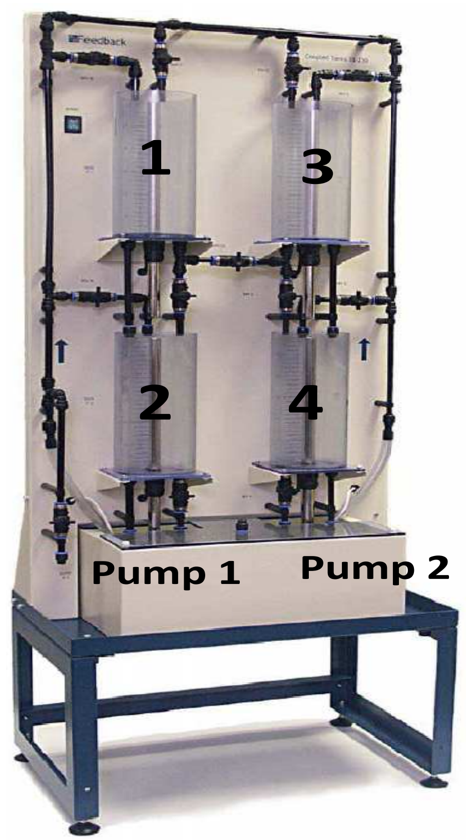

Figure 2.: Plant of four coupled tanks.

	Value	Unit	Description
h_i	0-25	cm	Water level of tank i
v_i	0-5	V	Voltage level of pump i
A	0.01389	m^2	Cross-sectional area
a_i	50.265e-6	m^2	Outlet area of tank i
a_{13}	50.265e-6	m^2	Outlet area between tanks 1 and 3
η	0.22	$\frac{cm}{V.s}$	Relating voltage and flow
h_1^0	9.55 (12.6)	cm	Reference level of tank 1
h_2^0	16.9 (12.6)	cm	Reference level of tank 2
h_3^0	7.6 (11)	cm	Reference level of tank 3
h_4^0	14.1 (11)	cm	Reference level of tank 4
v_1^0	3.3 (3.5)	cm	Voltage level of pump 1
v_2^0	2.6 (1.5)	cm	Voltage level of pump 2

Table 1.: Parameters of the plant. The terms in parentheses are related to the simulation experiments.

4.2 *Plant modeling*

The coupled tanks can be easily modeled by means of the following nonlinear model:

$$
\begin{aligned}
\frac{dh_1(t)}{dt} &= -\frac{a_1}{A}\sqrt{2gh_1(t)} + \eta u_1(t) - \frac{a_{13}}{A}\sqrt{2g(h_1(t)-h_3(t))},\\
\frac{dh_2(t)}{dt} &= \frac{a_1}{A}\sqrt{2gh_1(t)} - \frac{a_2}{A}\sqrt{2gh_2(t)},\\
\frac{dh_3(t)}{dt} &= -\frac{a_3}{A}\sqrt{2gh_3(t)} + \eta u_2(t) + \frac{a_{13}}{A}\sqrt{2g(h_1(t)-h_3(t))},\\
\frac{dh_4(t)}{dt} &= \frac{a_3}{A}\sqrt{2gh_3(t)} - \frac{a_4}{A}\sqrt{2gh_4(t)},
\end{aligned}
$$

where $h_i(t)$ $(i = 1, \ldots 4)$ denote the water level in the corresponding tank i; u_i $(i = 1, 2)$ are voltage applied to the pumps; a_i $(i = 1, \ldots 4)$ are the tank's outlet areas; a_{13} is the outlet area between tanks 1 and 3; η is a constant relating the control voltage with the water flow from the pump; A is the cross-sectional area of the tanks; and g is the gravitational constant.

This system is linearized around the equilibrium point given by h_i^0 and u_i^0, yielding:

$$\dot{\Delta h} = A\Delta h + B\Delta v, \tag{10}$$

where $\Delta h = \left[h_1 - h_1^0 \ \ldots \ h_4 - h_4^0\right]^T$ and $\Delta h = \left[v_1 - v_1^0 \quad v_2 - v_2^0\right]^T$.

4.3 *Experimental results*

In this section the experimental results are presented, using the described plant.

Delays are discrete uniformly distributed between 0 and 4 sampling times, while the disturbance are random bounded disturbances with $|w(k)| < 0.5$. The sampling time is $t_m = 9s$.

Fig. 3, 4, 5 and 6 show the outputs of tanks 2 and 4, with their respective references. Fig. 3 and 4 compare the performance of a classical MPC when the network under consideration is perfect and when it introduces dropouts. It can be seen how the dropouts make the performance much worse.

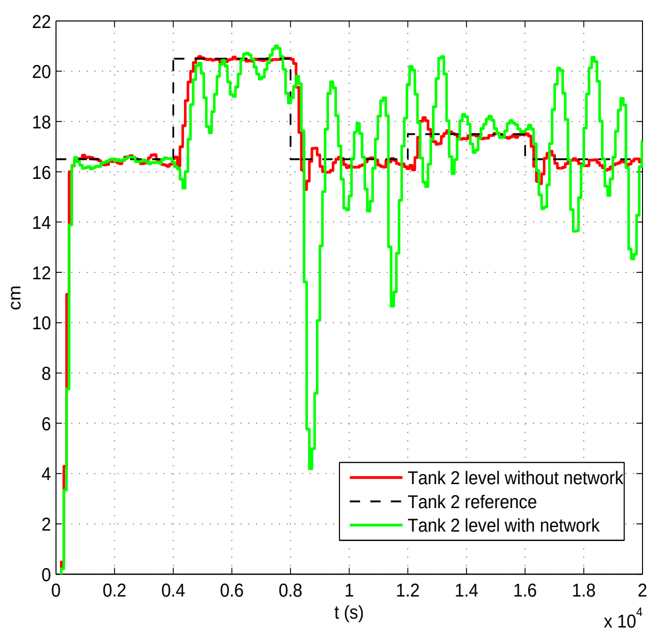

Figure 3.: Tanks 2 levels with a classical MPC

Fig. 5 and 6 consider the network with dropouts. They compare the classical MPC with the stochastic MPC presented in this chapter. The classical MPC has been calculated with the following matrices:

$$Q = \begin{bmatrix} 10 & 0 & 0 & 0 \\ 0 & 100 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 100 \end{bmatrix} \quad \text{and} \quad R = \begin{bmatrix} 50 & 0 \\ 0 & 50 \end{bmatrix}.$$

It can be seen how the proposed stochastic MPC mantains a remarkable performance despite the network-induced delays.

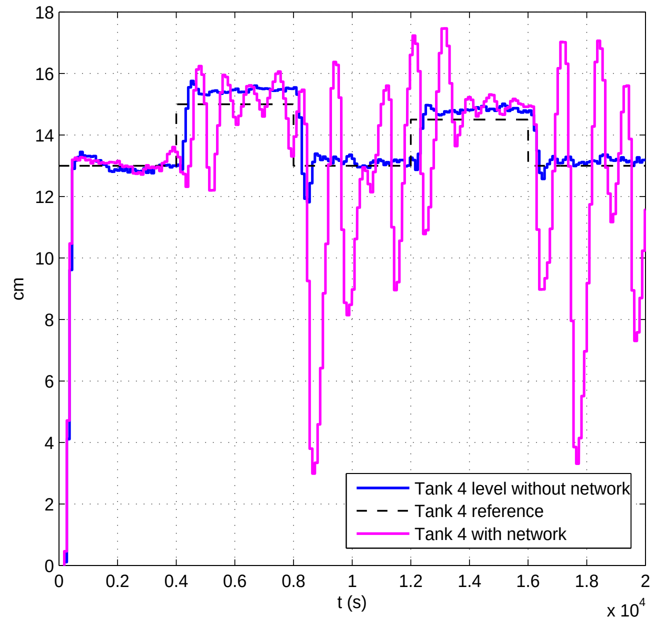

Figure 4.: Tanks 4 levels with a classical MPC

Table 2 shows the Integral Square Error (ISE) index for the system with the network, comparing the results with the classical MPC and with the the presented stochastic one. It can be seen how the proposed stochastic controller provides better results than the classical one.

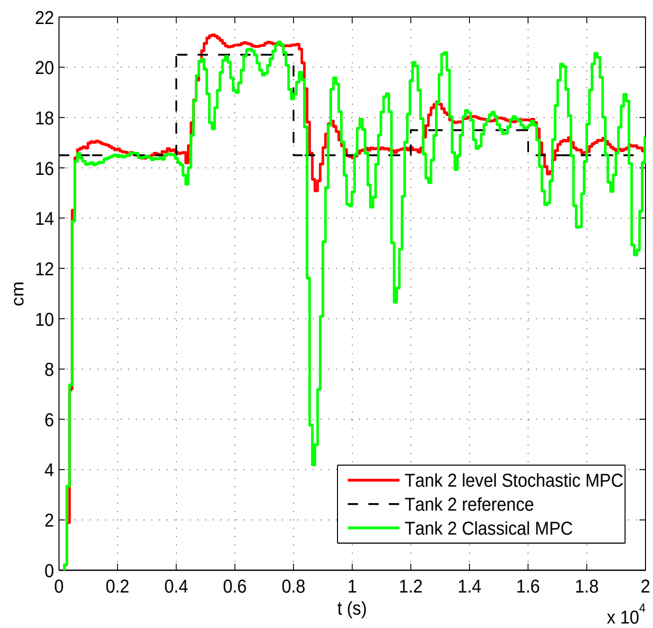

Figure 5.: Tanks 2 levels with a classical MPC and the presented stochastic MPC

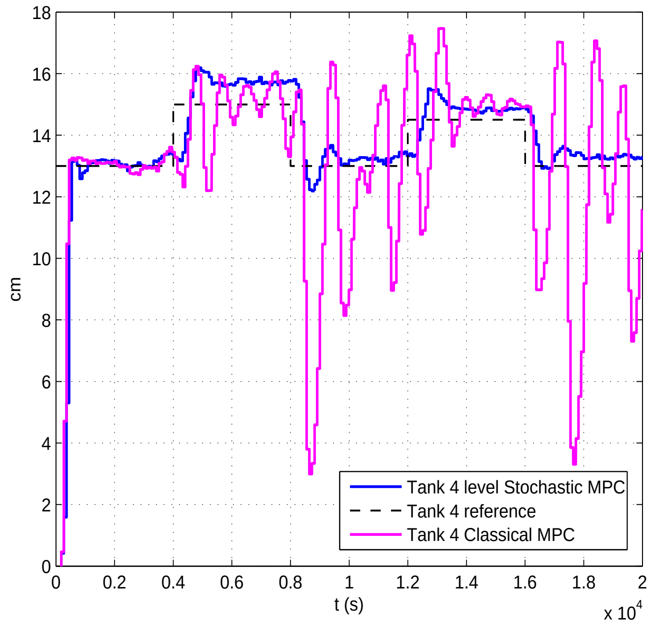

Figure 6.: Tanks 4 levels with a classical MPC and the presented stochastic MPC

Table 2.: Integral Square Error (ISE)

	Tank 2	Tank 4
Classical MPC	608	528
Stochastic MPC	532	402

5 Conclusions

This paper has presented a model predictive control strategy in order to deal with time-delays and packet dropouts introduced by a communication network in a Networked Control System.

A stochastical model predictive controller has been designed, showing how statistical information on packet delays and dropouts can be used in the design of a networked control system. Also, some experimental results have been presented.

Future works may include studying closed loop stability and performance issues.

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