A Model Predictive Approach to Wireless Networked Control

Jian Chen * **George W. Irwin,** * **Adrian McKernan** *
William G. Scanlon *

* *Intelligent System and Control Group, School of Electronics, Electrical Engineering and Computer Science Queen's University of Belfast,UK(e-mail: jchen04@qub.ac.uk, g.irwin@ee.qub.ac.uk,w.scanlon@qub.ac.uk and amckernan01@qub.ac.uk).*

Abstract: In Wireless Networked Control Systems (WNCS), time-varying and unknown delays can significantly degrade the closed-loop performance and even lead to instability. This paper proposes using Dynamic Matrix Control for WNCS, where, a *set* of predicted control signals corresponding to possible delays are sent to the plant. Here the most appropriate control signal is selected based on the round-trip delay as a QoS measure of the wireless channel condition. Results from Monte Carlo simulations on a cart-mounted inverted pendulum confirm the efficacy of the method. The random delay introduced by WNCS are modelled by an Inverse Gaussian distribution derived from experiments on an IEEE 802.11b network.

Keywords: Predictive control, wireless networked control system (WNCS), random communication delay

1. INTRODUCTION

Networked Control Systems (NCS) are spatially distributed systems in which the communication between the controllers, actuators, plant and sensors are interconnected through a communication network. In recent NCS research, various methods have been developed to solve the problem that the performance of a feedback control system is highly degraded by random time delays and data packet losses due to the communication channel (Hespanha et al., 2007). For example, in (Halevi and Ray, 1988), a methodology to control a linear plant over a network with a constant delay is proposed. The queuing technology in (Luck and Ray, 1994) shows how these mechanisms can be used to reshape random network delays to deterministic ones such that the NCS becomes time-invariant. The robust control method in (Goktas, 2000) details a networked controller designed in the frequency domain using robust control theory, where a priori information about the probability distribution of network delays is not required.

Wireless NCS in particular has attracted significant interest for future mechanical and process automation to address increasing installation and network cabling costs while offering mobility and the ability to operate in extreme environments. However, current theoretical issues for feedback control over wireless networks include limited bandwidth, time-varying and unknown delays and a high probability of data loss. This makes WNCS much more challenging for control design than the conventional wired alternative.

This work is motivated by (Colandairaj et al., 2007) on using co-design to optimize both the control and wireless communication network performance, and also (Liu et al., 2005) on using predictive control for wired NCS. The paper proposes an integrated control and communication approach to Wireless NCS where a Model Predictive Controller is used to compensate for network induced delays using the Round Trip Delay (RTD) as a channel performance Quality-of-Service (QoS). The predictive controller is designed based on Dynamic Matrix Control (DMC) (Cutler and Ramaker, 1980) with the computational effort moved from the plant to the remote controller, meaning that the existing plant side hardware can be retained and only a network node has to be added to the plant. The experimental channel characteristic of an IEEE 802.11b wireless network has been recorded and its probability distribution modelled for use in subsequent simulations. Monte Carlo studies show the feasibility and efficacy of the proposed method.

The paper is organised as follows. Section 2 derives the predictive control algorithm and the networked predictive control scheme. An application in the form of wireless control of a cart-mounted inverted pendulum is presented in Section 3. Section 4 presents the statistical analysis of the experimentally recorded RTD and simulation results for the closed-loop control system with delay in the forward channel. The paper ends with conclusions.

2. NETWORKED PREDICTIVE CONTROL SYSTEM

In a networked control system, a *set* of control sequence and output measurements can be transmitted from one location to another location virtually at the same time. Model Predictive Control (MPC) (Cutler and Ramaker, 1980; Clarke et al., 1987) can predict the necessary set of future control signals at one time and therefore provides a possible implementation for networked control. In this paper, a state-space formulation of multivariable model predictive control developed by (Ricker, 1990) is applied. The structure of a wireless networked predictive control system with communication delay in the forward channel only is shown in Fig 1. The communication delay in the feedback channel is not considered for simplicity here, though generalisation is possible.

Suppose the plant to be controlled is described by a discrete-time, linear, time-invariant, state-space model:

$$\tilde{x}(k+1) = \tilde{\Phi}\tilde{x}(k) + \tilde{\Gamma}\tilde{u}(k) \tag{1}$$

$$\tilde{y}(k) = \tilde{C}\tilde{x}(k) + \tilde{D}\tilde{u}(k) \tag{2}$$

where k is the current sampling instant, $\tilde{x}$ is a vector of n states, $\tilde{u}$ is a vector of m plant inputs, $\tilde{y}$ is a vector of p measured outputs, and $\tilde{\Phi}$, $\tilde{\Gamma}$, $\tilde{C}$ and $\tilde{D}$ are constant matrices of appropriate dimension. In this paper, all the measured and unmeasured disturbances are assumed to be zero.

An internal model is used to estimate the future state of the plant and provides a prediction of future plant outputs as a function of contemplated adjustments in the manipulated variables. The controller then chooses suitable values of $\tilde{u}$ to transmit to the plant such that the predicted plant outputs are optimal according to some specified criterion. The internal model is thus a part of the controller and its states are known exactly. The form of internal model predicting future states of the plant is described by:

$$\hat{x}(k+1|k) = \Phi\hat{x}(k|k-1) + \Gamma_m\tilde{u} + K\hat{d}(k|k) \tag{3}$$

$$\hat{y}(k|k-1) = C\hat{x}(k|k-1) \tag{4}$$

where $\hat{x}(k+1|k)$ is the one-step-ahead state estimate based on information available at sample time k, $\hat{y}(k|k-1)$ is the estimate of the plant outputs at sample time k based on information at sample instance $k-1$, K is a $(n\times p)$ constant estimator gain matrix, and $\hat{d}(k|k)$ is the current value of the estimator error given by:

$$\hat{d}(k|k) = \tilde{y}(k) - \hat{y}(k|k-1) \tag{5}$$

In the plant model, the Φ, Γ_m and C matrices are constant.

At the beginning of each sampling period k the control problem is as follows: the measurements of the plant output $\tilde{y}(k)$ have just become available and the state estimate $\hat{x}(k|k-1)$ and estimated error $\hat{d}(k|k)$ are calculated using Eq (3) and (5). The manipulated variables $\tilde{u}$ are sent to the plant and held constant for the remainder of the sampling period. In order to determine whether a given choice of $\tilde{u}$ is optimal, the plant outputs must be calculated. In MPC, this is done for a finite horizon of N sampling periods, starting with sample $k+1$. The state estimator in Eq (3)-(5) is the basis for this prediction, with Eq (5) used to eliminate steady-state offset. The optimal value of the future manipulated variable $\tilde{u}(k+i|k)$ at sample time $k+i$ is now defined, where $i = 0...N-1$. The linear prediction equation is derived from repeated use of Eq (3) and (4):

$$\psi(k) = H\mu(k) + Y_x\hat{x}(k|k-1) + Y_d\hat{d}(k|k) \tag{6}$$

where $\psi(k)$ is a pN vector of output estimates

$$\psi(k) = \left[\, \hat{y}^T(k+1|k)\ \hat{y}^T(k+2|k)\ \ldots\ \hat{y}^T(k+N|k) \,\right]^T \tag{7}$$

and $\mu(k)$ is a mN vector of future values of the manipulated variables

$$\mu(k) = \left[\, \tilde{u}^T(k|k)\ \tilde{u}^T(k+1|k)\ \ldots\ \tilde{u}^T(k+N-1|k) \,\right]^T \tag{8}$$

The variables $\hat{x}(k|k-1)$ and $\hat{d}(k|k)$ in Eq (6) are known at the beginning of period k. The pulse response matrix H and the matrixes Y_x and Y_d are constant and are given by:

$$H = \begin{bmatrix} H_1 & 0 & \cdot & \cdot & 0 \\ H_2 & H_1 & 0 & \cdot & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ H_{N-1} & H_{N-2} & \cdot & H_1 & 0 \\ H_N & H_{N-1} & \cdot & \cdot & H_1 \end{bmatrix} \tag{9}$$

$$Y_x = \left[\, (C\Phi)^T\ (C\Phi^2)^T\ \ldots\ (C\Phi^N)^T \,\right]^T \tag{10}$$

$$Y_d = \left[\, (CK)^T\ (C(\Phi+I)K)^T\ \ldots\ (C(\sum_{k-1}^{N}\Phi^{k-1})K)^T \,\right]^T \tag{11}$$

The pulse response matrices, H_k is calculated from:

$$H_k = C\Phi^{k-1}\Gamma_m \quad for\ \ k = 1...N \tag{12}$$

The reference model output is projected into the future in a similar manner:

$$\Psi_r(k) = H_r\mu_r(k) + Y_{xr}x_r(k) \tag{13}$$

where $\psi_r(k)$ is a pN vector of predicted values of the reference output.

$$\psi_r(k) = \left[\, \hat{y}_r^T(k+1|k)\ \hat{y}_r^T(k+2|k)\ \ldots\ \hat{y}_r^T(k+N|k) \,\right]^T \tag{14}$$

and $\mu_r(k)$ is a mN vector of known present and estimated future values of the reference input.

$$\mu_r(k) = \left[\, u_r^T(k|k)\ u_r^T(k+1|k)\ \ldots\ u_r^T(k+N-1|k) \,\right]^T \tag{15}$$

In Eq (15)

$$H_r = \begin{bmatrix} H_{r,1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ H_{r,N} & \cdots & H_{r,1} \end{bmatrix} \tag{16}$$

$$H_{r,i} = C_r\Phi_r^{i-1}\Gamma_r + D_r \quad for\ \ i = 1, N \tag{17}$$

$$Y_{xr} = \left[\, (C_r\Phi_r)^T\ (C_r\Phi_r^2)^T\ \ldots\ (C_r\Phi_r^N)^T \,\right]^T \tag{18}$$

The desired behavior of the outputs is represented by the vector $\psi_r(k)$, which must be known in order to define the optimization problem.

The objective function, accommodating inequality constraints upon the manipulated variables $\mu(k)$ and output $\psi(k)$ is represented by:

$$J = \min_{\mu(k)}\{[\psi_r(k) - \psi(k)]^T Q[\psi_r(k) - \psi(k)] + \Delta\mu^T(k) R\Delta\mu\} \tag{19}$$

subject to the linear inequality constraints

$$\mu_{min}(k) \leq \mu(k) \leq \mu_{max}(k) \tag{20}$$

$$|\Delta\mu(k)| \leq \Delta\mu_{max}(k) \tag{21}$$

$$\psi_{min}(k) \leq \psi(k) \leq \psi_{max}(k) \tag{22}$$

where $\Delta\mu(k)$ is defined by

$$\Delta\mu(k) = R_\Delta \mu(k) - \delta(k) \tag{23}$$

$$R_\Delta = \begin{bmatrix} I & 0 & 0 \cdots & 0 & 0 \\ -I & I & 0 \cdots & 0 & 0 \\ 0 & -I & I \cdots & 0 & 0 \\ . & . & . \cdots & . & . \\ 0 & 0 & 0 \cdots & I & 0 \\ 0 & 0 & 0 \cdots & -I & I \end{bmatrix} \tag{24}$$

$$\delta(k) = \begin{bmatrix} m^T(k-1) & 0 & 0 & \cdots & 0 \end{bmatrix}^T \tag{25}$$

The matrices Q and R are nonnegative tuning parameters for MPC (and are assumed to be diagonal here to simplify the tuning process).

To solve this optimization by standard quadratic programming (QP), a new independent variable is defined

$$v(k) = \mu(k) - \mu_{min}(k) \tag{26}$$

which must be nonnegative at any feasible solution. Then, using the equations from the previous section to eliminate $\Delta\ \mu(k)$ and $\psi(k)$, the optimization problem can be rewritten as

$$J = \max_{v(k)}\{a^T(k)v(k) - \frac{1}{2}v^T(k)Bv(k)\} \tag{27}$$

where

$$a(k) = H^T Q[\psi_r(k) - Y_x\hat{x}(k|k-1) - Y_v v(k) - Y_d\hat{d}(k|k)] + R_\Delta^T R R_\Delta \tag{28}$$

$$B = H^T Q H + R_\Delta^T R R_\Delta \tag{29}$$

The solution for the m variables is

$$v(k) = B^{-1}a(k) \tag{30}$$

Once the optimal and feasible value of $v(k)$ has been determined $\mu(k) = v(k) + \mu_{min}(k)$. The current and the $N-1$ predicted future manipulated variables as given in Eq (8) are therefore calculated by the controller and this signal sequence is transmitted across the network to the plant. The entire optimization procedure is repeated at the beginning of each sampling period, to provide the required closed-loop feedback control.

Figure 1 shows the model predictive control output transmitted across a wireless network to the plant. Here a timestamp is attached to each packetised control sequence before it sent out from the controller. When it arrives at the plant the timestamp is compared with the local time to calculate the RTD. In the simulation, the sensor and actuator clocks are assumed to be synchronised. To compensate for the network delay a buffer is placed at the actuator to store the received control sequence and then to select the necessary predicted control sample. The sensor and the actuator are time-driven (signal measured periodically) while the controller is event-driven (responds only on a signal arrival).

3. SIMULATION STUDY

The simulated plant was a linearized model of a cart-mounted inverted pendulum (Ogata, 2001). This constitutes a 4th order, single-input, two-output plant. Here the continuous-time plant is described in state-space form as:

$$\begin{bmatrix} \dot{x} \\ \ddot{x} \\ \dot{\theta} \\ \ddot{\theta} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & \frac{-(I+ml^2)b}{p} & \frac{m^2gl^2}{p} & 0 \\ 0 & 0 & 0 & 1 \\ 0 & \frac{-mlb}{p} & \frac{mgl(M+m)}{p} & 0 \end{bmatrix} \begin{bmatrix} x \\ \dot{x} \\ \theta \\ \dot{\theta} \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{(I+ml^2)b}{p} \\ 0 \\ \frac{ml}{p} \end{bmatrix} u \tag{31}$$

where x is the horizontal position of the cart, the input to the system u is the force acting on the cart. θ is the pendulum angular displacement from the vertical and the parameter p is:

$$p = I(M+m) + Mml^2 \tag{32}$$

The parameters p, b, m, l, g, I and M represent the material and physical properties of the cart and pendulum system as defined in Table 1. This system was selected as it is open-loop unstable and therefore constitutes a hard real-time application for the WNCS. It has also been previously used in the WNCS literature (Colandairaj, December 2006), thereby providing a useful basis for comparison.

The task of the controller is to produce the appropriate force on the cart to produce a step change in cart position while maintaining the balance of the inverted pendulum and meeting the performance criteria listed in Table 2. The DMC predictive controller was designed using the algorithm given in Section 2 with a sampling period $T = 0.005s$. The prediction and control horizons were both set as $130T = 0.650s$. Note that to obtain good closed-loop control performance, it is useful to select the prediction horizon to be close to the system rise time.

To make a quantitative comparison of closed-loop control performance under different channel conditions, the $ITAE$ (Integrated Time Area Error) performance index was used,

$$ITAE = \int_{t_0}^{t_f} t\,|e|\,dt, \sum_{k=k_0}^{k_f} k|e_k| \qquad (33)$$

where $t_0(k_0)$ and $t_f(k_f)$ are the initial and final times of the evaluation period in continuous (discrete) time and e is the error between the actual and reference trajectories. A normalized $ITAE$ was employed for better comparison between the perfect channel and delayed cases,

$$ITAE_N = log_{10}(\frac{ITAE}{ITAE_I}) \qquad (34)$$

where $ITAE_I$ represents the performance with a perfect channel. The greater the value of $ITAE_N$, the poorer the performance compared to the ideal undelayed case.

In order to test the system's tolerance to additional delay, a set of constant delays were applied to the forward channel without any additional compensation. These were multiples of the sampling time. At each sampling instance, only the first entry in the control sequence stored in the actuator buffer is then applied to the actuator and this is hold constant until updated by the arrival of a new control packet.

For a step demand in cart position from $0m$ to $0.2m$, the controller needs to provide the appropriate force to reach this set position, while keeping the pendulum balanced and satisfying the specifications in Table 2. For constant delays of T and $2T$, the step responses in cart position and pendulum angle, compared to those for a perfect channel condition are shown in Figures 2 and 3. It is clear that even with only a delay T in the forward channel the closed-loop performance deteriorates compared to the perfect channel and all the design criteria in Table 2 are violated. The step responses oscillate and take longer to reach steady-state. With delay period of $2T$, the control system becomes totally unstable as shown in Figure 3 and the performance indexes $ITAE_n$ are orders of magnitude larger. The pendulum in fact fell over shortly after the simulation started as the angle exceeded 90^o.

From these simulation results, it is clear that the DMC predictive controller without any additional compensation cannot handle even a constant network induced delay. The system is destabilized if the predictive control is not chosen to respond to changes in the channel QoS, as reflected in the network delay. This suggests the argument for co-design (Colandairaj et al., 2007) in wireless NCS.

4. ANALYSIS WITH DELAY IN FORWARD CHANNEL

4.1 Statistic analysis of measured Round Trip Delay (RTD)

The Round Trip Delay (RTD) distribution in a WLAN is usually unimodal and asymmetric (i.e. it is skewed) (D. Gunawardena and Massoulie, 2003). The experimentally recorded RTD delay measured from a real-time simulation of the cart-mounted inverted pendulum model with an IEEE802.11b WiFi card in a reverberation chamber (McKernan et al., 2008) had a similar characteristic due to the action of the back-off algorithm. This skewed distribution is caused by having a small percentage for long delays. These delays are because of contention (Waiting for the network to be free before transmission). When a collision occurs the contention window doubles each time. This leads to longer data queues which in turn causes the delay to increase exponentially.

For statistical modelling of the measured RTD, a Gamma distribution suggested in (R. Gamez and Fuertes, 2006) and an Inverse Gaussian distribution were both fitted to the experimental data. The latter gave the best fit as shown in the Cumulative Distribution Function (CDF) of Figure 4. The Inverse Gaussian CDF model of the measured delay in the WNCS is then given by:

$$P(\tau) = \Phi(\sqrt{\frac{\lambda}{\tau}}(\frac{\tau}{\mu} - 1)) + exp(\frac{2\lambda}{\mu})\Phi(-\sqrt{\frac{\lambda}{\tau}}(\frac{\tau}{\mu} + 1)) \qquad (35)$$

where τ represents the RTD, the shape parameter $\lambda = 1.79659$, the mean $\mu = 8.23547$ and the variance can be calculated as $\frac{\mu^3}{\lambda} = 310.897$. Here $\Phi(\cdot)$ is the normal (Gaussian) distribution CDF. The model in Eq (35) was used to generate the random RTD for use described in the simulation studies in the following subsection.

4.2 Random delay in the forward channel with compensation

In a practical wireless network, time-varying delays due to traffic congestion and collisions on the network are not constant. A random delay was therefore introduced in the forward channel to confirm that the DMC predictive control with delay compensation at the buffer (Figure 1) could perform effectively and maintain stability. The CDF of the delay is given in Figure 4. In the full range of Figure 4, notice that the minimum value of the experimentally measured delay is $0ms$, while the maximum delay is almost $400ms$ ($80T$). The experimentally recorded delays in Figure 4 are skewed to the left, showing that 90 percent of the measured delays are less than $17.25ms$ ($4T$).

To compensate for random delays the buffer at the plant side only take the latest generated control sequence when more than one such sequence arrive within a given sample interval. It then chooses the control signal to use according to the timestamp. As shown in Eq (36), $P(k_{min\{\tau_1,\tau_2,...\tau_k\}})$ is the latest predictive control sequence, and $\tilde{u} = \tilde{u}(k|k - min\{\tau_i\})$ is the optimal predicted control value for time k. If the buffer is not refreshed at the next sampling time, the next predicted control signal in the last control sequence received is selected to the actuator. Thus:

$$P(k_{\tau_i}) = \{\tilde{u}(k - \tau_i + j|k - \tau_i) \quad for \;\; i = 1, 2...k; \\ j = 0, 1, 2...N - 1\} \qquad (36)$$

The graphs in Figures 5 and 6 show the average step-responses of the cart-mounted inverted pendulum from 30 Monte-Carlo simulation trials with the random RTD generated from Eq (35). These suggest that the proposed DMC predictive scheme in Figure 1 can handle random transmission delay effectively in a wireless networked control system.

5. CONCLUSION

A predictive control technique for use in wireless NCS, based on Dynamic Matrix Control, is proposed and tested in simulation on a cart-mounted inverted pendulum. Here the RTD is the QoS measure of the wireless channel. This is used to choose the control signal in the received sequence at the actuator buffer. An Inverse Gaussian model for the RTD CDF derived from the practical measurement on an IEEE802.11b wireless network. This is used to facilitate realistic simulation studies which confirm the efficacy of the DMC-based predictive control.

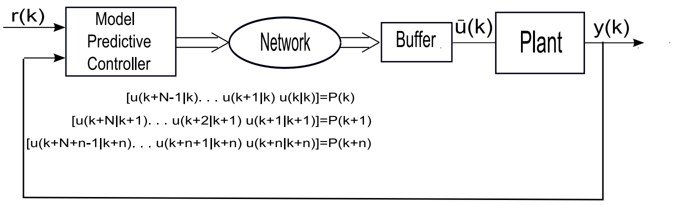

Fig. 1. The networked predictive control system with communication delay in the forward channel.

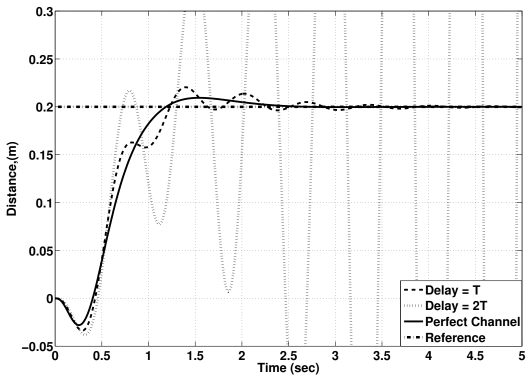

Fig. 2. Comparison of cart position step responses for DMC between perfect channel, one with T delay ($ITAE = 2.6 \times 10^{-4}$) and one with $2T$ delay ($ITAE = 1.6 \times 10^{-1}$).

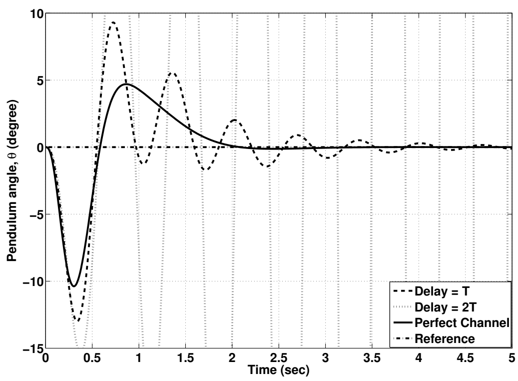

Fig. 3. Comparison of pendulum angle regulation for DMC between perfect channel, one with T delay ($ITAE = 1 \times 10^{-2}$) and one with $2T$ delay ($ITAE = 5.9$).

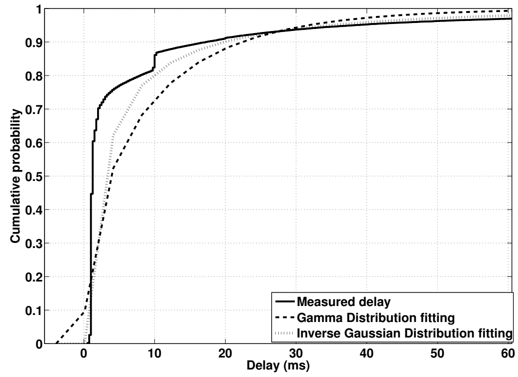

Fig. 4. Measured CDF of delay with fitted Gamma and Inverse Gaussian distributions.

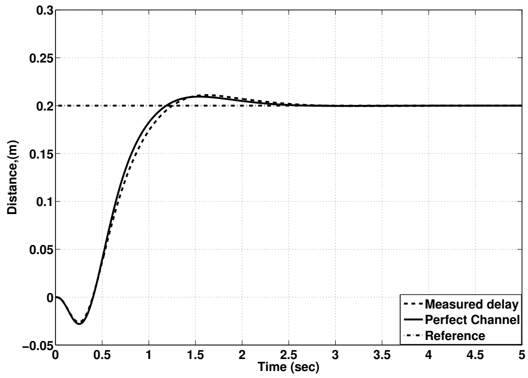

Fig. 5. Variation in average cart position step response under DMC control and delay compensation, for the measured random delay ($ITAE_n = 1.9 \times 10^{-3}$).

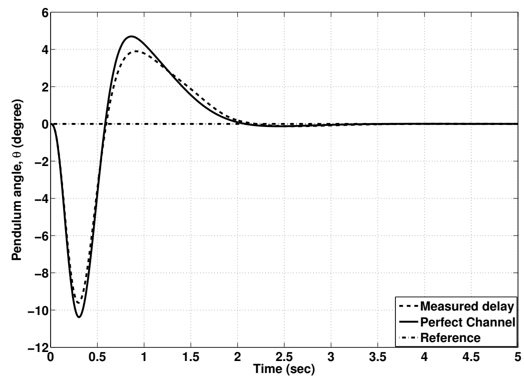

Fig. 6. Variation in average pendulum angle regulation for DMC control and delay compensation for the measured random delay ($ITAE_n = 1.5 \times 10^{-1}$).

Table 1. Material and physical properties for cart-mounted inverted pendulum

Symbol	Description	Value
M	Mass of cart	0.5 kg
m	Mass of pendulum	0.2 kg
b	Friction of cart	0.1 Nms^{-1}
l	Length of pendulum centre of mass	0.3 m
I	Inertia of pendulum	0.006 kgm^2
g	Gravity force	9.8 ms^{-2}

Table 2. Design criteria for cart-mounted inverted pendulum and comparison of closed-loop DMC performance with a perfect channel, and constant delays of T and $2T$ respectively

Parameter	Value	Perfect Channel	T delay	$2T$ delay
Settling time for cart position, x	$< 5s$	✓	x	x
Settling time for pendulum angle, θ	$< 5s$	✓	x	x
Rise time for x	$< 1s$	✓	x	x
overshoot for θ	$< 12^o$	✓	x	x
Accuracy of x and θ	2%	✓	x	x

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