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FAULT TOLERANCE IN NETWORKED CONTROL SYSTEMS UNDER INTERMITTENT OBSERVATIONS

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This paper presents an approach to fault tolerant control based on the sensor masking principle in the case of wireless networked control systems. With wireless transmission, packet losses act as sensor faults. In the presence of such faults, the faulty measurements corrupt directly the behaviour of closed-loop systems. Since the controller aims at cancelling the error between the measurement and its reference input, the real outputs will, in such a networked control system, deviate from the desired value and may drive the system to its physical limitations or even to instability. The proposed method facilitates fault compensation based on an interacting multiple model approach developed in the framework of channel errors or network congestion equivalent to multiple sensors failures. The interacting multiple model method involved in a networked control system provides simultaneously detection and isolation of on-line packet losses, and also performs a suitable state estimation. Based on particular knowledge of packet losses, sensor fault-tolerant controls are obtained by computing a new control law using fault-free estimation of the faulty element to avoid intermittent observations that might develop into failures and to minimize the effects on system performance and safety.

Keywords: network congestion, fault-tolerant control, fault diagnosis, networked control system, interacting multiple model.

1. Introduction

During the last years, fault-tolerant control has received more and more attention (Blanke *et al.*, 2000). The aim of Fault-Tolerant Control (FTC) is to adjust or to modify on-line the nominal control laws in order to maintain the safety of the operators and the reliability of the processes. The survey paper of Patton (1997) gives the state of the art in the field of fault accommodation. Almost all the methods can be categorised into two groups (Zhang and Jiang, 2008): passive and active approaches.

Passive FTC deals with a presumed set of system component failures considered at the controller design stage. An active FTC system is characterised by an on-line Fault Detection and Isolation (FDI) process and a control reconfiguration mechanism. According to the FDI module, the control reconfiguration mechanism is designed in order to take into account the possibility of fault occurrence. Advanced and sophisticated controllers have been developed with fault accommodation and tolerance capabilities, as, e.g., in the work of Noura *et al.* (2000). Nowadays, systems tend to be highly distributed, with communication networks being the core structure employed to transport the data. Moreover, there is an increasing trend to employ wireless networks for that role as they support mobility, increase the flexibility and simplify the cabling.

In an industrial plant, severe constraints may apply concerning the Quality of Service (QoS), and possibly the dependability of the system. This is the case for many embedded systems present in medical and industrial applications. The study and design of such applications, called Networked Control Systems (NCSs) as defined by Zhang *et al.* (2001), has become an important research field. Usually, NCSs are subject to unknown network induced delays and data dropouts. The control issues of NCSs, especially in the case of delays, have attracted the attention of many researchers, with taking into account network characteristics (see Tipsuwan and Chow, 2003).

When wireless networks are concerned, the quality of service of the communications can be relatively low compared to with networks. Various communication protocols for wireless networks have been proposed. Their relevance was studied by Decotignie (2002), De Pellegrini *et al.* (2006) and Willig *et al.* (2005). Nevertheless, most of the standard wireless protocols remain basically nondeterministic. The main difference between wired and wireless networks comes from the fact that losses cannot be neglected in wireless communications. Decotignie (2002) mentioned that compared with cables, radio transmissions suffer from Bit Error Rates (BERs) that are some orders of magnitude higher. BERs of 10^{-3} to 10^{-4} are usual whereas in cables one may expect BERs ranging from 10^{-7} to 10^{-9}. Consequently, radio transmission can be easily jammed by perturbed systems. This is especially true for ISM (Instrument, Scientific and Medical) bands. It may completely suppress all communications for long periods of time. A wireless transmission channel is subject to various disturbances which will cause transmission errors. This mostly corresponds to environmental noise and collisions. Although packet losses on a wireless network are intermittent, they might impact the behaviour of closed-loop systems.

In NCSs like sensor networks, in which the communications between the sensors and the controller are ensured thanks to wireless links, this means that losses may occur, and hence measurements can be lost, too. From the controller point of view, the measures are, in such a case, not available, which is the same result as a sensor fault. As a result, an FDI study of systems in which measurements are sent by a wireless channel will have to consider not only sensor faults but also packet losses. In that case, this means that the fault detection system will have to distinguish between a sensor fault and a packet loss. On the controller, it is already possible to add a promptness indicator which will be able to determine if a new measure was received during the sampling time. Promptness indicators were developed for wired industrial networks like WorldFip (CENELEC, 1996). However, it is not sufficient to totally ensure that the last data received were produced (by the sensing task) recently. Due to the asynchronism between the sensing and the communication tasks, a breakdown of the sensing task will not be detected by the previous indicator. This issue might be addressed by a freshness indicator. However, it needs resources and computations which are not always available on sensors.

To the best of our knowledge, theoretical and practical results considering simultaneous on-line detection and isolation of packet losses and also a suitable state estimation are rarely studied. A great amount of effort has been devoted to fault detection of networked control systems with missing measurements (He *et al.*, 2009; Wang *et al.*, 2009; Patan and Uciński, 2008). Some recent works focus their attention on fault detection based on a stochastic variable to describe the dropout or intermittent measurements without (Zhao *et al.*, 2009) or with (Mao *et al.*, 2009) communication time delays. Based on transition matrix probabilities of a packet loss, this paper will hence address active FTC analysis by considering both sensor faults and measurement losses without requiring special resources in sensors.

Xiong and Lam (2007) have recently considered the stabilisation of linear systems with a bounded packet loss under Markovian packet losses assumptions. According to this knowledge, this paper provides an efficient FDI module based on the Interacting Multiple Model (IMM) algorithm (Henk *et al.*, 1988) in order to develop a sensor fault masking method. In this study, the communication between the sensors and the controller will be assumed to be achieved thanks to a wireless network, and it will be also assumed that the delay remains small (compared with the sampling time). Here, the communications between the controller and the actuators are supposed not to be achieved through a network (or at least by a wired network on which both delay and packet losses are neglected).

The paper is organized as follows. In Section 2, a general formulation of the problem is given. Section 3 is devoted to present the IMM algorithm under channel errors or network congestion equivalent to sensor failures models according to a transition matrix probability. According to the FDI algorithm result, a sensor fault masking method is presented in Section 4 based on the fault-free state estimation generated by the interacting multiple model algorithm. A simulation example is given in Section 5 to illustrate the proposed method. Finally, concluding remarks are given in the last section.

2. Problem statement

2.1. Packet loss sources. In this paper, the closed-control loop is assumed to be achieved through a wireless sensors network. For that purpose, the IEEE 802.15.4 (defined by the IEEE Computer Society (2003) wireless protocol is chosen. This is the protocol used by the ZigBee technology. In contrast to Bluetooth and IEEE 802.11, IEEE 802.15.4 has been specifically developed for applications typical for industrial environments. In our case, the IEEE 802.15.4 network data rate will be 250 kb/s in a single channel within the 2.4 GHz band. This network is expected here to work in the contention access modality only, where access to the shared medium is controlled by means of a distributed CSMA/CA scheme. In such *unbeaconed* mode, the introduction of random waiting time leads to nondeterminism medium access. Moreover, Decotignie (2002) explains that collisions cannot be detected while sending a message since the power of remote emitters is much lower than that of the transmitter emission that masks the others. Data packets are hence repaired at the MAC layer on bursty channels like in wireless networks. The error is consequently detected hop-by-hop (and not end-to-end like in TCP), and packet losses are repaired by a packet retransmission protocol like ARQ. However, there is no forwarding error correction coding.

As noticed by De Pellegrini *et al.* (2006), the radio transmission system is a first cause of losses, particulary in hostile environments, where several types of noise may cause transmission errors. De Pellegrini *et al.* (2006) showed that these kinds of errors are mostly due to the co-existence of different wireless technologies in a single environment and in the same frequency band. Indeed, the 2.4 GHz band hosts BT, IEEE 802.15.4, IEEE 802.11, and possibly other systems. This specific issue is addressed by Willig *et al.* (2005). The second cause of losses deals with the MAC protocol and, specifically, the presence of collisions in the CSMA/CA scheme. Collisions are created by simultaneous access to the medium when the medium is free or because radio communication suffers from the so-called *hidden terminal effect*.

In the next section, the characterisation of packet losses will be achieved by simulations of an industrial networked control system using the IEEE 802.15.4 MAC protocol.

2.2. Packet loss prediction. In order to be able to isolate a packet loss occurrence, special attention has to be paid to wireless channel models. In the literature, various models have been used. The most popular works in this field are based on the Gilbert/Elliot model (see, for instance, Willig *et al.*, 2002). Various modifications of this model have been then proposed. Used in conjunction with experimental measurements, the Packet Error Rate (PER) in the BAD state might be adjusted in order to achieve an average PER ranging from 10^{-3} to 10^{-4}, as explained by De Pellegrini *et al.* (2006) and Willig *et al.* (2002). However, such models do not allow characterising the packet loss ratio dedicated to each communication.

To achieve this objective of per communication packet loss prediction, we propose to use channel noise models in order to simulate bit errors on a wireless communication sketch. Our method is based on experimental measurements achieved on a real plant (an overhead travelling crane presented in Section 5.1). In the work of Cuzzocrea *et al.* (2008) a measurement survey was carried out in order to draw the map of electromagnetic disturbances induced from the environment and originating from the process equipment itself. An important observation was that the communication is mainly affected by a series of impulses of varying duration and amplitude. These results were then introduced as environmental noise in a global simulation of the NCS by using the TrueTime library (Andersson *et al.*, 2007). This simulation integrates process modelling, closed-loop control, an IEEE 802.15.4 wireless network for communication between sensors and a controller and, finally, environmental noise models.

A promptness indicator was also added on the controller in order to produce packet loss traces. It might be viewed as a healthy indicator of the network. Indeed, the controller maintains a signal per sensor which indicates if a new packet has been received during the last sampling time. This indicator consumes hence few resources so that it might be implemented on a device such as the controller. Based on it, the controller might know if a new value has been received and hence adapt its computations. Figure 1(b) represent the evolution of such indicators when two stations periodically (each 10 ms) send data on an IEEE 802.15.4 network facing an impulsional noise. Figure 1(a) shows the associated packet losses according to the network point of view.

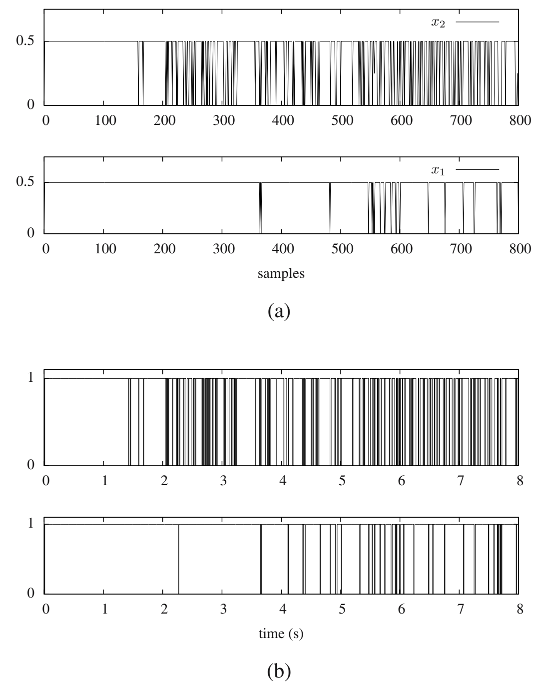

Fig. 1. Simulation of packet losses on a sample network: packet losses showing the quality of the transmission of the two measurements on the wireless network (0.5 indicates a successful transmission, 0.25 a retransmission due to a collision and 0 a packet loss (a), associated promptness indicators (1 indicates a successful transmission during the last period and 0 a packet loss) (b).

The signal is assumed to be able to detect if the signal level in the receiving node is larger than the receiver signal threshold. The Signal-to-Noise Ratio (SNR) is then computed by taking into account the environmental noise and all other transmissions (which act as background noise). A packet is assumed to be correctly received only if the percentage of bit errors is lower than the error coding threshold. Hence, packet losses will occur if the noise it much larger than the signal level. Since the longer the distance between the sender and the receiver, the higher the SNR sensible to the environmental noise, and packet losses are specific for each communication as shown in Fig. 1. Moreover, additional losses are possible if collisions occur, i.e., if the medium access is not able to send the packet. This corresponds to the 0.25 signal level in Fig. 1(a). Also note that Fig. 1(b) might highlight situations when network induced delays are larger than the sampling time such that no measures were received.

The simulations show that it is possible to dynamically determine the packet losses ratio (also called the failure rate) for each communication. Relatively to loss sources, packet loss rates were observed as time varying (and intermittent). Simulations enable us to classify three situations (modes): no losses, intermittent losses for a given traffic and a special case corresponding to a wireless network out of order. The promptness computation algorithm is then extended in order to dynamically determine the probability to move from one situation to another. Assume four modes j such that $j = 0$ stands for the case when all communications are successful, $j = 1$ and $j = 2$ when only the first (and, respectively, the second) communication is unsuccessful, and $j = 3$ denotes the case where all communications are unsuccessful. Considering simulations of Fig. 1, the final transition probabilities are given by

$$\Pi = \begin{array}{c} \\ j=0 \\ j=1 \\ j=2 \\ j=3 \end{array} \begin{array}{cccc} j=0 & j=1 & j=2 & j=3 \\ \hline 0.8226 & 0.0065 & 0.1565 & 0.0145 \\ 0.4762 & 0.0476 & 0.3333 & 0.1429 \\ 0.6187 & 0.1079 & 0.2158 & 0.0576 \\ 0.6190 & 0.0476 & 0.2381 & 0.0952 \end{array}$$

The value in the matrix Π represents the probability to move from one mode to another. By comparing $\Pi_{2,2}$ and $\Pi_{0,2}$, it can be noticed that bursty noise is taken into account. This matrix might be computed at each sampling time thanks the promptness indicators. At this point, the problem might be hence resumed as follows: Detect and isolate measurements errors (channel errors or packet losses) on the controller equivalent to sensor failures and, finally, reconfigure the control.

3. Fault detection, isolation and estimation module

In the spirit of fault diagnosis, the basic idea of the approach is to reconstruct the state of the system from subsets of measurements in the presence of an intermittent package loss which corresponds to a channel error or network congestion and causes a straight packet loss. The objective is to build a bank of filters where each filter is based on a "faulty" model under the knowledge of a transition probability matrix from one mode to another. In order to solve this problem, let us consider a linear system in the stochastic case defined as

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) + \xi(k), \\ y(k) = Cx(k) + \eta(k), \end{cases} \tag{1}$$

where $x \in \mathbb{R}^n$ is the state vector, $u \in \mathbb{R}^p$ is the input vector, and $y \in \mathbb{R}^m$ is the output vector. Here $\xi \in \mathbb{R}^n$ (respectively, $\eta \in \mathbb{R}^m$) represents the plant noise vector (resp., the measurement noise vector). A, B and C are constant matrices with appropriate dimensions.

According to the dynamic behavior of a packet loss, which is similar to a fault on a sensor, sensor failures are considered to represent network failures in the fault diagnosis approach. Each j-th faulty output can be written as

$$y_j^f(k) = \beta_j y_j(k), \tag{2}$$

where y_j and y_j^f denote the j-th nominal and faulty sensor, respectively, with $\beta_j \in [0, 1]$. A sensor failure corresponds to $\beta_j = 0$.

As proposed by Zhang and Li (1998) in the multi model framework with the interacting multiple model algorithm, such a linear system in the presence of faults/failures can be considered a stochastic hybrid system. The system mode sequence is then an indirectly hidden Markov chain where a transition probability matrix Π from Mode i to Mode j is a design parameter. Consequently, a sensor failure is modelled by setting to zero the appropriate column of the output matrix C:

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) + \xi(k), \\ y(k) = [C + F_j]x(k) + \eta(k), \end{cases} \tag{3}$$

where the matrix F_j contains zero elements except that the j-th row is taken to be the negative of the j-th row of C.

In this paper, simultaneous sensor "failures" are assumed to occur. Consequently, $q+1 = 2^m$ (with $y \in \mathbb{R}^m$) models should be considered in the set of possible failure modes. Here the number q of rows ($q \leq m$) in matrix F_j can be the negative of the corresponding row of C. Compared with the works of Zhang and Li (1998) or Theilliol *et al.* (2008), which extended the interaction multiple model algorithm to a nonlinear system, this paper takes into account not only a single fault, but a set of faults designed by the matrix $\bar{C}_j = [C + F_j]$ defining the faulty model. It attempts to extend the interaction multiple model algorithm, developed by Zhang and Li (1998), to the network problem. The four steps of the interacting multiple model algorithm are briefly outlined below.

Interaction. $\forall j \in 0, \ldots, q$, a predicted mode probability is calculated:

$$\mu^{j-} = \sum_{t=0}^{q} \pi_t^j \mu^t(k-1), \tag{4}$$

where $\mu^t(k-1)$ represents the conditional mode probability associated with the j-th faulty sensor and π_t^j is an element of the transition probability matrix Π from one mode to another. We have

$$\begin{aligned} &P_j\,(k-1|k-1) \\ &= \sum_{t=0}^{q} P_t\,(k-1|k-1)\,\mu^t(k) \\ &\quad + \sum_{t=0}^{q} [\widehat{x}\,(k-1|k-1) - \widehat{x}_j\,(k-1|k-1)] \\ &\quad \times [\widehat{x}\,(k-1|k-1) - \widehat{x}_j\,(k-1|k-1)]\,\mu^t(k). \end{aligned} \tag{5}$$

A mixed state is estimated by

$$\widehat{x}_j(k-1|k-1) = \sum_{t=0}^{q} \mu^t(k)\widehat{x}_t(k-1|k-1), \tag{6}$$

with the associated covariance given in (5), where

$$\mu^t(k) = \frac{\pi_t^j \mu^t(k-1)}{\mu^{j-}} \tag{7}$$

defines the mixing probability.

Filtering. $\forall j \in 0,\dots,q$, a predicted state is calculated as follows:

$$\widehat{x}_j(k|k-1) = A\widehat{x}_j(k-1|k-1) + Bu(k-1), \tag{8}$$

with the associated covariance equivalent to

$$P_j(k|k-1) = AP_j(k-1|k-1)A + Q^j. \tag{9}$$

The measurement residual and the filter gain can be computed as

$$r_j(k) = y_j(k) - \overline{C}_j\widehat{x}_j(k|k-1), \tag{10}$$

$$K_j(k) = P_j(k|k-1)(\overline{C}_j)^T(\Omega_j)^{-1}, \tag{11}$$

with $\Omega_j = \overline{C}_jP_j(k|k-1)(\overline{C}_j)^T + R_j$.

In this way, a filtered state can be estimated as

$$\widehat{x}_j(k|k) = \widehat{x}_j(k|k-1) + K_j(k))r_j(k), \tag{12}$$

with the following associated covariance matrix:

$$P_j(k|k) = P_j(k|k-1) - K_j(k)\Omega_j(K_j(k))^T. \tag{13}$$

Mode probability calculation. $\forall j \in 0,\dots,q$, a classical likelihood function based on residuals distribution is determined as

$$\ell_j(k) = \frac{\exp(-0.5r_j(k)(\Omega_j)^-1(r_j(k))^T)}{\sqrt{2\pi\Omega_j}}. \tag{14}$$

According to this function, a mode probability can be calculated as follows:

$$\mu^j(k) = \frac{\mu^{j-}\ell_j(k)}{\sum_{t=0}^{q}\mu^{t-}\ell_t(k)}. \tag{15}$$

It should highlighted that the mode probabilities μ^j provide an indication of the active mode at each sampling period k. Mode probabilities can be used to isolate the faulty sensor. Moreover, they can be used in a supervision scheme in order to provide operators with information about the occurrence of a possible failure.

Combination. Based on the previous steps, the state estimate is computed by a weighted sum of the following form:

$$\widehat{x}(k|k) = \sum_{j=0}^{q} \mu^j(k)\widehat{x}_j(k|k), \tag{16}$$

used in the performance index evaluation. Moreover, a fault-free estimation can be established as $\widehat{y}(k|k) = C\widehat{x}(k|k)$ used in a control law: the control law is becoming “robust” against failures and faults, as proposed in the next paragraph.

4. Sensor fault masking

Around an operating point, the following discrete state space representation is considered:

$$\begin{cases} x(k+1) = Ax(k) + Bu(k), \\ \quad y(k) = Cx(k), \\ \quad z(k) = C_rx(k), \end{cases} \tag{17}$$

where $A \in \mathbb{R}^{n\times n}$, $B \in \mathbb{R}^{n\times p}$, $C \in \mathbb{R}^{m\times n}$ and $C_r \in \mathbb{R}^{h\times n}$ are the state, the control, the output and the output reference matrices, respectively. Here $x \in \mathbb{R}^n$ is the state space, $u \in \mathbb{R}^p$ is the input vector, and $z \in \mathbb{R}^h$ corresponds to the measured output vector while $y \in \mathbb{R}^n$ represents the system outputs that will track the reference inputs $r \in \mathbb{R}^h$.

In order to maintain controllability, the number of outputs h that can track a reference input vector r cannot exceed the number of control inputs $p \geq h$. For this study, a Linear Quadratic Regulator (LQR) is considered to design the controller of a multi-input and multi-output system. Since the feedback control can only guarantee the stability and dynamic behaviour of the closed-loop system, a complementary controller is required to track the reference input vector r in the sense that the steady-state response is

$$\lim_{k\to+\infty} y = r. \tag{18}$$

Various techniques have been developed to achieve steady-state tracking of the reference input. Among them, a feedforward control law based on a command generator tracker (Zhang and Jiang, 2002) can be considered,

$$u^{\text{nom}}(k) = -K_{\text{forward}}^{\text{nom}}r(k) - K_{\text{feedback}}^{\text{nom}},\widehat{x}(k), \tag{19}$$

where $K_{\text{forward}}^{\text{nom}}$ is synthesized on the basis of the closed-loop model-following principle and $\widehat{x}(k)$ represents the state estimate obtained classically, for instance, by means of a Kalman filter.

However, in the presence of sensor faults, the faulty measurements corrupt directly the closed-loop behaviour. Moreover, the controller aims at cancelling the error between the measurement and its reference input. But in this case, the real outputs are different from the desired value and may drive the system to its physical limitations or even to instability. Sensor fault-tolerant control can be obtained by computing a new control law using fault-free estimation of the faulty element to avoid faults that could develop into failures and to minimize the effects on the system performance as defined in Eqn. (16).

From the control point of view, sensor fault-tolerant control does not require any modifications of the control law and is also called "sensor masking", as suggested by Wu *et al.* (2006). The only requirement is that the "estimator" provides an accurate estimate of the system output after a network fault occurs. Fault diagnosis in the developed strategy is of paramount importance to compensate for these faults and to preserve the system performances. Moreover, it should be highlighted that the model probabilities (Eqn. (15)) provide an indication of the mode in effect at any time.

5. Application: An overhead travelling crane

5.1. Process description. Figure 2 shows the synoptic view of the plant. A metal bar (length: 1.2 m, weight: 1 kg) is positioned along a 6 m length axis by two linear motors(12 kg/each). The maximum speed is equal to 4 m/s with a maximum acceleration of 4 g. The goal of

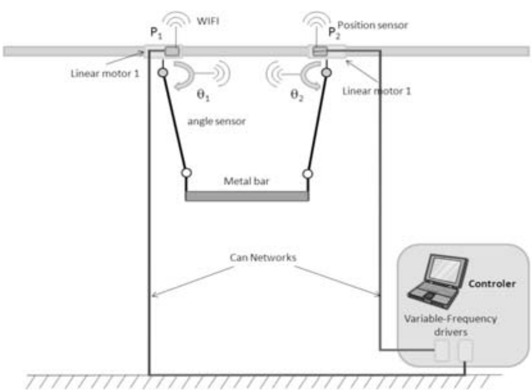

Fig. 2. Synoptic of the overhead travelling crane benchmark.

the control is to shift the metal bar to a reference position under the constraint to keep the bar horizontal. The measurements used correspond to angle measurements at the motor (θ_1 and θ_2) and position measurements provided by variable-frequency drives (p_1 and p_2). The transmissions of the measurements between the sensors and the controller are achieved thanks to a wireless network based on the IEEE 802.15.4 protocol as illustrated in Fig. 3.

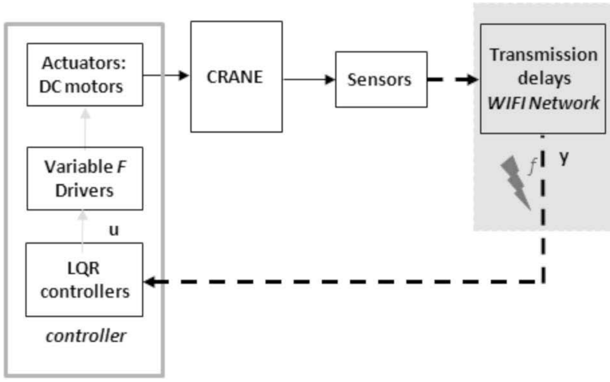

Fig. 3. Networked control overhead travelling crane scheme.

As the two positions are measured by sensors, the output vector is $y = [\ p_1 \quad p_2\ ]^T$. The control input vector is associated with the motor drive $u = [\ u_1 \quad u_2\ ]^T$. The purpose is to control the system around an operating position. Under the assumption that the θ_1 and θ_2 angles of the metal bar are equal to zero, a discrete state space representation can be obtained using a Taylor expansion with a sampling period $T_s = 0.1$ s with the state vector x equal to

$$x = [\ p_1 \quad p_2 \quad \theta_1 \quad \theta_2 \quad \dot{p}_1 \quad \dot{p}_2 \quad \dot{\theta}_1 \quad \dot{\theta}_2\ ]^T. \qquad (20)$$

These outputs are controlled using the multivariable control law described previously. The control matrix pair of the augmented plant is controllable, and the nominal tracking control law, designed by an LQR technique, provides feedback/forward gain matrices ($K_{\text{feedback}}^{\text{nom}}/K_{\text{forward}}^{\text{nom}}$) with $\mathrm{diag}(Q) = [\ 10 \quad 10 \quad 1 \quad 1 \quad 0 \quad 0 \quad 10 \quad 10\ ]^T$ fixed by the noise level. Four faulty models have been considered: a fault-free case ($j = 0$), a network problem associated with p_1 ($j = 1$) and p_2 ($j = 2$), and a network out of order, i.e., simultaneously p_1 and p_2 ($j = 3$).

The results shown in the following figures are responses with respect to set-point changes. In the simulation, a Gaussian noise is added to each output signal. The reference inputs correspond to step changes for p_1, and p_2 which excited the whole behaviour of the nonlinear system.

Firstly, the validation of the tracking control is shown in Fig. 4, where step responses are considered for a range of 20 s. Reference inputs r are step changes for p_1 and p_2. The dynamic responses demonstrate that a tracker is synthesised correctly. As illustrated in Fig. 4, the θ_1 and θ_2 angles of the metal bar are closed which corresponds to the assumption.

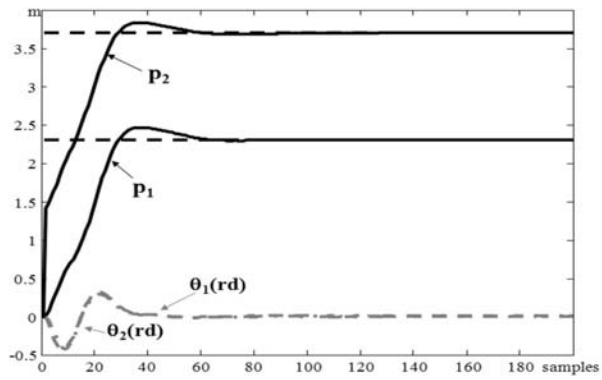

Fig. 4. System outputs controlled by a classical LQR control law in a fault-free case.

As presented in Section 2.2, different network configurations were simulated in order to identify the transition probability matrix Π. In the first simulation, the controller is assumed to be fixed in coordinates $(0, 1)$, i.e., in front of the first motor at the start of the simulation. Moreover, the maximum number of retransmissions in the case of a collision is limited to 3. It is also assumed that the motors are sending simultaneously the position measurements p_1 and p_2:

$\Pi_a =$

	$j=0$	$j=1$	$j=2$	$j=3$
$j=0$	0.8017	0.0353	0.1008	0.0622
$j=1$	0.5349	0.1163	0.3256	0.0233
$j=2$	0.5652	0.1217	0.2609	0.0522
$j=3$	0.6042	0.0625	0.2500	0.0833

In the second case, it is now assumed that the position measurements are not sent simultaneously. This leads to a new matrix defined by

$\Pi_b =$

	$j=0$	$j=1$	$j=2$	$j=3$
$j=0$	0.8226	0.0065	0.1565	0.0145
$j=1$	0.4762	0.0476	0.3333	0.1429
$j=2$	0.6187	0.1079	0.2158	0.0576
$j=3$	0.6190	0.0476	0.2381	0.0952

Compared with the first case, fewer packet losses occurs. This is due to the fact that, in the first case, since the transmission of the position measurements is synchronised, collisions occur, which leads to packet losses. By adding an offset, this kind of loss is eliminated so that the probability to move in the fault-free case ($j = 0$) is increased. The impact of the collisions is also linked to the number of retransmission trials. Indeed, the following matrix was obtained by limiting the retransmission threshold to 1:

$\Pi_c =$

	$j=0$	$j=1$	$j=2$	$j=3$
$j=0$	0.7847	0.0053	0.1993	0.0107
$j=1$	0.3571	0.0714	0.5000	0.0714
$j=2$	0.5317	0.0341	0.3902	0.0439
$j=3$	0.3000	0.1500	0.3500	0.2000

Here more packet losses occur since there are fewer possibilities to successfully transmit the position measurements.

Finally, it might be noticed in the previous matrix that the transition probabilities are relatively different between the cases $j = 1$ and $j = 2$, i.e., the position measurement of the first and the second motor. This is related to the position of the motors $(p_1, 0)$ and $(p_2, 0)$ during the simulation and the fixed position of the controller. Indeed, Fig. 4 shows that the motors are moving away from the controller $(0, 1)$ so that the relevant SNR is more and more sensitive to the environmental noise. And since the second motor set point is higher than that of the first one, the second motor is already more sensible to this noise as shown by Fig. 1. Yet, if the controller is now mobile so that it follows the metal bar moving, a new matrix might be obtained,

$\Pi_d =$

	$j=0$	$j=1$	$j=2$	$j=3$
$j=0$	0.9974	0	0.0013	0.0013
$j=1$	1.0000	0	0	0
$j=2$	1.0000	0	0	0
$j=3$	1.0000	0	0	0

Here fewer packet losses occur since the distance is significantly decreased so that the impact of the noise is also decreased.

To conclude, a transition probability matrix Π might be dynamically defined. However, this matrix remains only valid for a given set of network and plant parameters. For instance, the sampling period was fixed according to the dynamics of the plant in order to guarantee the stability of the closed-loop. The transmission period of the measurements θ and p along the network has been defined according to this sampling period. In order to take into account packet losses, the Shannon theorem should be used and adapted to the transmission period so that, by sending more packets, measurements will finally be computed on the controller. However, if the transmission period decreases, this might be problematic in a nondeterministic network like IEEE 802.15.4 since the percentage of packet losses due to collisions will increase.

In this paper, the reconfiguration method will be illustrated according to the case identified by the matrix Π_b. It might also be noticed that only position measurement packet losses are taken into account—it is assumed that no packet losses appear for the transmission of control inputs. Moreover, this paper does not focus on the impact of network induced delays on the quality of control (interested readers might consult the work of Tipsuwan and Chow (2003)).

5.2. Results and comments. The consequence of an intermittent loss of a package is considered on the first and second channels dedicated to deliver sensor measurements. As illustrated in Fig. 5, packet losses increase with the distance between the controller and the motors.

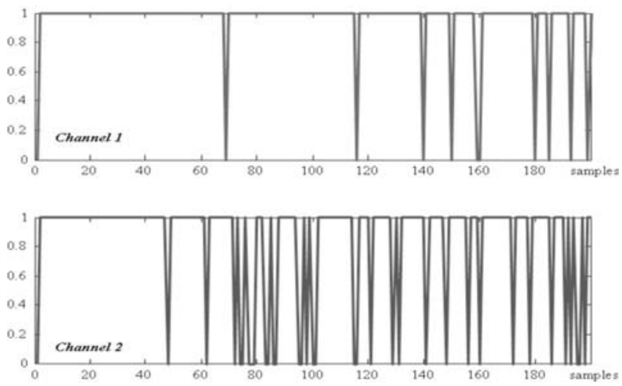

Fig. 5. Promptness indicators of packet losses (1 indicates a successful transmission during the last period and 0 a packet loss).

The control law tries to cancel the static error created by the corrupted output: all sensors deliver a value equal to zero. Consequently, the real output is different from the reference input and the control law is different from its nominal value. As presented by Sinopoli *et al.* (2004), the closed-loop system is unstable (see Fig. 6). Figure 7

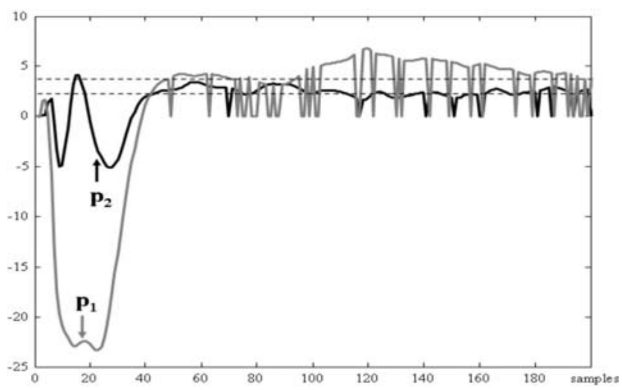

Fig. 6. System outputs controlled by classical LQR control with an intermittent loss of a package.

presents the dynamic evolution of the mode probabilities μ^j. When a packet is lost, the observation obtained by the receiver is equal to zero and the mode probability μ^0 is down to zero. Compared with the promptness indicators illustrated in Fig. 5, Fig. 7 shows clearly the capabilities of the interacting multiple model algorithms to detect and isolate faults. Without network congestion, the "fault-free" model is always close to dynamic evolution of the promptness indicators (equal to 1). Otherwise, the mode probability $\mu^3(k)$ presents some abrupt variations due to the simultaneous network problem on both sensors. According to these probabilities, it is possible to detect and isolate the fault.

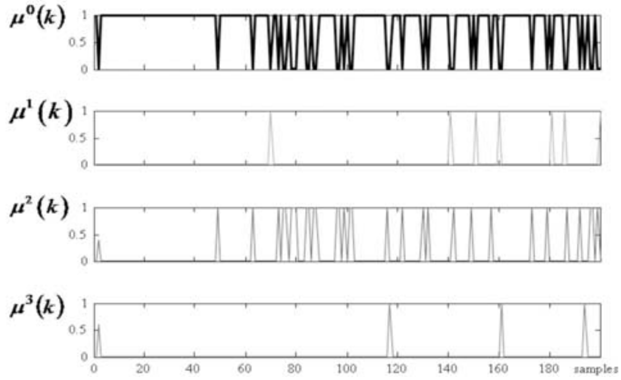

Fig. 7. Mode probabilities evolution with an intermittent loss of a package.

Moreover, based on a suitable model probability estimate, the state estimate, defined in (16), is not corrupted by an intermittent loss of a package. As illustrated in Figs. 8 and 9, with the sensor fault-tolerant control method the real levels follow the reference inputs r close to the nominal case.

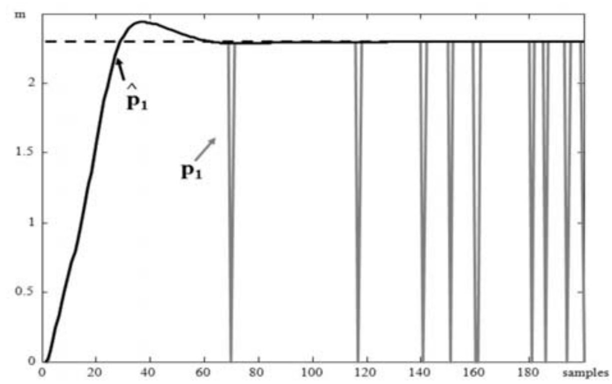

Fig. 8. Estimated and measured system output p_1 controlled by an FTC scheme with an intermittent loss of a package.

6. Conclusion

In this paper, an approach was proposed to tackle the impact of packet losses on FDI/FTC design of a networked control system. A particular kind of NCS consisting of a closed-loop control system integrating a wireless sensor network was considered. Focusing only on packet losses (delays were not studied here), it was shown that packet losses might lead to additional kinds of sensor faults which can impact on the system stability. The developed idea is therefore that the FDI/FTC system has to be adapted to packet loss characteristics, especially to the intermittent one. An FDI/FTC design based on the interacting multiple model approach algorithm based on the transition probability matrix was proposed in order to

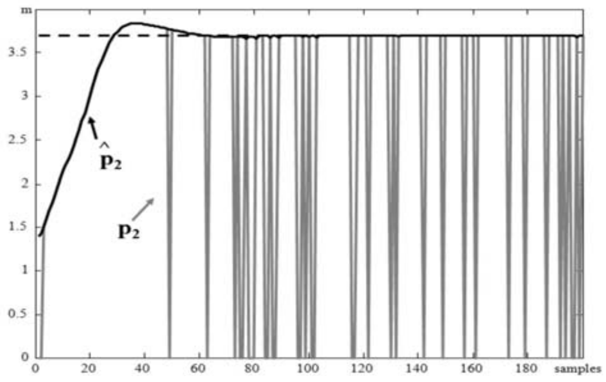

Fig. 9. Estimated and measured system output p_2 controlled by an FTC scheme with an intermittent loss of a package.

minimize the effects of packet losses on the system performance and safety. Future works should consider sensitivity analysis of the developed method against the uncertainty of failure rates. Moreover, in order to consider a more general case such as problem of time delay, future works will be extended to the network control systems with wireless communication between the controller and the actuators.

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