Networked Predictive Control for Time-varying Delay Compensation with an Application to Automotive Mechatronic Systems

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Abstract: The variable-time delay introduced by communication networks is the main factor that deteriorates the performance of Networked Control Systems (NCSs). In this paper, a new networked predictive control strategy is proposed with the aim of controlling the output of a physical plant, while compensating the effects of the time-varying delay. It is assumed that the delays in the communication network are bounded and three methods of considering the delays by the predictive control algorithm are proposed. Furthermore, a new method by which the controller is adapted to the difference between the desired reference and the plant output is proposed. Then, the proposed strategy is applied in order to control the clutch piston displacement and to decrease the influence of the variable-time delay induced in the NCS on the control performance of an electro-hydraulic actuated wet clutch. The performance of the proposed strategy is demonstrated by simulation results and corresponding comparisons prove the significance of this method.

Keywords: Predictive Control, Networked Control Systems, Time-Varying Delay, Delay Compensation, Wet Clutch Control.

1. INTRODUCTION

Feedback control systems over real-time communication networks, also called Networked Control Systems (NCSs), are now widely used in different industries, ranging from automated manufacturing plants to automotive and aero-spatial applications. These NCSs have many attractive advantages which include low cost, simple installation and maintenance, increased system agility, higher reliability and greater flexibility (Jiangang et al., 2007), but the use of communication networks makes it necessary to deal with the effects of the network-induced delays in the control loop. These delays may be unknown and time-varying and may deteriorate the performances of the control systems designed without considering them and even destabilize the closed-loop control system (Jiangang et al., 2007). Existing constant time-delay control methodologies may not be directly suitable for controlling a system over a communication network since network delays are usually unpredictable and time-varying. Therefore, to handle network delays in a closed-loop control system over a communication network, an advanced methodology is required, a significant emphasis being on developing control methodologies to handle the network delay effect in NCSs (Tipsuwan and Chow, 2003).

Various research has been on compensating the time-varying delays induced in NCSs and numerous control strategies were reported in the literature: multiple-delay Smith predictor based controller for systems with bounded uncertain delay (Ibeas et al., 2007), variable-period sampling scheme for NCSs with random time delay based on back-propagation neural network prediction (Jiangang et al., 2007), Smith dynamic predictor combined with fuzzy immune PID control (Du and Qian, 2008), predictive networked controller based on Smith predictor that includes an adaptation loop to decrease the influence of the communication delay on the control performance (Velagic, 2008) and even model predictive control (Gielen and Lazar, 2009).

The predictive control strategies were initially utilized for slow processes: oil refineries, petrochemicals, pulp and paper, primary metal industries, gas plant (Tran and Vlacic, 2006), but starting with the evolution of hardware components and algorithms, the possibility to implement these types of control algorithms to fast processes, which have reduced sampling periods, appeared: vehicle engine and traction control, aero-spatial applications, autonomous vehicles, power generation and distribution (Gu et al., 2009).

As such, in order to decrease the influence of the time-varying delay induced in a NCS on the control system performance, in this paper, a networked controller based on a new predictive strategy is proposed, the delays that appear in the NCS being taken into account by the presented strategy. It is assumed that the delays in the communication network are bounded and three methods of considering the delays by the predictive control algorithm are proposed: an average delay method, an identification method, which uses an estimated model that includes the delays in the plant model, and an adaptation method, which adapts the control algorithm to the time-varying delays in the communication network. Furthermore, a new method by which the controller is adapted to the difference between the desired reference and the plant output is proposed. The strategy is then tested on a network-controlled wet clutch actuated by an electro-hydraulic valve, which is a subsystem

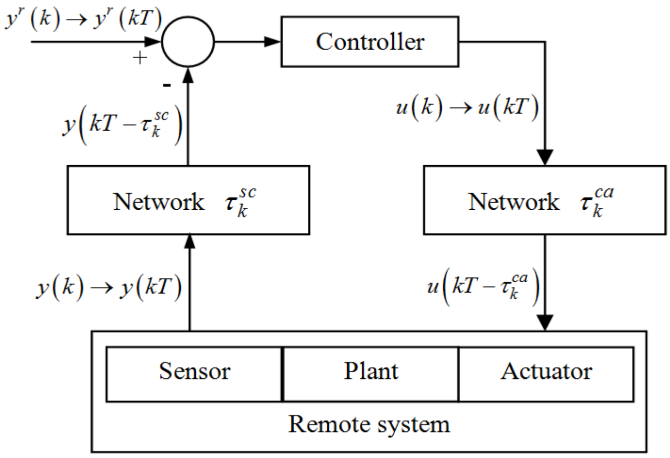

Fig. 1. NCS configuration and network delays.

of the automatic transmission of a Volkswagen vehicle and the main control goal is to make the clutch plates position track a given external reference. Comparisons were made with two different networked controllers: a PI controller and a Smith-like predictive controller with adaptation to communication delay developed in (Velagic, 2008), in order to illustrate the performance of the proposed method. The effectiveness of the proposed solution is shown by a performance analysis on a set of simulation results.

This paper is organized as follows. Section 2 describes the time-varying network-induced delays and in Section 3, the predictive control strategy is presented. Section 4 describes, firstly, the model of the valve-clutch system and, secondly, consists of the experimental results and discussion. The paper ends with a concluding chapter in Section 5.

2. DELAYS IN NCSS

NCSs are composed of a central controller and a remote system containing a physical plant, sensors and actuators (Fig. 1). The controller and plant are located at different spatial locations and directly connected through a network to form a closed control loop (Yang et al., 2006).

When sensors, actuators and controllers exchange data across the network, various delays with variable length occur due to sharing the common network medium. These delays are called network-induced delays and can vary widely according to the transmission time of messages and the overhead of the network. Usually, these network delays are randomly time-varying (Rodriguez and Menendez, 2007) and can be categorized from the direction of data transfers as the sensor-to-controller delay τ^{sc} and the controller-to-actuator delay τ^{ca}.

Generally, both the controller and the actuator are event-driven and the sensor is time-driven, sampling the plant output every period. When one sampling begins, the data sampled by the sensor $y(k)$ will be sent to the controller via the communication network, the delay τ_k^{sc} occurring during this interval. Then, the controller computes the control data $u(k)$ according to the sampling data and then the control data will be sent to the actuator via the communication network, the delay τ_k^{ca} occurring in this interval. The actuator acts on the plant in no time once it receives the control data.

The delays τ^{sc} and τ^{ca} are composed of at least the following parts (Tipsuwan and Chow, 2003): waiting time delay τ^W, frame time delay τ^F and propagation delay τ^P. These three delay parts are fundamental delays that occur on a local area network, e.g., CAN.. When the control or sensory data travel across networks, there can be additional delays such as the queuing delay at a switch or a router and the propagation delay between network hops. The delays τ^{sc} and τ^{ca} also depend on other factors such as maximal bandwidths from protocol specifications and frame or packet sizes.

In fact, both network delays can be longer or shorter than the sampling time T_s. Although the controller processing delay τ^c always exists, this delay is usually small compared to the network delays and could be neglected.

3. NETWORKED PREDICTIVE CONTROL STRATEGY

Predictive control techniques have been introduced mainly in order to deal with plants that have complex dynamics (unstable inverse systems, time-varying delay, etc.) and plant model mismatch. They are of a particular interest from the point of view of both broad applicability and implementation simplicity, being applied on large scale in industry processes, having good performances and being robust at the same time.

Consider the plant described by the CARIMA (Controlled AutoRegressive Integrated Moving Average) model (Camacho and Bordons, 2004)

$$A\left(z^{-1}\right) y(k) = z^{-d} B\left(z^{-1}\right) u(k-1) + \frac{e(k)\, C\left(z^{-1}\right)}{D\left(z^{-1}\right)}, \quad (1)$$

where d is the delay of the process and $e(k)$ is white noise with zero mean value.

$A\left(z^{-1}\right)$ and $B\left(z^{-1}\right)$ are the system polynomials

$$\begin{aligned} A\left(z^{-1}\right) &= 1 + a_1 z^{-1} + \ldots + a_{n_A} z^{-n_A}, \\ B\left(z^{-1}\right) &= b_0 + b_1 z^{-1} + \ldots + b_{n_B} z^{-n_B}, \end{aligned} \quad (2)$$

where n_A and n_B represent the polynomials degrees and $C\left(z^{-1}\right)$ and $D\left(z^{-1}\right)$ are the disturbances polynomials

$$\begin{aligned} C\left(z^{-1}\right) &= 1, \\ D\left(z^{-1}\right) &= 1 - z^{-1}. \end{aligned} \quad (3)$$

3.1 Prediction model

The prediction model is given by

$$\begin{aligned} \hat{y}(k+j|k) &= G_{j-d}\left(z^{-1}\right) D\left(z^{-1}\right) z^{-d-1} u(k+j) + \\ &+ \frac{H_{j-d}\left(z^{-1}\right) D\left(z^{-1}\right)}{C\left(z^{-1}\right)} u(k-1) + \frac{F_{j-d}\left(z^{-1}\right)}{C\left(z^{-1}\right)} y(k) \end{aligned} \quad (4)$$

with $j = \overline{hi, hp}$, where hi is the minimum prediction horizon and hp is the prediction horizon. $u(k+j-1\,|k),\ j = \overline{1, hc}$ is the future control, computed at time k and $\hat{y}(k+j|k)$ are the predicted values of the output, hc being the control horizon.

For determining the polynomials $F_{j-d}\left(z^{-1}\right)$, $G_{j-d}\left(z^{-1}\right)$ and $H_{j-d}\left(z^{-1}\right)$ two Diophantine equations are used. The first is:

$$\frac{C\left(z^{-1}\right)}{A\left(z^{-1}\right) D\left(z^{-1}\right)} = E_{j-d}\left(z^{-1}\right) + z^{-(j-d)} \frac{F_{j-d}\left(z^{-1}\right)}{A\left(z^{-1}\right) D\left(z^{-1}\right)}, \quad (5)$$

where

$$\begin{aligned} E_{j-d}\left(z^{-1}\right) &= 1 + e_1 z^{-1} + \ldots + e_{n_E} z^{-n_E}, \\ F_{j-d}\left(z^{-1}\right) &= f_0 + f_1 z^{-1} + \ldots + f_{n_F} z^{-n_F}, \end{aligned} \quad (6)$$

with

$$\begin{aligned} n_E &= j - d - 1, \\ n_F &= \max\left(n_A + n_D - 1, n_C - (j - d)\right). \end{aligned} \tag{7}$$

The second Diophantine equation is

$$\begin{aligned} E_{j-d}\left(z^{-1}\right) B\left(z^{-1}\right) = C\left(z^{-1}\right) G_{j-d}\left(z^{-1}\right) + \\ + z^{-(j-d)} H_{j-d}\left(z^{-1}\right), \end{aligned} \tag{8}$$

where

$$\begin{aligned} G_{j-d}\left(z^{-1}\right) &= g_0 + g_1 z^{-1} + ... + g_{n_G} z^{-n_G} \\ H_{j-d}\left(z^{-1}\right) &= h_0 + h_1 z^{-1} + ... + h_{n_H} z^{-n_H}, \end{aligned} \tag{9}$$

with:

$$\begin{aligned} n_G &= j - d - 1, \\ n_H &= \max\left(n_C, n_B + d\right) - 1. \end{aligned} \tag{10}$$

The prediction model yields as

$$\begin{aligned} \hat{y}\left(k + j|k\right) = G_{j-d}\left(z^{-1}\right) D\left(z^{-1}\right) z^{-d-1} u\left(k + j\right) + \\ + \hat{y}_0\left(k + j|k\right) \end{aligned} \tag{11}$$

where

$$\begin{aligned} \hat{y}_0\left(k + j|k\right) = \frac{H_{j-d}\left(z^{-1}\right) D\left(z^{-1}\right)}{C\left(z^{-1}\right)} u\left(k - 1\right) + \\ + \frac{F_{j-d}\left(z^{-1}\right)}{C\left(z^{-1}\right)} y\left(k\right) \end{aligned} \tag{12}$$

represents the free response.

Considering as inputs $D(z^{-1})u(k)$ and collecting the j-step predictors in a matrix notation, the prediction model can be written as

$$\hat{\mathbf{y}} = \mathbf{G}\mathbf{u}_d + \hat{\mathbf{y}}_0 \tag{13}$$

where

$$\hat{\mathbf{y}} = \left[\hat{y}(k + hi\,|k), \hat{y}(k + hi + 1\,|k), \ldots, \hat{y}(k + hp\,|k)\right]^T, \tag{14}$$

$$\mathbf{G} = \begin{bmatrix} g_{hi-d-1} & \cdots & g_0 & 0 & \cdots & 0 \\ g_{hi-d} & \cdots & g_1 & g_0 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ g_{hc-1} & \cdots & \cdots & \cdots & \cdots & g_0 \\ g_{hp-d-1} & \cdots & \cdots & \cdots & \cdots & g_{hp-hc-1} \end{bmatrix}, \tag{15}$$

$$\mathbf{u}_d = \left[D(z^{-1})u(k), \ldots, D(z^{-1})u(k + hc - 1)\right]^T, \tag{16}$$

$$\hat{\mathbf{y}}_0 = \left[\hat{y}_0(k + hi\,|k), \hat{y}_0(k + hi + 1\,|k), \ldots, \hat{y}_0(k + hp\,|k)\right]^T. \tag{17}$$

The objective function is based on the minimization of the tracking error and on the minimization of the controller output, the control weighting factor λ being introduced in order to make a trade-off between these objectives

$$J = \left(\mathbf{G}\mathbf{u}_d + \hat{\mathbf{y}}_0 - \mathbf{w}\right)^{\mathrm{T}} \left(\mathbf{G}\mathbf{u}_d + \hat{\mathbf{y}}_0 - \mathbf{w}\right) + \lambda {\mathbf{u}_d}^{\mathrm{T}} \mathbf{u}_d, \tag{18}$$

subject to $D(z^{-1})u(k + i) = 0$ for $i \in [hc, hp - d - 1]$, where $\mathbf{w}$ is the reference trajectory vector with the components $w(k + j\,|k)$, $j = \overline{hi, hp}$. Minimizing the objective function ($\partial J / \partial u_d = 0$), the optimal control sequence yields as

$$\mathbf{u}_d^* = \left(\mathbf{G}^{\mathrm{T}}\mathbf{G} + \lambda \mathbf{I}_{hc}\right)^{-1} \mathbf{G}^{\mathrm{T}} \left[\mathbf{w} - \hat{\mathbf{y}}_0\right]. \tag{19}$$

Using the receding horizon principle and considering that $\gamma_j, j = \overline{hi, hp}$ are the elements of the first row of the matrix $\left(\mathbf{G}^{\mathrm{T}}\mathbf{G} + \lambda \mathbf{I}_{hc}\right)^{-1} \mathbf{G}^{\mathrm{T}}$, the following control algorithm results:

$$D\left(z^{-1}\right) u\left(k\right) = \sum_{j=hi}^{hp} \gamma_j \left[w\left(k + j\,|k\right) - \hat{y}_0\left(k + j\,|k\right)\right]. \tag{20}$$

With $\hat{y}_0\left(k + j|k\right)$ from (12), the control algorithm can be rewritten as

$$\begin{aligned} & C(z^{-1})D(z^{-1})u(k) = \\ & - \sum_{j=hi}^{hp} \gamma_j H_{j-d}(z^{-1}) D(z^{-1}) u(k - 1) - \\ & - \sum_{j=hi}^{hp} \gamma_j F_{j-d}(z^{-1}) y(k) + \sum_{j=hi}^{hp} \gamma_j C(z^{-1}) w(k + j), \end{aligned} \tag{21}$$

3.2 *Delay modeling*

Consider that the delay introduced by the communication network d_c is time-varying, but bounded

$$d_m \le d_c \le d_M, \tag{22}$$

where d_m is the minimum delay and d_M is the maximum delay that appear in the communication network.

In this paper, three methods of considering the communication delay proposed to be used by the predictive algorithm (Caruntu and Lazar, 2009; Caruntu et al., 2010) are discussed, which will be presented in the sequel.

Average method The delay considered by the prediction model is calculated using

$$d = \frac{d_m + d_M}{2}. \tag{23}$$

Identification method The delay is considered equal to the minimum delay that can appear in the communication network

$$d = d_m \tag{24}$$

and instead of the polynomial B, another polynomial $\tilde{B}$, identified in order to model the system including the delays between d_m and d_M is introduced

$$\tilde{B}\left(z^{-1}\right) = \tilde{b}_0 + \tilde{b}_1 z^{-1} + ... + \tilde{b}_{n_{\tilde{B}}} z^{-n_{\tilde{B}}}, \tag{25}$$

with

$$\begin{aligned} & n_{\tilde{B}} = n_B + d_M - d_m, \\ & \tilde{b}_0 = \tilde{b}_1 = ... = \tilde{b}_{n_{\tilde{B}}} = \frac{b_0 + b_1 + ... + b_{n_B}}{n_{\tilde{B}} + 1}, \\ & B(1) = \tilde{B}(1), \end{aligned} \tag{26}$$

Adaptation method At each sampling time the delay is calculated using

$$d = 2 \frac{\sum_{i=1}^{N} \tau^{sc_i}}{N}, \tag{27}$$

where τ^{sc_i} is the communication delay from sensor-to-controller in i-th step. In this way, the average value of N previous delays is calculated.

The adaptation method is designed in order to adapt the control algorithm to the variable-time delays that appear in the communication network. The adaptation algorithm is derived with assumption that the average communication delays from sensor-to-controller and from controller-to-actuator are equal, both being variables.

Unlike for the other two modeling methods, in the case of the adaptation method the upper bound of the delays can be unknown.

3.3 λ-scheduling

Being known that λ is the parameter used to make the trade-off between the minimization of the tracking error and the minimization of the controller output, it is easy to observe that by increasing λ, the process output tracks the reference more slowly, and by decreasing λ, the process output tracks the reference faster, but with an overshoot, as it will be shown in Subsection 4.2. So, the proposed solution is to modify the parameter λ on-line depending on the error between the desired reference and the process output.

Consider the following error

$$e_k = \frac{y_k^r - y_k}{y_k^r}, \tag{28}$$

which takes values in the interval $[1, 0]$.

Then, λ can be calculated using

- linear functions:

$$\lambda_k = a_1 e_k + b_1, \tag{29}$$

- nonlinear functions:

$$\lambda_k = a_1 e_k^2 + b_1 e_k + c, \tag{30}$$

- piecewise affine (PWA) functions:

$$\lambda_k = \begin{cases} a_1 e_k + b_1, e_k \in [e_1, e_2], \\ a_2 e_k + b_2, e_k \in (e_2, e_3], \\ \dots, \\ a_N e_k + b_N, e_k \in (e_N, e_{N+1}], \end{cases} \tag{31}$$

where a_i, b_i and c are suitable chosen constants, for $i = \overline{1, N}$.

Now, considering that λ^{min} and λ^{max} are two values sufficiently small and large, respectively, for λ, it is easy to make a connection between e_k and λ_k such that

$$\begin{aligned} \lambda_k &= (1 - e_k)(\lambda^{max} - \lambda^{min}) + \lambda^{min} = \\ &= -(\lambda^{max} - \lambda^{min}) e_k + \lambda^{max}, \end{aligned} \tag{32}$$

so, as the error e_k decreases, the parameter λ_k increases.

4. ILLUSTRATIVE EXAMPLE

Clutch control is seen more and more as an important enabling technology for the automotive industry, being central for automatic gear shifting and traction control for improved safety, drivability, comfort and fuel economy. During the last years this topic has been actively researched and the attention has focused on modelling and developing control methods for automated clutch actuators (Morselli et al., 2003; Van Der Heijden et al., 2007; Langjord et al., 2008; Neelekantan, 2008).

All of the above control solutions assume that the sensors, controllers and actuators are directly connected, which is not realistic. Rather, in modern vehicles, the control signals from the controllers and the measurements from the sensors are exchanged using a communication network, e.g., Controller Area Network (CAN) or Flexray, among control system components. This brings up a new challenge on how to deal with the effects of the network-induced delays and packet losses in the control loop.

In this paper, a network-controlled wet clutch actuated by an electro-hydraulic valve is used to illustrate the effectiveness of the proposed delay modeling methodology and the performance of the proposed predictive control scheme. The goal of the control algorithm is to achieve zero steady-state error and fast response of the valve-clutch system to step references for the clutch piston displacement, while compensating the time-varying delays introduced by CAN.

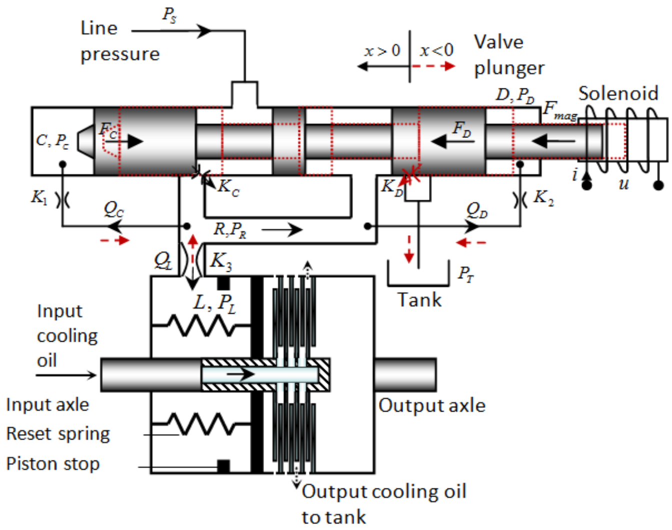

Fig. 2. Charging phase of the valve clutch system (dashed - discharging phase).

4.1 Valve-clutch system model

The model of the valve-clutch system, which is represented in Fig. 2, designed based on physical principles for flow and fluid dynamics, is briefly described below by the following equations (Balau et al., 2009; Lazar et al., 2010):

- force balance for the valve plunger:

$$F_{mag} - A_C P_C + A_D P_D = M_v s^2 x + K_e x \tag{33}$$

with

$$F_{mag} = \frac{k_a i^2}{2(k_b + x)^2}, \quad L_S \frac{di}{dt} + R_S i = u, \tag{34}$$

where F_{mag} is the electromagnetic force that acts on the plunger, P_C represents the oil pressure in chamber C exerted on area A_C on the left end of the plunger, P_D represents the oil pressure in chamber D exerted on area A_D on the right end of the plunger, M_v is the plunger mass, $K_e = 0.43w(P_{S_0} - P_{R_0})$ is the flow force spring gradient, P_s is the supply pressure, P_R is the reduced pressure, w represents the area gradient of the main orifice, x represents the displacement of the plunger, s is the Laplace operator, k_a and k_b are constants, L_s the solenoid induction and R_s the resistance, i is the current in the solenoid and u is the input voltage;

- flow continuity in the chambers C, D, R and L:

$$Q_C = K_1 (P_R - P_C) = \frac{V_C}{\beta_e} s P_C - A_C s x, \tag{35}$$

$$Q_D = K_2 (P_R - P_D) = \frac{V_D}{\beta_e} s P_D + A_D s x, \tag{36}$$

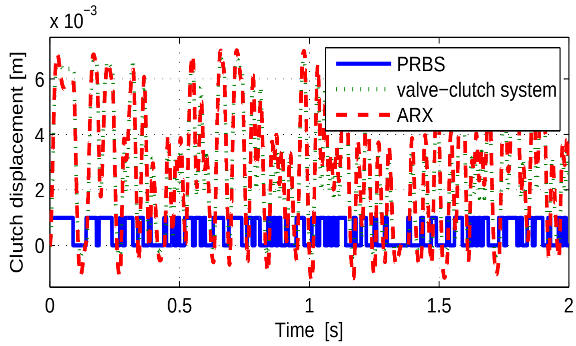

Fig. 3. Valve-clutch and simulation models responses.

$$\begin{aligned} &K_C\left(P_S-P_R\right)-Q_L-k_lP_R-K_1\left(P_R-P_C\right)-\\ &\quad -K_2\left(P_R-P_D\right)+K_qx=\frac{V_t}{\beta_e}sP_R,\\ &Q_L+K_1\left(P_C-P_R\right)+K_2\left(P_D-P_R\right)-\\ &\quad -K_D\left(P_R-P_T\right)-k_lP_R+K_qx=\frac{V_t}{\beta_e}sP_R, \end{aligned} \tag{37}$$

$$Q_L=K_3\left(P_R-P_L\right)=\frac{V_L}{\beta_e}sP_L+A_Lsx_p, \tag{38}$$

where K_1, K_2, K_3 are the flow-pressure coefficients of the restrictors, K_C is the flow-pressure coefficient corresponding to the main orifice, P_L represents the oil pressure in the clutch chamber exerted on area A_L, V_C, V_D, V_L represent the chambers volumes, K_q is the flow gain of the main orifice, k_l is the leakage coefficient, V_t represents the total volume of the chamber where the pressure is being controlled, β_e is the bulk modulus and x_p is the clutch displacement (output of the system);

- force balance for the clutch piston:

$$A_LP_L=M_ps^2x_p+Kx_p, \tag{39}$$

where K is the force flow spring rate for the clutch and M_p is the mass of the piston.

Using the parameters estimated experimentally or already given by Continental Automotive Romania or the manufacturer (see Table A.1 in Appendix A), the model of the valve-clutch system was validated by comparing the simulation results with data obtained on a real test-bench at Continetal Automotive Romania (Lazar et al., 2010).

In order to apply the predictive control strategy, a CARIMA model for the valve-clutch system was developed, using as input the supply voltage u and as output the clutch piston displacement x_p. The system was identified with an ARX equivalent model employing the design model, utilizing as input a PRBS (PseudoRandom Binary Sequence) signal. These sequences are successions of squared pulses, width modulated, that approximate a discrete white noise and their richness in frequencies helps capturing the dynamical behavior of the system.

The ARX model is given by the following system polynomials

$$\begin{aligned} &A\left(z^{-1}\right)=1-1.781z^{-1}+0.8039z^{-2},\\ &B\left(z^{-1}\right)=0.00003312z^{-1}+0.0001122z^{-2}. \end{aligned} \tag{40}$$

For disturbances model, the polynomial C is considered to equal one and $D\left(z^{-1}\right)=1-z^{-1}$ for obtaining a zero steady-state error.

4.2 Simulation results

This section presents the validations of the proposed predictive control strategy investigated on the valve-clutch system model using the Matlab/Simulink program.

In this paper, the equation developed in (Herpel et al., 2009) it is used to determine the upper bound of the communication delays that appear on CAN in automotive applications

$$d_j\le\frac{(j+2)\cdot l}{R-\sum_{i=0}^{j-1}(l/c_i)}, \tag{41}$$

where $l=136$ bits denotes the maximum frame length including the 6 bit CS time, $R=500$ kbps is the rate of a high-speed CAN and c_i is the cycle length of the i-th priority message and j is the priority of the node for which the upper bound is being calculated. A cycle length c_n, corresponding to a message of priority n, represents the period after which the message is repeated.

Using typical values for the parameters in (41), it yields that the sum of the delays $(\tau^{sc}+\tau^{ca})$ is randomly distributed in the interval $[0,12T_s]$, where $T_s=1$ms is the sampling period of the system. Furthermore, being components of the same powertrain subsystem it can be considered that the communication delays from sensor to controller and from controller to actuator have the same values and they are uniformly distributed (see Fig. 4).

The predictive control algorithm described in Section III was designed using the CARIMA model of the electro-hydraulic actuated clutch with the system polynomials from (40). It was considered that $d_m=0$ and $d_M=12$ from (41) and the predictive control strategy with the three methods was applied using the following parameters: $hc=na+1=3$, $hi=d+1$, $hp=hc+d$. The control action was then applied to the initial model of the valve-clutch system.

The results obtained are compared with two different controllers: a PI controller and a Smith-like predictive controller with adaptation to communication delay developed in (Velagic, 2008).

The λ-scheduling method was designed starting from the average delay method. As it can be seen in Fig. 5, for $\lambda_1=3\cdot10^{-5}$, the response of the system has a big overshoot, but it reaches the steady-state faster. For $\lambda_2=9.5\cdot10^{-5}$, the response of the system has no overshoot and it reaches the steady-state in a reasonable period of time, while for $\lambda_3=12\cdot10^{-5}$, the response of the system is really slow and for sure it has no overshoot. So, for $\lambda^{min}=\lambda_1$ and for $\lambda^{max}=\lambda_3$, the relation (32) becomes:

$$\lambda_k=-9\cdot10^{-5}e_k+12\cdot10^{-5}. \tag{42}$$

A step signal was applied as the reference for the clutch piston displacement and it was desired that the system tracks the reference signal as fast as possible, the following figures showing the controlled outputs and the reference signal. In Fig. 6 the clutch displacements obtained using the PI controllers and the Smith predictor are represented.

Fig. 7 illustrates the reference clutch displacement value and the responses of the system with communication delay when the predictive strategy is applied. It can be seen that the system tracks the reference signal, having no steady state error and it has a rise time in accordance with the needs in this kind of automotive applications.

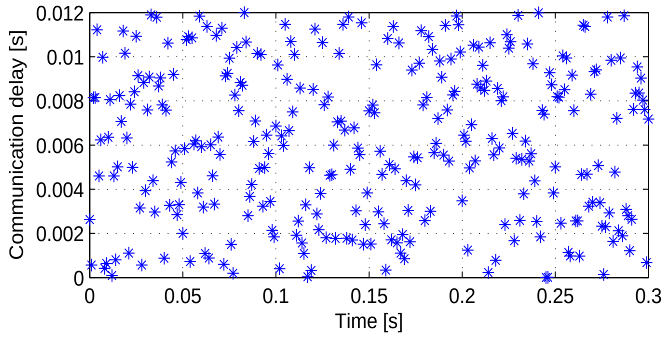

Fig. 4. Time distribution of communication delay.

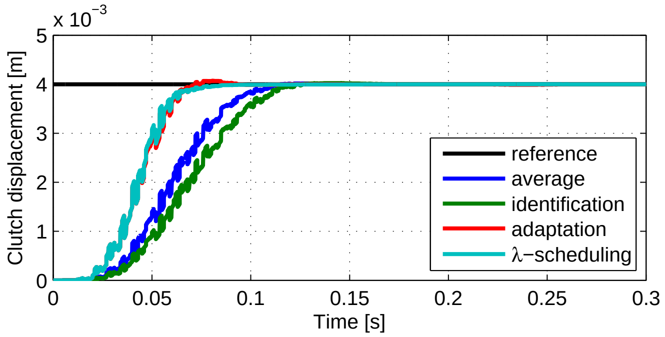

Fig. 7. Clutch displacements.

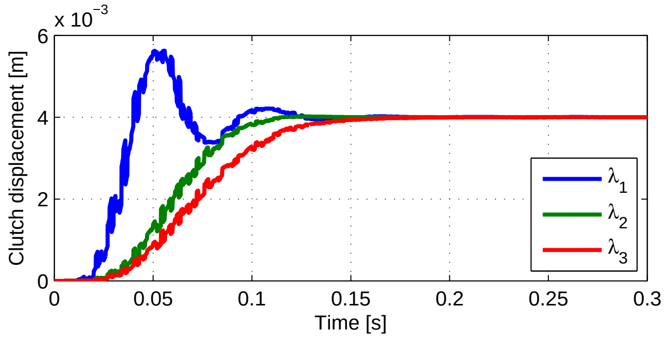

Fig. 5. Clutch displacements for different λs.

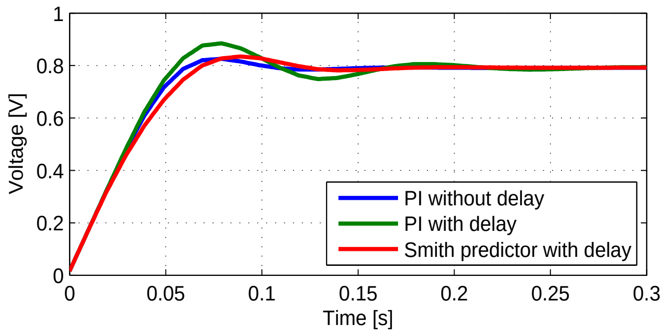

Fig. 8. Voltage signals.

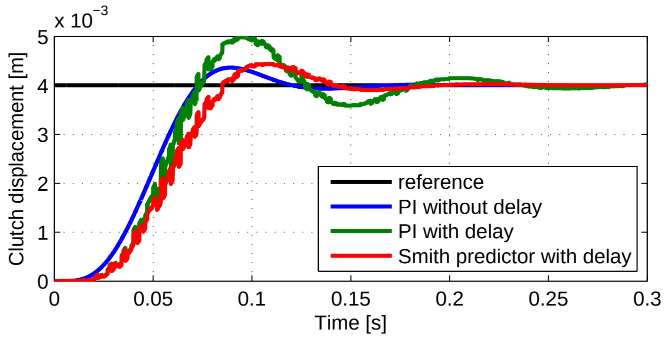

Fig. 6. Clutch displacements.

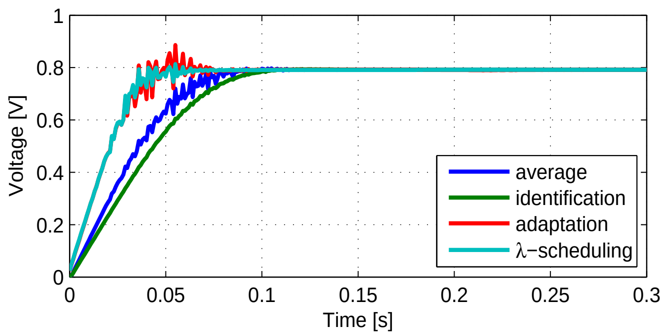

Fig. 9. Voltage signals.

The responses are clearly different from those obtained with the PI controller and the Smith predictor. The set-point response for the PI and the Smith-like predictive controllers have an obvious overshoot, while the set-point curves for the predictive methods are similar except that the rise time for the adaptation and λ-scheduling methods is much smaller than those for the other methods and all the responses have almost no overshoot.

In Fig. 8, the voltage signals (control signals) for the PI controllers and for the Smith predictor were represented. Fig. 9 illustrates the voltage signals (control signals) for the predictive methods. It can be seen that the variations of the voltage signal are much smaller for the proposed identification method, while the variations are much bigger for the adaptation method.

Also, in Fig. 10, the delay used by the average method is represented and compared with the value of the delay used by the adaptation method for $N = 20$ from (27).

It can be concluded that the performances of the predictive control methods are better than the performances of the Smith predictor proposed in (Velagic, 2008).

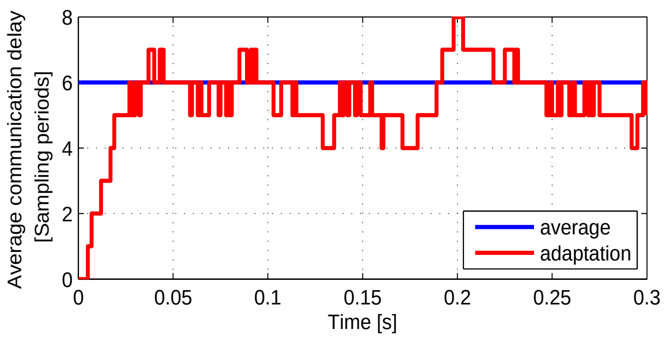

Fig. 10. Average communication delay.

5. CONCLUSION

In order to overcome the influences of communication delays on the NCS performance, a new networked predictive control strategy is proposed in this paper. The strategy was then applied to control a wet clutch actuated by an electro-hydraulic valve with the aim of decreasing the influence of the communication time-varying delays on the closed-loop control performances over CAN. Comparisons were made with a PI controller and a Smith-like predictive controller with adaptation to communication delay developed in (Velagic, 2008), in order to illustrate the performance of the proposed approaches. The experiments designed to test the strategies developed in this paper verify the better performances of the proposed methods.

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Appendix A. PARAMETER VALUES

Table A.1. Valve-clutch parameter values

Symbol	Value	Unit
K_e	1000	[N/m]
K	900	[N/m]
M_v	25e-3	[kg]
β_e	1.6e+9	[N/m^2]
$K_C = K_D$	7.58e-11	[(m^3/s)/(N/m^2)]
K_1	5.50e-10	[(m^3/s)/(N/m^2)]
K_2	3.52e-9	[(m^3/s)/(N/m^2)]
K_3	1.26e-8	[(m^3/s)/(N/m^2)]
K_q	5.3418	[(m^3/s)/(N/m^2)]
w	3e-3	[m]
P_S	1e+6	[N/m^2]
P_T	0	[N/m^2]
k_l	2e-9	[(m^3/s)/(N/m^2)]
V_C	7.53e-8	[m^3]
V_D	1.04e-7	[m^3]
V_t	3.2e-4	[m^3]
V_L	2.51e-5	[m^3]
A_C	3.66e-5	[m^2]
A_D	2.94e-5	[m^2]
A_L	7.75e-4	[m^2]
α	2e-5	[m]
M_p	0.5	[kg]
k_a	0.005	[Nm ^{2}/A^2]
k_b	0.01	[m]
L_s	0.01	[H]
R_s	0.5	[Ω]