ARCIR ESTIREZ Delivrable E1

State of the art on Networked Control Systems

Abstract

This report summarizes the state of the art of identification, estimation and control for Networked Systems. By a networked system we mean a control system, where the communication between the plant and the controller is subject to loss or delay of information. A typical example of such systems is a control system where the controller uses a wireless network to communicate with the sensors and actuators.

Index Terms

Networked Control Systems, Estimation, Identification

I. Introduction

In the last decade, *networked control systems* (abbreviated by NCS) [110] have received a lots of attention from researchers in systems and control. NCSs are present in the majority of modern control devices. A NCS is a control system whose components (plants, sensors, embedded control algorithms and actuators) are spatially distributed [19], [42], [90], [98], [107], [110]. In such systems, the controller and the plant exchange information via a communication network. The defining feature of an NCS is that control and feedback signals are exchanged among the system's components in the form of digital information packages. The primary advantages of an NCS are reduced wiring, ease of diagnosis and maintenance and increased flexibility. However, the use of communication networks leads to a number of technical problems: limited information bandwidth, communication delays, complex interactions between control algorithms and real-time scheduling protocols, etc. These problems may lead to poor system performance and even

1 – University Lille Nord de France, LAGIS, UMR CNRS 8219, Ecole Centrale de Lille, Cite Scientifique, BP 48, 59651 Villeneuve d'Ascq cedex, France

3 – Équipe Projet Non-A, INRIA Lille-Nord Europe, France.

4 - URIA, Ecole des Mines de Douai, France

instability if not appropriately taken into account [106], [55]. For this reason, research on NCSs aims at developing control algorithms which can handle the technical problems explained above.

In this report we will give an overview of the state-of-the-art of modelling, control, estimation and identification of NCSs. The outline of this report is as follows. In Section II we present a brief overview of various aspects of NCS which were studied by the systems and control community. In Section III we present a brief overview of mathematical models of NCSs. These models are primarily used for analyzing the performance and stability of NCSs and for synthesizing control laws which are resilient to communication constraints. In Section IV we present an overview of state estimation algorithms for NCSs. Finally, in Section V we present an overview of system identification algorithms for NCSs.

II. Complex phenomena in NCS

Below we will give a brief overview of the various problems which occur in NCSs and their formalization.

Time delays

The use of time-delay models is unavoidable in NCS since the transmission of information through a network is not instantaneous [22], [26], [36], [49], [69], [43], [109]. The challenge here is to deal with the infinite dimensional nature of the obtained system.

Limited bandwidth and data quantization

Network links with limited capacity and bandwidth can be modelled in various manners. A first model consists in including into the control loop a *quantization* process, which basically constrains a signal evolving in a continuous set of values to a relatively small and possibly *saturated* discrete set. For studies in the case of systems of the quantization effect [14], [25], [41], [56], [71]. Another model has been proposed to describe the discretization in time of the exchanged information [20], [29], [87].

Asynchronous communication: event-triggered and self-triggered control

Since the various components of a NCS communicate with each other via a network, and the exchange of information via a network is never instantaneous or lossless, the components of a NCS function in an asynchronous manner. For example, sensor data is sampled in an asynchronous manner. On the one hand, this asynchronism may represent an undesired phenomena (jitters [70], [99], [8], [32], [44], [66], [95] or packet drop-out [57], [93], [94]) and it may be a source of instability. On the other hand, asynchronism may deliberately be introduced in the control loop via scheduling algorithms, in order to reduce the number of data transmissions and, therefore, optimize the computational costs [15], [18], [18], [39]. This corresponds to the recent research trend of *event-based control*, where a data is transmitted only if a particular event has occurred [17], [40], [58], [62], [96], [2], [100], [103]. Note that in *self-triggered control* [54], [104], [105], [60], [61], [4], [3], [5], [6], events are generated artificially: at each sampling instant the next admissible sampling interval based on previously received data and the knowledge of the plant dynamics.

Data loss

At last, we would like to mention the effect of communication constraints [13], [24], [46], [88] in NCS: not all sensor and actuator signals can be transmitted at the same time. This phenomena needs a particular attention since both continuous time-dynamics and scheduling protocols have to be jointly analyzed.

III. MODELLING AND ANALYSIS OF NCSS

For the purposes of this section, we will fix the architecture of a typical NCS considered in the literature. A typical NCS consists of a plant, a sampled-data control, and appropriate interface elements as represented in Figure 1, in which the blocks A/D and D/A correspond to an analog-to-digital converter (a sampler) and a digital-to-analog converter (a zero-order hold) respectively. As a rule, the plant is modeled by a Linear Time-Invariant (LTI) system, although more general models could also be considered. For the sake of simplicity, let us assume that the controller is a linear state-feedback. The controller is activated at time instances t_k, $k = 0, 1, 2, \ldots$. Between these time instances, the control input remains constant. When activated, the controller samples the current state and applies a linear state-feedback to it in order to calculate the next control input. The NCS then can be represented by the following equations.

$$\dot{x}(t) = Ax(t) + Bu(t), \ \forall t \geq 0, \tag{1a}$$

$$u(t) = Kx(t_k), \ \forall t \in [t_k, t_{k+1}), \ k \in \mathbb{N}, \tag{1b}$$

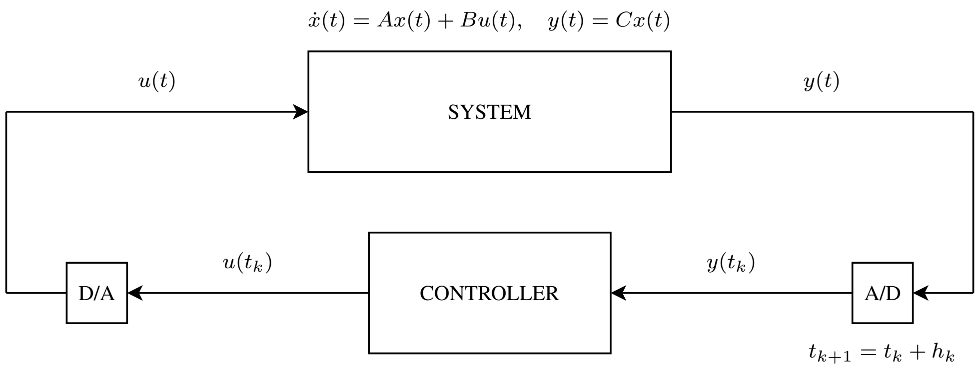

Figure 1: System with sampled sensor and control signals

The following associated discrete-time model at instants t_k is

$$x_{k+1} = \Lambda(h_k)x_k, \ \forall k \in \mathbb{N}, \tag{2}$$

with $\Lambda(h) := \mathrm{e}^{Ah} + \int_0^h \mathrm{e}^{As} ds BK$, $x_k := x(t_k)$. It is well known that for a constant sampling interval $h_k = T, \forall k \in \mathbb{N}$, the discrete-time system (2) is asymptotically stable if and only if the matrix $\Lambda(T)$ is Schur, i.e. all its eigenvalues are strictly within the unit circle. However, in the case of time-varying sampling intervals, the analysis of sampled-data systems is quite complex, even in the LTI case.

Example Consider the LTI sampled-data system (1) with

$$A = \begin{bmatrix} 0 & 1 \\ -2 & 0.1 \end{bmatrix}, \ B = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \ K = \begin{bmatrix} 1 & 0 \end{bmatrix}. \tag{3}$$

It is stable for both constant sampling intervals $T_1 = 1.5$s and $T_2 = 3$s, as both matrices $\Lambda(T_1)$ and $\Lambda(T_2)$ are Schur. One may think that alternating the sampling interval between T_1 and T_2 will not affect the stability. However, the sampled-data system with periodically time-varying sampling intervals $T_1 \to T_2 \to T_1 \to \cdots$ is unstable (see Figure 2, left). This is due to the fact that the Schurness of transition matrices is not preserved under matrix product, i.e. the matrix $\Lambda(T_2)\Lambda(T_1)$ is not Schur.

For instance, the sampled-data system (1), (3) is unstable for both constant sampling periods $T_3 = 2.1$s and $T_4 = 4$s, but it is stable under the periodically time-varying sampling $T_3 \to T_4 \to T_3 \to \cdots$ (see Figure 2, right). Indeed, the system transition matrix $\Lambda(T_4)\Lambda(T_3)$ is Schur.

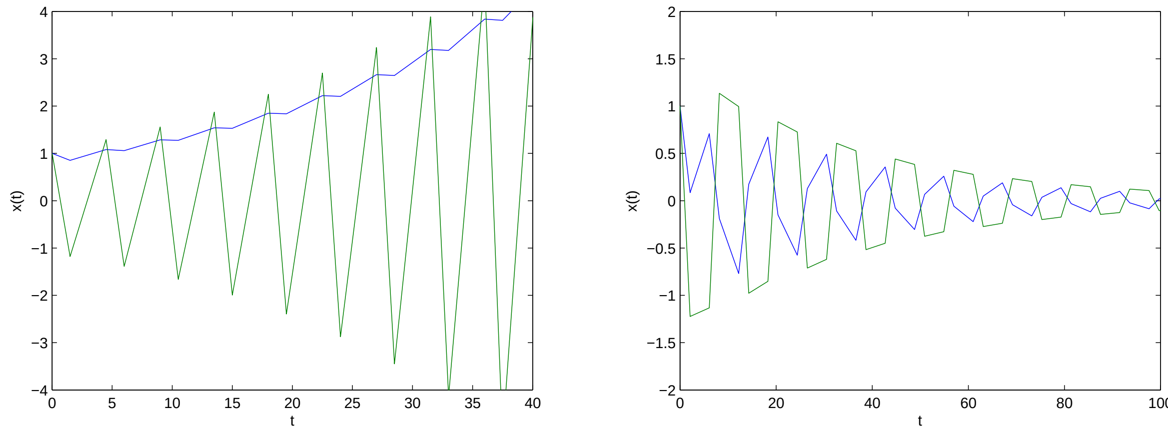

Figure 2: Periodically time-varying sampling. Left: $T_1 = 1.5s \rightarrow T_2 = 3s \rightarrow T_1 \rightarrow \cdots$ - Unstable. Right: $T_3 = 2.1s \rightarrow T_4 = 4s \rightarrow T_3 \rightarrow \cdots$ - Stable

The example above demonstrates the need to analyze the stability of the closed-loop system (1a)-(1b). In order to do this, the closed-loop system is modeled either as a time-delayed system, a hybrid system, an LPV system or as an interconnection of an LTI system with a nonlinear feedback, and then the appropriate tools from time-delayed systems, hybrid systems, LPV respectively or small gain type arguments are used. We will discuss these approaches one by one.

A. *Time-delay approach*

This approach was initiated in [63] and further developed in [31] and in several other works [30], [51], [59], [92], [97], [111]. It consists in considering the discrete-time dynamics induced by the digital controller as a delay effect. For system (1), we may re-write $u(t) = Kx(t_k) = Kx(t - \tau(t))$, where the delay $\tau(t) = t - t_k$, $\forall t \in [t_k, t_{k+1})$, is piecewise-linear, and satisfies $\dot{\tau}(t) = 1$ for $t \neq t_k$, and $\tau(t_k) = 0$. The LTI system with sampled data (1) is then re-modeled with a time-varying delay

$$\dot{x}(t) = Ax(t) + BKx(t - \tau(t)), \ \forall t \geq 0, \tag{4}$$

In this context of delay systems [89], stability is studied using Lyapunov-Krasovskii or Lyapunov-Razumikhin functionals [37] depending on the past system state values. LMI stability criteria are given in [30], [31], [91]. For the nonlinear case, we point to the works in [51], [59], [97], [111].

B. Hybrid system approach

In this approach, the LTI sampled-data system (1) is modelled as an impulsive system (i.e. a dynamical system with discontinuous state variables, representing the sampling effect), with the state $\xi(t) = [x^T(t),\, z^T(t)]^T$, where $z(t) = x(t_k)$, $\forall t \in [t_k, t_{k+1})$:

$$\begin{cases} \dot{\xi}(t) = \begin{bmatrix} A & BK \\ 0 & 0 \end{bmatrix} \xi(t), & t \neq t_k,\, \forall k \in \mathbb{N},, \\ \xi(t_k) = \begin{bmatrix} x(t_k^-) \\ x(t_k^-) \end{bmatrix}, & t = t_k, \forall k \in \mathbb{N}. \end{cases}$$

Stability analysis in this context involves Lyapunov functions with discontinuities at the impulse times [12], [68]. For nonlinear systems, the $\mathcal{L}_p$-stability properties have been studied in the more general context of networked control systems (NCS) [73]. See also [16], [74], [77], for a particularization to the sampled-data case.

C. Discrete-time approach, convex-embedding and LPV models

For system (1) with time-varying sampling intervals in $[\underline{h}, \bar{h}]$, $\underline{h} > 0$, the convex-embedding approach [21], [33], [43], [36], uses the properties of the transition matrix $\Lambda(t - t_k) = e^{A(t-t_k)} + \int_0^{t-t_k} e^{As} ds BK$, describing the evolution of $x(t)$ over the sampling interval with respect to the initial value $x(t_k)$. The idea is to express the stability problem as a finite number of LMIs, by embedding the matrix $\Lambda(\theta)$, $\theta \in [\underline{h}, \overline{h}]$ in a larger polytope $\bar{\mathcal{W}} :=$ conv$\{\Lambda_i, i = 1, \cdots, N\}$ with finite number of vertices Λ_i. For quadratic Lyapunov functions $V(x) = x^T P x$, simple LMIs dependent on the polytope vertices may be obtained:

$$P \succ 0,\ \Lambda_i^T P \Lambda_i - P \prec 0,\ \forall i \in \{1, \cdots, N\}. \tag{5}$$

A continuous-time stability analysis based on convexification arguments has been proposed in [28], [45]. The discrete-time approach has also been considered in the case of nonlinear sampled-data systems [7], [52], [65], [72], [75]. However the developments are complex even in the case of periodic sampling.

D. I/O approach

In this approach, the sampling effect is seen as a perturbation $w(t) = x(t_k) - x(t) = -\int_{t_k}^{t} \dot{x}(\tau)d\tau$, and tools from robust control theory are used to guarantee the system's stability. The main idea is to write the sampled-data system (1) on each interval $[t_k, t_{k+1})$ as the feedback interconnection of the operator $\Delta_{sh} : y \to w$ defined by: $w(t) = (\Delta_{sh}\, y)(t) = -\int_{t_k}^{t} y(\tau)d\tau$, $\forall t \in [t_k, t_{k+1})$, with an LTI system

$$\mathbf{G} := \begin{cases} \dot{x}(t) = A_{cl}x(t) + B_{cl}w(t), \\ y(t) = \dot{x}(t), \end{cases} \tag{6}$$

where $A_{cl} = A + BK$ and $B_{cl} = BK$. The stability may be studied using classical robust control tools based on frequency domains analysis of the interconnection. See [49], [64], for a study based on the small gain theorem and [34] for a more general Integral Quadratic Constraints (IQCs) and Kalman-Yakubovich-Popov Lemma analysis. Extensions to nonlinear sampled-data systems have been provided in [76], [78]–[80] using dissipation theory.

IV. Observer design problem

For NCSs, it is not realistic to assume that the entire state of the plant is measured. Hence, for control design we need observers to estimate the state of the plant.

In the majority of papers, observer design for NCSs is considered under the assumption that the network causes packet dropouts with certain probability and/or packet delays whose length has a certain probability distribution (see, for example, [42], [48] and [93]).

In [67] a linear observer for NCSs is proposed. It is assumed that the communication is subject to time delay and sampling, but the effect of communication protocols is ignored. That paper gives sufficient conditions guaranteeing asymptotic stability, by using a *Lyapunov-Krasovskii* approach. In [23], the authors focus on the observer and protocol design for NCSs under packet based communications constraints. They derive sufficient conditions in terms of matrix inequalities for existence of an *observer-protocol pair* that asymptotically reconstructs the systems state. Such an approach allows them to relate observer design for networked systems under communication constraints to observer design for *switches systems*. In [38], a class of stochastic protocols and observers are presented that minimize the upper bound on the estimation error covariance under communication constraints.

A framework for the synthesis of full order observers for nonlinear NCSs has been proposed in [84], via an emulation-like approach, that encompasses the methods proposed in [50]. Provided that the continuous-time observer is sufficiently robust to measurement errors, sufficient conditions are given to guarantee global convergence of the observation error for various in network processing implementations and *Lyapunov Uniformly Globally Asymptotically Stable* protocols. The same framework for nonlinear NCSs affected by disturbances is presented in [85]. In that paper, stability analysis is trajectory-based and carried out using small-gain arguments. This allows them to derive computable bounds on the *maximum allowable transmission interval.* In [86], reduced-order observers are built for networked control systems subject to scheduling. In that paper, a model is derived for observer design. This model is based on a different set of coordinates. It is shown that if the continuous-time observer is built to ensure some *input-to-state stability* properties for the observation error while ignoring the network, then this property will be maintained semiglobally and practically w.r.t. the *maximum allowable transmission interval*, when the system measurements are sent through a network controlled by a *Lyapunov Uniformly Globally Asymptotically Stable* protocol, under mild conditions. In [1] a *Lyapunov* approach is proposed for a class of nonlinear *triangular* NCS. The results of [1] guarantee exponential stability of the observation error. Moreover, when compared to approaches which are based on small gain arguments, [1] yields improved bounds on maximum allowable transmission interval.

V. IDENTIFICATION OF NETWORKED CONTROL SYSTEMS

The topic of identification of NCSs is in its infancy. One of the reason for this is that there is no consensus yet in the research community on the class of mathematical models for NCSs. In other words, the term networked control systems denotes a class of applications, rather than a class of mathematical models. Nevertheless, there are a number of papers dealing with identification of models under communication constraints.

In this section we are interested in the literature on the following problem: estimate the parameters of a mathematical model which captures the behavior of a control system for which the actuators and sensors are subject to communication constraints typical for a computer network such as delays, packet losses, etc. There are only a few papers on this topic: [27], [47], [101], [102], [108].

In all of the papers cited above, the basic setup is illustrated by Figure 3. The setup is as

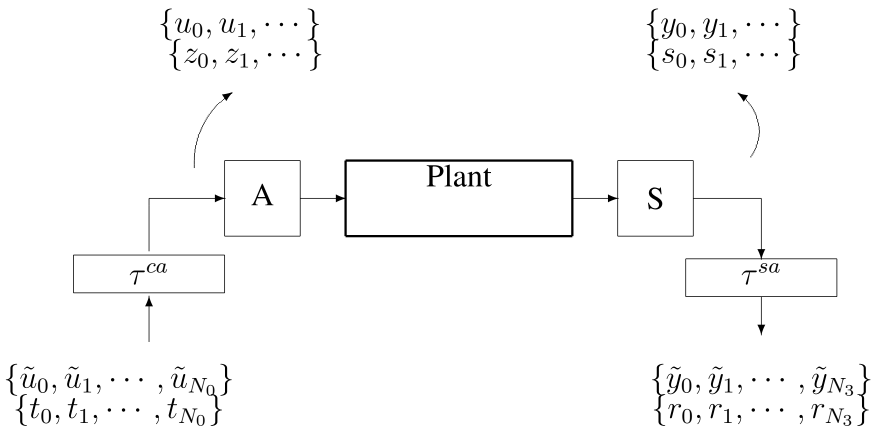

Figure 3: Identification architecture for networked control systems: A denotes the actuator, S denotes the sensor, τ^{ca} is the network induced delay from the experimenter to the experimenter, and τ^{sa} is the network induced delay from the sensor to the experimenter

follows. There is an experimenter which sends inputs to the plant and which receives outputs of the plant sampled by the sensors. Due to delays and possible packet losses, the arrival time of an input at the actuator may differ from the time this input was sent. Likewise, the time an output is received may differ from the time it was sent.

More precisely, the experimenter sends the inputs $\tilde{U} = \{\tilde{u}_i\}_{i=1}^{\infty}$ at time instances $\{t_i\}_{i=1}^{\infty}$. Then, some of these values will be received by the actuator in a certain order $U = \{u_i\}_{i=1}^{\infty}$ at time instants $\{z_i\}_{i=1}^{\infty}$. The sensor is assumed to sample the continuous output at time instances $\{s_i\}_{i=1}^{\infty}$ and to send them over the network. The output sampled by the sensor at time s_i is denoted by y_i. The output arrives to the experimenter in possibly different order at time instances $\{r_i\}_{i=1}^{\infty}$. The output which arrives at time r_i is denoted by $\widetilde{y}_i$.

The plant itself is assumed to be a continuous-time linear system

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) \end{aligned} \tag{7}$$

The goal is to identify the transfer function $H(s) = C(sI - A)^{-1}B$ of (7), using a finite portion of the information at the experimenters disposal, i.e. using $\{(\widetilde{y}_i, r_i)\}_{i=1}^{N}$ and $(\widetilde{u}_i, t_i)\}_{i=1}^{N}$.

The motivation for the identification problem is that often the model of the plant is not known, or it is only partially known. However, for control synthesis, a model of the physical plant is necessary. Note that the plant model is formulated in continuous time, while the measurement of the experimenter are necessarily in discrete time. This means that the proposed identification problem is related to continuous-time system identification [35].

In order to make the problem more tractable, some simplifying assumptions are made regarding the delays and packet losses imposed by the network. More precisely, it is assumed that each input sent to the actuator arrives with a bounded delay or lost forever. Moreover, it is assumed that the difference between the subsequent time instances at which inputs are sent belong to a certain interval. That is, it is assumed that there exists a sequence of delays $\{\tau_j^{ca} \in \mathbb{R}\}_{j=0}^{\infty}$ such that

$$\begin{aligned} &\forall i \in \mathbb{N} \quad \exists j \in \mathbb{N} : z_i = t_j + \tau_j^{ca} \\ &\tau_{min}^{ca} \leq \tau_i^{ca} \leq \tau_{max}^{ca}, \quad i = 0, 1, 2, \dots, \end{aligned} \tag{8}$$

and that

$$h_{min}^{t} \leq t_{i+1} - t_i \leq h_{max}^{t}, \quad i = 0, 1, 2, \dots \tag{9}$$

It is assumed that every packet arrives with a delay which satisfies the bounds above. In practice, it means that if a packet arrives with a delay which exceeds the bounds, then it is considered to be lost and it is discarded. This can be implemented by using time stamping.

In a similar manner, for the output it is assumed that there exists a sequence of delays $\{\tau_j^{ca} \in \mathbb{R}\}_{j=0}^{\infty}$, such that

$$\forall i \in \mathbb{N} \quad \exists j \in \mathbb{N}, \tau_j^{ca} \geq 0 : z_i = t_j + \tau_j^{sa}.$$

Moreover, it is assumed that the time instances $\{s_i\}_{i=1}^{\infty}$ at which the sensor samples the outputs satisfy

$$h_{min}^{s} \leq s_{i+1} - s_i \leq h_{max}^{s}, \quad i = 0, 1, 2, \dots \tag{10}$$

form some constants $h_{min}^{s}, h_{max}^{s} \geq 0$.

Furthermore, it is assumed that the each measurement sampled by the sensor is sent together with the sampling time, that is, for every $j \in \mathbb{N}$, not only $\widetilde{y}_j$ is known, but also the time instant s_j when it was sent. Note that this is not a trivial assumption, as it implies that the clock of the sensor and the clock of the experimenter are synchronized.

A. Results of [47]

Here $s_k = kh$, and since, the sampling time is known to the experimenter, this assumption amounts to knowing $y_k = y(kh)$ directly. Moreover, it is assumed that the experimenter generates the inputs $\widetilde{u}_k$ at time instances $t_k = kh$, and that the sequence $\{\widetilde{u}_k\}_{k=0}^{\infty}$ is a sample path of a Gaussian white noise process. The time delays τ_j^{ca} are assumed to be uniformly distributed, and independent from each other and from $\{\widetilde{u}_k\}_{k=0}^{\infty}$. Furthermore, the plant is assumed to be a stable linear SISO system. Note that this latter is a standard assumption in control.

The paper then considers that discrete-time system

$$\begin{aligned} x((k+1)h) &= Fx(kh) + B_d U_k \\ y(kh) &= Cx(kh), \end{aligned} \tag{11}$$

Here $x(kh)$ is the state of the plant at time kh, and $F = e^{Ah}$. The new input U_k is defined as $U_k = \begin{bmatrix} \hat{u}_{k-l} \\ \dots \\ \hat{u}_{k-d} \end{bmatrix}$, where for $i = k-l, \dots, k-d$, $\hat{u}_i = \widetilde{u}_i$, if $\widetilde{u}_i$ arrives at the actuator during the interval $[kh, (k+1)h)$, and $\hat{u}_i = 0$ otherwise. The matrix B_d is formed using entries of the form $e^{Ahi}B$, $i = l, \dots, d$. The constant d is determined based on the bound τ_{max}^{ca}. Intuitively, the idea behind this discrete-time model is as follows: the state at $x((k+1)h)$ depends on the state at kh and on all the input values which arrive during the interval $[kh, (k+1)h)$. This can include inputs sent at kh or before. However, due to the input delays, it is enough to consider past inputs which were sent at a time instance from the interval $[(k-d)h, (k-l)h)$ where d is the smallest integer such that $\tau_{max}^{ca} \le dh$, and l is the largest integer such that $\tau_{min}^{ca} \ge lh$.

The system (11) is then a stationary stochastic linear system driven by Gaussian noise. Then the outputs $\widetilde{y}_k = y(kh)$ and the inputs U_k form an ARMA model. The coefficients of this ARMA model can be used to estimate the matrices F. In turn, the coefficients of the ARMA model can be estimated from the empirical covariances of the data $\{\widetilde{y}_i, \widetilde{u}_i\}_{i=0}^{N}$, by using a Levinson-type algorithm. Note that while U_k is not directly measurable, the covariance $E[y(kh)U_l^T]$ can be deduced from the covariances $E[y(kh)\widetilde{u}_l^T]$, using the assumption on the distribution of the delays and inputs. In the same way, the covariances of U_k can be computed analytically, using the known distribution of the delays and inputs. The covariances $E[y(kh)\widetilde{u}_l^T]$ and $E[y(kh)y^T(lh)]$ can be estimated from the data available to the experimenter. Finally, the original continuous-time system matrix A can be recovered from F by taking logarithms. In order to recover B, the knowledge of A and techniques from continuous-time system identification are used.

B. Result of [102]

This was one of the first papers on the topic of system identification of networked systems. The paper introduces a general problem formulation, which is similar to the one described above. The assumptions are similar to that of [47]: the plant is assumed to be a SISO system, the sending times $\{s_i\}_{i=1}^{\infty}$ of the sensor are assumed to be known, the delays are assumed to be uniformly distributed on an interval. In addition, the inputs $\widetilde{u}_i$ are assumed to be chosen independently of the outputs and sending times, and they are sent whenever an output is received. That is, $t_i = r_i$, $i \in \mathbb{N}$. Then sensor samples at sampling times $s_i = kh$, and it uses time stamping to indicate the time a packet was sent. The internal clock of the sensor is thus assumed to be synchronized with that of the experimenter.

The paper uses techniques from continuous-time system identification to identify the transfer function of the plant. That is, the derivatives $y^{(k)}(t_i)$ of the outputs at arrival times are estimated, using filters. The transfer function of the continuous-time plant is estimated using the estimated values of the derivatives.

C. Results of [108]

This paper proposes sufficient conditions on the measured data, such that if the data satisfies these conditions, then there exists a unique model from a model class which is consistent with the data. The assumptions of this paper are similar to that of [47], [102]. The main difference is that the plant model is assumed to be a discrete-time model, and hence the delays are discrete too. Moreover, the identification is assumed to take place in closed-loop, i.e. the experimenter is a controller.

D. Results of [27], [101]

In these papers the basic setup is the one discussed above, however, it is assumed that if an input $\widetilde{u}_j$ arrives after $\widetilde{u}_i$ for some $i < j$, then $\widetilde{u}_j$ will be ignored. Moreover, the potential delays from the experimenter to the actuators are assumed to be bounded: if a package arrives with too long a delay, it is discarded. That is, $u_i = \widetilde{u}_{j_i}$ for some $j_i \in \mathbb{N}$, and $j_1 < j_2 < \cdots$. The same holds for the outputs $\widetilde{y}_i$, i.e. there exists $l_1 < l_2 < \cdots$ such that $\widetilde{y}_{l_i} = y_i$. The plant model is assumed to be discrete-time linear system. The papers claim to use interpolation techniques to reconstruct missing data points, and then they claim that they use various versions of linear least squares techniques. However, too many details are missing to be able to seriously evaluate the claims of the papers.

VI. Conclusions

We have presented an overview of the state-of-the-art in modelling, control, observer design and system identification of NCSs. Based on this overview we can conclude that while significant progress has been made in control and state estimation of NCSs, there are still many open problems and challenges. Perhaps the main challenge is come up with solutions which work under realistic assumptions. Most of the existing results on control and state estimation apply only under very restrictive assumptions. For control, for instance, it is often assumed that the whole state is available or a static output-feedback controller can be used. Moreover, it is often assumed that the sensors and actuators can transmit data simultaneously, or that the delays and transmission intervals are constant. The computation time of the control law is rarely taken into account. Moreover, even if one of these hypothesis is relaxed, some other, not necessarily realistic, assumptions are still kept. Understanding how to combine observer and controller synthesis remains an issue. It is not clear if counterparts of the separation principle could be formulated for NCSs. Furthermore, most of the existing results on control deal with the problem of stability. While this problem is extremely important, in practice one would also like to address more sophisticated problems such as tracking, regulation, optimization of performance indices. In the context of this project, the research effort of the consortium will be directed towards addressing the issues raised above.

From the presented overview it is clear that the topic of systems identification of NCSs is in its infancy. There is no consensus yet on the class of models which one should identify or on the sets of assumptions which should be made. In a way, the problem is that NCSs represent a class of physical control systems, rather than a class of mathematical models. Since the topic of systems identification is to estimate model parameters based on measurement data, it is necessary to fix the class of models one is interested in. Moreover, that class of models should be useful for control and state estimation. Based on the present overview, we expect to work on identification of LPV, hybrid and time-delayed models. These model classes are all used for modelling NCSs and the members of the consortium have an extensive experience in using these model classes for control and estimation of NCSs. Moreover, the members of the consortium have experience in system identification of these model classes.

Based on the discussion above, our working hypothesis will be that NCs are modelled by LPV, hybrid, or time-delayed systems. For their identifiability analysis, we will use the approaches developed for these system classes [9]–[11], [53], [81]–[83]. The specific choices of assumptions on these models will be elaborated in later deliverables, based on the results at hand.

REFERENCES

[1] T. Ahmed-Ali and F. Lamnabhi-Lagarrigue. High gain observer design for some networked control systems. *IEEE Transactions on Automatic Control*, 57(4):995–1000, 2012.

[2] A. Albert. Comparison of event-triggered and time-triggered concepts with regard to distributed control systems. *Embedded World*, 55(9):235–252, 2004.

[3] A. Anta and P. Tabuada. Isochronous manifolds in self-triggered control. In *48th IEEE Conference on Decision and Control*, pages 3194–3199, Shanghai, China, 2009.

[4] A. Anta and P. Tabuada. To sample or not to sample: self-triggered control for nonlinear systems. *IEEE Transactions on Automatic Control*, 55(9):2030–2042, 2010.

[5] A. Anta and P. Tabuada. Exploiting isochrony in self-triggered control. *IEEE Transactions on Automatic Control*, 57(4):950–962, 2012.

[6] J. Araujo, A. Anta, M. Mazo Jr., J. Faria, A. Hernandez, P. Tabuada, and K.-H. Johansson. Self-triggered control over wireless sensor and actuator networks. In *International Conference on Distributed Computing in Sensor Systems*, Barcelona, Spain, 2011.

[7] A. Astolfi, D. Nesic, and A.R. Teel. Trends in nonlinear control. In *47th IEEE Conference on Decision and Control*, pages 1870 – 1882, 2008.

[8] A. Balluchi, P. Murrieri, and A. L. Sangiovanni-Vincentelli. Controller synthesis on non-uniform and uncertain discrete-time domains. In *Proc. Conf. Hybrid Systems: Computation and Control*, pages 118–133, 2005.

[9] L. Belkoura. Identifiability of a class of systems described by convolution equations. *Automatica*, 41:505–512, 2005.

[10] L. Belkoura and Y. Orlov. Identifiability analysis of linear delay-differential systems. *IMA Journal of Math. Control and Information*, 19(8), 2002.

[11] L. Belkoura, J.P. Richard, and M. Fliess. Parameters estimation of systems with delayed and structured entries. *Automatica*, 2009.

[12] C. Briat and A. Seuret. A looped-functional approach for robust stability analysis of linear impulsive systems. *Systems & Control Letters*, 61(10):980 – 988, 2012.

[13] R. Brockett. Stabilization of motor networks. In *Proc. IEEE Conf. Decision & Control*, volume 2, pages 1484–1488, 1995.

[14] R.W. Brockett and D. Liberzon. Quantized feedback stabilization of linear systems. *IEEE Trans. Autom. Control*, 45:1279–1289, 2000.

[15] G. Buttazzo and L. Abeni. Adaptive workload management through elastic scheduling. *Real-Time Systems*, 23(1):7–24, 2002.

[16] D. Carnevale, A.R. Teel, and D. Nešić. A Lyapunov proof of an improved maximum allowable transfer interval for networked control systems. *IEEE Transactions on Automatic Control*, 52(5):892 – 897, 2007.

[17] A. Cervin and K.-J. Aström. On limit cycles in event-based control systems. In *46th IEEE Conference on Decision and Control*, pages 3190–3195, New Orleans, Louisiana, USA, 2007.

[18] A. Cervin, J. Eker, B. Bernhardsson, and K.-E. Arzen. Feedback-feedforward scheduling of control tasks. *Real-Time Systems*, 23(1):25–53, 2002.

[19] J. Chen, K.-H. Johansson, S. Olariu, I.-C. Paschalidis, and I. Stojmenovic. Guest editorial special issue on wireless sensor and actuator networks. *IEEE Transactions on Automatic Control*, 56(10):2244–2246, 2011.

[20] T. Chen and B. Francis. *Optimal sampled-data control systems*. Springer, 1993.

[21] M.B.G. Cloosterman, L. Hetel, N. van de Wouw, W.P.M.H. Heemels, J. Daafouz, and H. Nijmeijer. Controller synthesis for networked control systems. *Automatica*, 46(10):1584–1594, 2010.

[22] M.B.G. Cloosterman, N. van de Wouw, W.P.M.H. Heemels, and H. Nijmeijer. Stability of networked control systems with uncertain time-varying delays. *IEEE Trans. Autom. Control*, 54:1575 – 1580, 2009.

[23] D. Dačić and D. Nešić. Observer design for wired linear networked control systems using matrix inequalities. *Automatica*, 44:2840–2848, 2008.

[24] D.B. Dačić and D. Nešić. Quadratic stabilization of linear networked control systems via simultaneous protocol and controller design. *Automatica*, 43:1145–1155, 2007.

[25] D.F. Delchamps. Stabilizing a linear system with quantized state feedback. *IEEE Trans. Autom. Control*, 35:916–924, 1990.

[26] L. Dritsas and A. Tzes. Robust stability analysis of networked systems with varying delays. *Int. J. Control*, 82:2347 2355, 2009.

[27] Minrui Fei, Dajun Du, and Kang Li. A fast model identification method for networked control system. *Applied Mathematics and Computation*, 205(2):658 – 667, 2008. Special Issue on Advanced Intelligent Computing Theory and Methodology in Applied Mathematics and Computation.

[28] C. Fiter, L. Hetel, W. Perruquetti, and J.-P. Richard. A state dependent sampling for linear state feedback. *Automatica*, 48(8):1860–1867, 2012.

[29] G. Franklin, D. Powell, and M. Workman. *Digital Control of Dynamic Systems*. Addison-Wesley Longman Publishing Co., Inc., 3rd edition, 1997.

[30] E. Fridman. A refined input delay approach to sampled-data control. *Automatica*, 46(2):421–427, 2010.

[31] E. Fridman, A. Seuret, and J.-P Richard. Robust sampled-data stabilization of linear systems: An input delay approach. *Automatica*, 40(8):1441–1446, 2004.

[32] H. Fujioka. A discrete-time approach to stability analysis of systems with aperiodic sample-and-hold devices. *IEEE Trans. Autom. Control*, 54:2440–2445, 2009.

[33] H. Fujioka. A discrete-time approach to stability analysis of systems with aperiodic sample-and-hold devices. *IEEE Transactions on Automatic Control*, 54(10):2440–2445, 2009.

[34] H. Fujioka. Stability analysis of systems with aperiodic sample-and-hold devices. *Automatica*, 45(3):771–775, 2009.

[35] Hugues Garnier and Liuping Wang. *Identification of Continuous-time Models from Sampled Data*. Springer Publishing Company, Incorporated, 1st edition, 2008.

[36] R. Gielen, S. Olaru, M. Lazar, W. Heemels, N. Van de Wouw, and S.-I. Niculescu. On polytopic inclusions as a modeling framework for systems with time-varying delays. *Automatica*, 46(3):615–619, 2010.

[37] K. Gu, V. Kharitonov, and J. Chen. *Stability of time-delay systems*. Boston: Birkhauser, 2003.

[38] V. Gupta, T. Chung, B. Hassibi, and R.M. Murray. On a stochastic sensor selection algorithm with applications in sensor scheduling and dynamic sensor coverage. *Automatica*, 42:251–260, 2006.

[39] W.P.M.H. Heemels, K.-H Johansson, and P. Tabuada. An introduction to event-triggered and self-triggered control. In *51st IEEE Conference on Decision and Control*, pages 3270–3285, 2012.

[40] W.P.M.H Heemels, J.-H. Sandee, and P.P.J. Van Bosch. Analysis of event-driven controllers for linear systems. *International Journal of Control*, 81(4):571–590, 2008.

[41] W.P.M.H. Heemels, H. Siahaan, A. Juloski, and S. Weiland. Control of quantized linear systems: an l_1-optimal control approach. In *Proc. American Control Conference*, pages 3502–3507, 2003.

[42] J.P. Hespanha, P. Naghshtabrizi, and Yonggang Xu. A survey of recent results in networked control systems. *Proceedings of the IEEE*, 95(1):138 – 162, 2007.

[43] L. Hetel, J. Daafouz, and C. Iung. Stabilization of arbitrary switched linear systems with unknown time-varying delays. *IEEE Transactions on Automatic Control*, 51(10):1668–1674, 2006.

[44] L. Hetel, J. Daafouz, and C. Iung. Analysis and control of LTI and switched systems in digital loops via an event-based modeling. *Int. J. Control*, 81:1125–1138, 2008.

[45] L. Hetel, A. Kruszewski, W. Perruquetti, and J.-P Richard. Discrete and intersample analysis of systems with aperiodic sampling. *IEEE Transactions on Automatic Control*, 56(7):1696–1701, 2011.

[46] Dimitris Hristu and Kristi Morgansen. Limited communication control. *Syst. Control Lett.*, 37:193–205, 1999.

[47] Yasir Irshad, Magnus Mossberg, and Torsten Sderstrm. System identification in a networked environment using second order statistical properties. *Automatica*, 49(2):652 – 659, 2013.

[48] Z. Jin, V. Gupta, and R.M. Murray. State estimation over packet dropping networks using multiple description coding. *Automatica*, 42:1441–1452, 2006.

[49] C.-Y. Kao and B. Lincoln. Simple stability criteria for systems with time-varying delays. *Automatica*, 40(8):1429 – 1434, 2004.

[50] I. Karafyllis and C. Kravaris. From continuous-time design to sampled-data design of observers. *IEEE Transactions on Automatic Control*, 54(9):2169–2174, 2009.

[51] I. Karafyllis and M. Krstic. Nonlinear stabilization under sampled and delayed measurements, and with inputs subject to delay and zero-order hold. *IEEE Transactions on Automatic Control,*, 57(5):1141 – 1154, 2012.

[52] D. Laila, D. Nešić, and A. Astolfi. 3 sampled-data control of nonlinear systems. In Antonio Loría, Françoise Lamnabhi-Lagarrigue, and Elena Panteley, editors, *Advanced Topics in Control Systems Theory*, volume 328 of *Lecture Notes in Control and Information Science*, pages 91–137. Springer London, 2006.

[53] L. Lee and K. Poolla. Identifiability issues for parameter varing and multidimensional linear systems. In *Proceedings of the Conference on Mechanical Vibration and Noise*, Sacremento, California, USA, September 1997.

[54] M.-D. Lemmon, T. Chantem, X.-S. Hu, and M. Zyskowski. On self-triggered full-information h-infinity controllers. In *10th International Conference on Hybrid Systems: Computation and Control*, Pisa, Italy, 2007.

[55] X.-G. Li, A. Cela, S. Niculescu, and A. Reama. Some problems in the stability of networked-control systems with periodic scheduling. *International Journal of Control*, 83(5):996–1008, 2010.

[56] D. Liberzon. On stabilization of linear systems with limited information. *IEEE Trans. Autom. Control*, 48:304–307, 2003.

[57] Xiangheng Liu and A. Goldsmith. Kalman filtering with partial observation losses. *Proc. IEEE Conf. Decision & Control*, 4:4180–4186, 2004.

[58] J. Lunze and D. Lehmann. A state-feedback approach to event-based control. *Automatica*, 46(1):211–215, 2010.

[59] F. Mazenc, M. Malisoff, and T.N. Dinh. Robustness of nonlinear systems with respect to delay and sampling of the controls. *Automatica*, 49(6):1925 – 1931, 2013.

[60] M. Mazo Jr., A. Anta, and P. Tabuada. On self-triggered control for linear systems: guarantees and complexity. In *European Control Conference*, Budapest, Hungary, 2009.

[61] M. Mazo Jr., A. Anta, and P. Tabuada. An ISS self-triggered implementation of linear controllers. *Automatica*, 46(8):1310–1314, 2010.

[62] M. Mazo Jr. and P. Tabuada. Decentralized event-triggered control over wireless sensor/actuator networks. *IEEE Transactions on Automatic Control*, 56(10):2456–2461, 2011.

[63] Y. Mikheev, V. Sobolev, and E. Fridman. Asymptotic analysis of digital control systems. *Automation and Remote Control*, 49(9):1175–1180, 1988.

[64] L. Mirkin. Some remarks on the use of time-varying delay to model sample-and-hold circuits. *IEEE Transactions on Automatic Control*, 52(6):1109–1112, 2007.

[65] S. Monaco, D. Normand-Cyrot, and C. Califano. From chronological calculus to exponential representations of continuous and discrete-time dynamics: A Lie-algebraic approach. *IEEE Transactions on Automatic Control*, 52(12):2227 – 2241, 2007.

[66] L.A. Montestruque and P. Antsaklis. Stability of model-based networked control systems with time-varying transmission times. *IEEE Trans. Autom. Control*, 49:1562–1572, 2004.

[67] P. Naghshtabrizi and J. P. Hespanha. Designing an observer-based controller for a network control system. In *Proceedings of the 44th IEEE Conference on Decision and Control and 2005 European Control Conference*, pages 848–853, 2005.

[68] P. Naghshtabrizi, J.-P. Hespanha, and A.-R. Teel. Exponential stability of impulsive systems with application to uncertain sampled-data systems. *Systems and Control Letters*, 57(5):378–385, 2008.

[69] P. Naghshtabrizi, J.P. Hespanha, and A.R. Teel. Stability of delay impulsive systems with application to networked control systems. In *Proc. American Control Conf.*, pages 4899–4904, New York, USA, 2007.

[70] Payam Naghshtabrizi and J.P. Hespanha. Stability of networked control systems with variable sampling and delay. In *44th Allerton Conf. Communications, Control & Computing*, 2006.

[71] G.N. Nair and R.J. Evans. Stabilizability of stochastic linear systems with finite feedback data rates. *SIAM J. Control Optim.*, 43:413–436, 2004.

[72] D. Nešić and A.R. Teel. A framework for stabilization of nonlinear sampled-data systems based on their approximate discrete-time models. *IEEE Transactions on Automatic Control*, 49(7):1103 – 1122, 2004.

[73] D. Nešić and A.R. Teel. Input-output stability properties of networked control systems. *IEEE Transactions on Automatic Control*, 49(10):1650 – 1667, 2004.

[74] D. Nešić, A.R. Teel, and D. Carnevale. Explicit computation of the sampling period in emulation of controllers for nonlinear sampled-data systems. *IEEE Transactions on Automatic Control*, 54(3):619 – 624, 2009.

[75] D. Nešić, A.R. Teel, and P.V. Kokotović. Sufficient conditions for stabilization of sampled-data nonlinear systems via discrete-time approximations. *Systems & Control Letters*, 38(4?5):259 – 270, 1999.

[76] H. Omran, L. Hetel, and J.-P. Richard. Local stability of bilinear systems with asynchronous sampling. In *4th IFAC Conference on Analysis and Design*, Eindhoven, The Netherlands, 2012.

[77] H. Omran, L. Hetel, J.-P. Richard, and F. Lamnabhi-Lagarrigue. Stability of bilinear sampled-data systems with an emulation of static state feedback. In *IEEE 51st Annual Conference on Decision and Control*, pages 7541 – 7546, 2012.

[78] H. Omran, L. Hetel, J.-P. Richard, and F. Lamnabhi-Lagarrigue. On the stability of input-affine nonlinear systems with sampled-data control. In *European Control Conference (ECC)*, pages 2585 – 2590, 2013.

[79] H. Omran, L. Hetel, J. P. Richard, and F. Lamnabhi-Lagarrigue. Stabilité des systèmes non linéaires sous échantillonnage apériodique. *Journal Européen des Systèmes Automatisés*, 2014.

[80] H. Omran, L. Hetel, J.-P. Richard, and F. Lamnabhi-Lagarrigue. Stability analysis of bilinear systems under aperiodic sampled-data control. *Automatica*, 2014.

[81] Y. Orlov, L. Belkoura, J.P. Richard, and M. Dambrine. On identifiability of linear time-delay systems. *IEEE Transactions on Automatic Control*, 47(8), 2002.

[82] M. Petreczky, L. Bako, and S. Lecouche. Minimality and identifiability of sarx systems. In *16th IFAC Symposium on System Identification (SYSID), Brussel*, 2012.

[83] M. Petreczky, L. Bako, and J.H. van Schuppen. Identifiability of discrete-time linear switched systems. In *Hybrid Systems: Computation and Control*, pages 141–150. ACM, 2010.

[84] R. Postoyan and D. Nešić. A framework for the observer design for networked control systems. In *Proceedings of the 2010 American Control Conference*, pages 3678–3683, Baltimore, USA, 2010.

[85] R. Postoyan and D. Nešić. A framework for the observer design for networked control systems. *IEEE Transactions on Automatic Control*, 57(5):1309–1314, 2012.

[86] R. Postoyan and D. Nešić. On emulated nonlinear reduced-order observers for networked control systems. *Automatica*, 48:645–652, 2012.

[87] K. Åström and B. Wittenmark. *Computer-controlled systems: theory and design*. Prentice-Hall information and system sciences series. Prentice-Hall, Upper Saddle River, NJ, 1997.

[88] Henrik Rehbinder and Martin Sanfridson. Scheduling of a limited communication channel for optimal control. *Automatica*, 40:491–500, 2004.

[89] J.-P Richard. Time delay systems: an overview of some recent advances and open problems. *Automatica*, 39(10):1667–1694, 2003.

[90] J.-P. Richard and T. Divoux. *Systèmes commandés en réseau*. IC2 Systèmes Automatisés. Hermès-Lavoisier, 2007.

[91] A. Seuret. A novel stability analysis of linear systems under asynchronous samplings. *Automatica*, 48(1):177–182, 2012.

[92] A. Seuret and J.P. Richard. Control of a remote system over network including delays and packet dropout. In *17th IFAC World Congress*, 2008.

[93] B. Sinopoli, L. Schenato, M. Franceschetti, K. Poolla, M.I. Jordan, and S.S. Sastry. Kalman filtering with intermittent observations. *IEEE Trans. Autom. Control*, 49:1453–1464, 2004.

[94] S.C. Smith and P. Seiler. Estimation with lossy measurements: jump estimators for jump systems. *IEEE Trans. Autom. Control*, 48:2163–2171, 2003.

[95] Y.S. Suh. Stability and stabilization of nonuniform sampling systems. *Automatica*, 44:3222–3226, 2008.

[96] P. Tabuada. Event-triggered real-time scheduling of stabilizing control tasks. *IEEE Transactions on Automatic Control*, 52(9):1680–1685, 2007.

[97] A.R. Teel, D. Nesic, and P.V. Kokotović. A note on input-to-state stability of sampled-data nonlinear systems. In *Proceedings of the 37th IEEE Conference on Decision and Control*, volume 3, pages 2473 – 2478, 1998.

[98] Y. Tipsuwan and M.-Y. Chow. Control methodologies in networked control systems. *Control Eng. Pract.*, 11:1099–1111, 2003.

[99] N. van de Wouw, P. Naghshtabrizi, M.B.G. Cloosterman, and J.P. Hespanha. Tracking control for sampled-data systems with uncertain sampling intervals and delays. *Int. J. Robust & Nonlinear Control*, 20:387–411, 2010.

[100] M. Velasco, P. Marti, and E. Bini. On lyapunov sampling for event-driven controllers. In *48th IEEE Conference on Decision and Control*, pages 6238–6243, Shanghai, China, 2009.

[101] Hongwei Wang, Chengcheng Guo, and Jie Lian. A new identification method of networked control system. In *Intelligent Control and Information Processing (ICICIP), 2012 Third International Conference on*, pages 248–253, July 2012.

[102] Jiandong Wang, Wei Xing Zheng, and Tongwen Chen. Identification of linear dynamic systems operating in a networked environment. *Automatica*, 45(12):2763 – 2772, 2009.

[103] X. Wang and M.-D. Lemmon. Event design in event-triggered feedback control systems. In *47th IEEE Conference on Decision and Control*, pages 2105–2110, Cancun, Mexico, 2008.

[104] X. Wang and M.-D. Lemmon. Self-triggered feedback control systems with finite-gain $\mathcal{L}_2$ stability. *IEEE Transactions on Automatic Control*, 54(3):452–467, 2009.

[105] X. Wang and M.-D. Lemmon. Self-triggering under state-independent disturbances. *IEEE Transactions on Automatic Control*, 55(6):1494–1500, 2010.

[106] B. Wittenmark, J. Nilsson, and M. Torngren. Timing problems in real-time control systems. In *American Control Conference*, pages 2000–2004, Seattle, Washington, USA, 1995.

[107] T.C. Yang. Networked control system: a brief survey. *IEE Proc. Control Theory & Applications*, 153:403–412, 2006.

[108] Cong Zhang, Wei Wang, and Hao Ye. Informative conditions for a data set in an {MIMO} networked control system. *Neurocomputing*, 121(0):309 – 316, 2013.

[109] L. Zhang, Y. Shi, T. Chen, and B. Huang. A new method for stabilization of networked control systems with random delays. *IEEE Trans. Autom. Control*, 50:1177–1181, 2005.

[110] W. Zhang, M.S. Branicky, and S.M. Phillips. Stability of networked control systems. *IEEE Control Syst. Mag.*, 21:84–99, 2001.

[111] Y. Zheng, D. Owens, and S. Billings. Fast sampling and stability of nonlinear sampled-data systems: Part 2. *The IMA Journal of Mathematical Control & Information*, 7:13 – 33, 1990.