Optimal estimation in networked control systems subject to random delay and packet drop

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Abstract

In this paper we study optimal estimation design for sampled linear systems where the sensors measurements are transmitted to the estimator site via a generic digital communication networks. Sensor measurements are subject to random delay or might even be completely lost. We show that the minimum error covariance estimator is time-varying, stochastic, and it does not converge to a steady state. Moreover, this estimator is independent of the communication protocol and can be implemented using a finite memory buffer if and only if the delivered packets have a finite maximum delay. We also present two alternative time-invariant estimator architectures and, surprisingly, we show that stability does not depend on packet delay but only on the packet loss probability. Finally, algorithms to compute critical packet loss probability and estimators performance in terms of error covariance are given and applied to some numerical examples.

I. Introduction

Recent technological advances in MEMS, DSP capabilities, computing, and communication technology are revolutionizing our ability to build massively distributed networked control systems (NCS) [1]. These networks can offer access to an unprecedented quality and quantity of information which can revolutionize our ability in controlling of the environment, such as fine grane building environmental control [2], vehicular networks and traffic control [3], surveillance and coordinated robotics [4]. However, they also pose challenging problems arising from the fact that sensors, actuators and controllers are not physically co-located and need to exchange information via a digital communication network. In particular, measurement and control packets are subject to random delay and loss. These problems are particularly evident in wireless communication networks which are rapidly replacing wired communication infrastructures in many engineering areas [5]. This is happening because wireless systems are easier and cheaper to deploy and avoid cumbersome cabling and device positioning. Besides, new technologies like wireless sensor networks (WSNs), which are large networks of spatially distributed electronic devices – called nodes – capable of sensing, computation and wireless communication, will enable the development of applications previously unfeasible [6] [7]. For example, WSN has been used for animal habitat monitoring in inhospitable regions [8] and microclimate monitoring in forests [9]. These are typical example of large scale fine grain sensor data-collection applications where information is collected and then analyzed off-line.

However, WSN are going to be employed also for real-time applications. For example consider a WSN deployed in a forest whose nodes are equipped with temperature and humidity sensors, as graphically shown in the left panel of Fig. 1. The same network could be employed for monitoring climate variations (data-collection application) or for wild-fire detection and tracking (real-time application) [10]. Despite the fact that these two applications adopt the same infrastructure, they obviously have different packet delay and packet loss requirements, as shown in right panel of Fig. 1. In fact, in data-collection applications it is only necessary to extract all data regardless of packet delay, while in real-time control applications both delay and packet loss are relevant. Unfortunately, the design of communication protocols for communication networks has to deal with unavoidable tradeoffs between packet loss and packet delay. In fact, communication protocols that aim at reducing packet loss require retransmission of lost packets and packet delivery acknowledgment, which increase traffic and consequently delay. Viceversa,

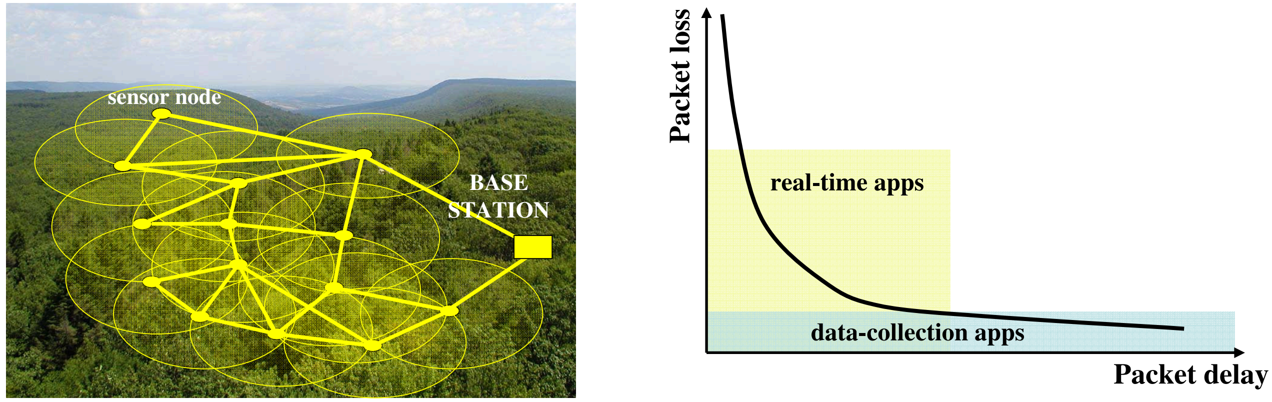

Fig. 1. Pictorial representation of Wireless Sensor Network for forest monitoring or wildfire detection *(left)*. The small dots indicate the location of the sensing nodes, the shaded circles indicate the sensing regions and the segments the communication links. Tradeoff curve typical of many network communication protocols and constraint regions for real-time and data-collection applications *(right)*.

reducing time delay requires dropping of packets to mitigate traffic and packet collisions (see solid line in right panel of Fig. 1). Therefore, it is not trivial to design communication protocols for control systems since both delay and packet loss negatively impact estimation and closed loop performance of controlled systems. Currently, communications protocols and networked control systems are designed separately. In particular, protocols are design based on conservative heuristics which specify what the maximum time delay and maximum packet loss should be, but with no clear understanding of their impact on the overall application performance. On the application side, control systems are not specifically designed to exploit information about packet loss and delay statistics of the communication protocols they will run on. From these observations few questions arise. For example, how should we design estimators for networked systems that take into account simultaneous random delay and packet loss? How can we estimate their performance? When is the closed loop system stable? How can we choose between a communication protocol with a large packet delay and a small packet loss and a protocol with a small packet delay and a large packet loss, in terms of best performance of a specific real-time application? These are the questions that motivate this work.

This paper is organized as follows. In the next section we give an overview on relevant previous work and we state our contribution. Section III formalizes the minimum variance estimation problem and the packet arrival process modeling. In Section IV the minimum variance estimation problem is solved in full generality and conditions on memory requirements are given. In Section V we derive stability conditions and quantify performance in terms of expected estimation error covariance of minimum variance estimators with constant gains under i.i.d. packet arrival with known statistics. These suboptimal estimators provide an upper bound for the performance of the time-varying optimal filter proposed in Section IV. Section VI shows how estimation performance can be improved when sensors with computational resources are physically co-located. This architecture also provides a lower bound for performance of the time-varying optimal filter of Section IV. Section VII gives some numerical examples to illustrate the use of the tools derived in the previous sections. Finally, in Section VIII we state our conclusions and give directions for future work.

II. Previous Work and Contribution

Classical control has mainly focused on systems with constant delay [11] or with small delay perturbation known as jitter [12]. Recently several groups have looked at networked control systems with large random delay measurement and control or packet loss. The survey paper [13] nicely reviews several results in this area. These results can be divided into two main groups: the first group focuses on variable delay but no packet drop, while the second group focuses on packet loss but no delay.

Within the first group, some authors derived stability conditions in terms of LMIs for closed loop continuous time linear systems with stochastic sampling time [14][15], and Nesic at al. [16] obtained Lyapunov-like stability conditions for continuous time nonlinear systems with unknown but bounded sampling time. These works simply determine stability for a given closed loop system, and there is no controller synthesis specifically designed to take into account delay. With this respect, Yue et al. [17] proposed an LMI approach for the design of stabilizing controllers for bounded delay, while Nilsson at al. [18] extended LQG optimal control design to sampled linear systems subject to stochastic measurement and control packet delay, and showed how the optimal controller gains are time-delay dependent. The previous results rely on the major assumption that there is no packet loss or there are at most m consecutive packet drops.

In the second group of results, there has been a considerably effort to apply optimal control and estimation to discrete time systems where measurements and control packets can be dropped with some probability, but have otherwise no delay. This framework is equivalent of saying that all packets have either no delay or infinite delay. For example, in [19][20][21] the authors proposed compensation techniques for i.i.d Bernoulli packet-drop communication networks and derived stability conditions for closed loop discrete time system. Elia et al. [22][23] proposed a stochastic perturbation approach for general MIMO LTI discrete time systems and showed that the optimal controller design is equivalent to solving a convex LMI optimization problem. Sinopoli at al. [24] looked specifically at minimum variance estimation design for packet-drop networks and showed that the optimal estimator is necessarily time-varying, and these results have been extended to LQG controller design in [25] and [26]. Finally, a number of researches has explored specific mechanisms to improve estimation performance such as exploiting local computation at the sensor location [27][28], controlled communication [29][28], and network topology [30].

The previous two groups of results suffer from some limitations. In fact, even with retransmission mechanisms present in all current digital communication networks, and in particular in the wireless ones, it is impossible to guarantee that all packets are correctly delivered to the destination. On the hand, in wireless sensor networks which implement multi-hop communication, delay is not negligible and is subject to large variations. Therefore, none of the modelings considered so far, i.e. random delay but no packet loss and packet loss but no delay, fully represent control systems interconnected by digital communication networks. Very little work has been done considering simultaneous packet drop and packet delay leading to somewhat conservative results as they are based on worst-case scenarios [31] [32].

In this paper we propose a probabilistic framework to analyze estimation where observation packets are subject to arbitrary random delay and packet loss. This allows packets to arrive in burst or even out of order at the receiver side, as long as the measurements are time-stamped at the sensor side. We derive the optimal estimator in mean square sense and we show that the minimum error covariance estimator is time-varying, stochastic and does not converge to a steady state. Moreover, this estimator design is independent of the specific communication protocol adopted and can be implemented using a finite memory buffer if and only if the delivered packets have a finite maximum delay. In particular, the memory length is equal to the maximum packet delay. We also present two alternative estimator architectures which constrain the estimator gains to be constant rather than stochastic as for the true optimal estimator. In particular we show how to compute the optimal constant gains if the packet arrival statistic is stationary and known. We derive necessary and sufficient condition for stability of the estimator. Surprisingly we show that stability does not depend on packet delay but only on a critical packet loss probability which depends on the unstable eigenvalues of the system to be estimated. We also provide quantitative measures for the expected error covariance of such estimators which turn out to be the solution of some modified algebraic Riccati equations and Lyapunov equations. These measures can be used to compare different communication protocols for real-time control applications. Very importantly, these results do not depend on the specific implementation of the digital communication network (fieldbuses, Bluetooth, ZigBee, Wi-Fi, etc ..) as long as the packet arrival statistics are known, i.i.d and stationary.

III. Problem formulation

Consider the following discrete time linear stochastic plant:

$$x_{t+1} = Ax_t + w_t \quad (1)$$

$$y_t = Cx_t + v_t, \quad (2)$$

where $t \in \mathbb{N} = \{0, 1, 2, \ldots\}$, $x, w \in \mathbb{R}^n$, $y \in \mathbb{R}^m$, $A \in \mathbb{R}^{n\times n}$, $y \in \mathbb{R}^m$, $C \in \mathbb{R}^{m\times n}$, (x_0, w_t, v_t) are Gaussian, uncorrelated, white, with mean $(\bar{x}_0, 0, 0)$ and covariance (P_0, Q, R) respectively. We also assume that the pair (A, C) is observable, $(A, Q^{1/2})$ is controllable, and $R > 0$.

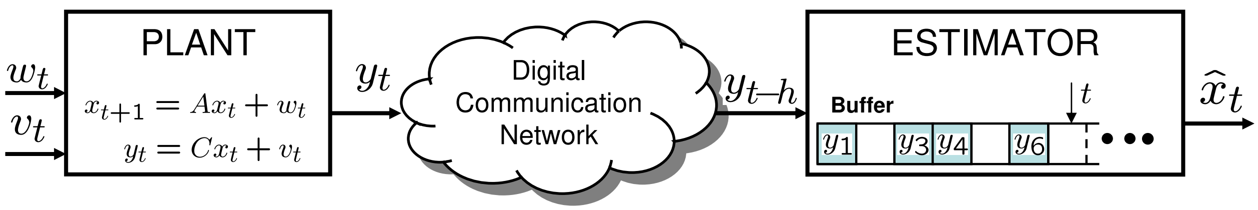

Fig. 2. Networked systems modeling. Sampled observations at the plant site are transmitted to the estimator site via a digital communication network. Due to retransmission and packet loss, observation packets arrive at the estimator site with possibly random delay.

Measurements are time-stamped, encapsulated into packets, and then transmitted through a digital communication network (DCN), whose goal is to deliver packets from a source to a destination (see Fig. 2). Time-stamping of measurements are necessary to reorder packets at the receiver side as they can arrive out of order. Modern DSNs are in general very complex and can greatly differ in their architecture and implementation depending on the medium used (wired, wireless, hybrid), and on the applications they are meant to serve (real-time monitoring, data extraction, media-related, etc ..). In our work we model a DSN as a module between the plant and the estimator which delivers observation measurements to the estimator with possibly random delays. This model allows also for packets with infinite delay which corresponds to observation loss. We assume that all observation packets correctly delivered to the estimator site are stored in an infinite buffer, as shown in Fig. 2. The arrival process is modeled by defining the random variable γ_k^t as follows:

$$\gamma_k^t = \begin{cases} 1 & \textit{if } y_k \text{ has arrived at the estimator before or at time } t,\ t \geq k \\ 0 & \textit{otherwise} \end{cases} \quad (3)$$

From this definition it follows that $(\gamma_k^t = 1) \Rightarrow (\gamma_k^{t+h} = 1, \forall h \in \mathbb{N})$, which simply states that if packet y_k is present in the receiver buffer at time t, then it will be present for all future times. We also define the packet delay $\tau_k \in \{\mathbb{N}, \infty\}$ for observation y_k as follows:

$$\tau_k = \begin{cases} \infty & \textit{if } \gamma_k^t = 0, \forall t \geq k \\ t_k - k & \textit{otherwise}, \text{ where } t_k \stackrel{\Delta}{=} \min\{t \mid \gamma_k^t = 1\} \end{cases} \quad (4)$$

where t_k is the arrival time of observation y_k at the estimator site . Since the packet delay can be random, observation measurements can arrive out of order at the estimator site (see Fig. 3, $t = 5$). Also it is possible that between two consecutive sampling periods no packet (see Fig. 3, $t = 4$) or multiple packets (see Fig. 3, $t = 6$) are delivered. In our work we do not consider quantization distortion due to data encoding/decoding since we assume that observation noise is much larger then quantization noise, as it is the case for most DSNs where packets allocate hundreds of bits for measurement data[1]. Also we do

[1]For example, ATM communication protocols adopts packets with 384-bit data field, Ethernet IEEE 802.3 packets allows for at least 368 bits for data payload, Bluetooth for 499 bits [13] and IEEE 802.15.4 for up to 1000 bits. This assumption might not hold for multimedia signal like audio and video signals, which however are not in the scope of this work.

not consider channel noise since we assume that if any bit error incurred during packet transmission is detected at the receiver, then the packet is dropped.

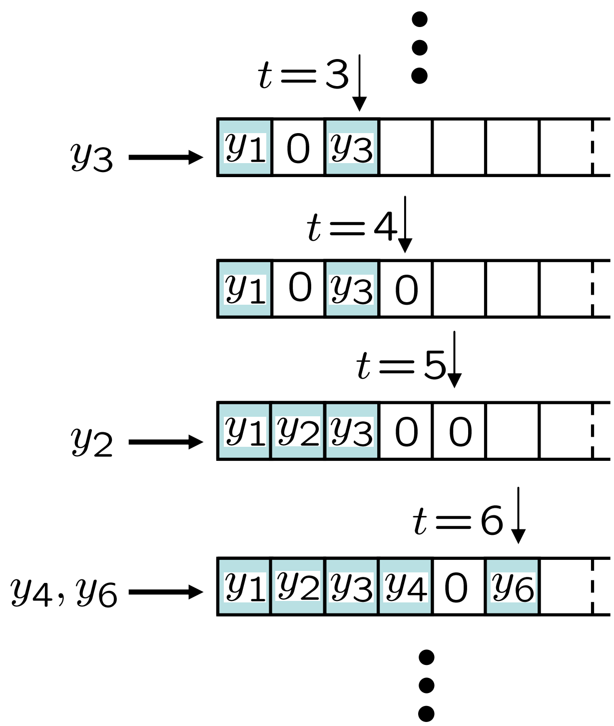

Fig. 3. Packet arrival sequence and buffering at the estimator location. Shaded squares correspond to observation packets that have been successfully received by the estimator. Cursor indicates current time.

If observation y_k is not yet arrived at the estimator at time t, we assume that a zero is stored in the k-slot of the buffer, as shown in Fig. 3[2]. More formally, the value stored in the k-slot of the estimator buffer at time t can be written as follows:

$$\tilde{y}_k^t = \gamma_k^t y_k = \gamma_k^t C x_k + \gamma_k^t v_k \tag{5}$$

Our goal to compute the optimal mean square estimator $\hat{x}_{t|t}$ which is given by:

$$\hat{x}_{t|t} \stackrel{\Delta}{=} \mathbb{E}[x_t \mid \tilde{\mathbf{y}}_t, \boldsymbol{\gamma}_t, \bar{x}_0, P_0] \tag{6}$$

where $\tilde{\mathbf{y}}_t = (\tilde{y}_1^t, \tilde{y}_2^t, \ldots, \tilde{y}_t^t)$ and $\boldsymbol{\gamma}_t = (\gamma_1^t, \gamma_2^t, \ldots, \gamma_t^t)$. It is important to remark that the estimator above has the information weather a packet has been delivered or not, and it is not equivalent to computing $\hat{x}_{t|t} \neq \check{x}_{t|t} \stackrel{\Delta}{=} \mathbb{E}[x_t \mid \tilde{\mathbf{y}}_t, \bar{x}_0, P_0]$. The latter estimator would in fact consider the zero entries of the buffer as true measurements and not as dummy variables, thus providing a lower performance. It is also useful to design the estimator error and error covariance as follows:

$$e_{t|t} \stackrel{\Delta}{=} x_t - \hat{x}_{t|t} \tag{7}$$

$$P_{t|t} \stackrel{\Delta}{=} \mathbb{E}[\, e_{t|t} e_{t|t}^T \mid \tilde{\mathbf{y}}_t, \boldsymbol{\gamma}_t, \bar{x}_0, P_0] \tag{8}$$

[2]In practice, any arbitrary value can be stored in the buffer slots corresponding to the packets which have not arrived, since as it will be shown later, the optimal estimator does not use those values as they do not convey any information about the state x_t. Our choice of storing a zero simply reduces some mathematical burden.

The estimate $\hat{x}_{t|t}$ is optimal in the sense that it minimizes the error covariance, i.e. given any estimator $\tilde{x}_{t|t} = f(\tilde{\mathbf{y}}_t, \boldsymbol{\gamma}_t)$, where f is a measurable function, we always have

$$\mathbb{E}[(x_t - \tilde{x}_{t|t})(x_t - \tilde{x}_{t|t})^T \mid \tilde{\mathbf{y}}_t, \boldsymbol{\gamma}_t, \bar{x}_0, P_0] \geq P_{t|t}.$$

Another property of the mean square optimal estimator is that $\hat{x}_{t|t}$ and its error $e_{t|t} \triangleq x_t - \hat{x}_{t|t}$ are uncorrelated, i.e. $\mathbb{E}[e_{t|t}\, \hat{x}_{t|t}^T] = 0$. This is a fundamental property since it gives rise to the separation principle for the LQG optimal control, which is of the most widely used tool in control system design [33] [26].

IV. Minimum Error Covariance Estimator Design

In this section we want to compute the optimal estimator given by Equation (6). First, it is convenient to define the following variables:

$$\begin{aligned} \hat{x}^t_{k|h} &\triangleq \mathbb{E}[x_k \,|\, \gamma^t_h, \ldots, \gamma^t_1, \tilde{y}^t_h, \ldots, \tilde{y}^t_1, \bar{x}_0, P_0] \\ P^t_{k|h} &\triangleq \mathbb{E}[(x_k - \hat{x}^t_{k|h})(x_t - \hat{x}^t_{k|h})^T \,|\, \gamma^t_h, \ldots, \gamma^t_1, \tilde{y}^t_h, \ldots, \tilde{y}^t_1, \bar{x}_0, P_0] \end{aligned}$$

from which it follows that, with a little abuse of notation, $\hat{x}_{t|t} = \hat{x}^t_{t|t}$ and $P_{t|t} = P^t_{t|t}$.

It is also useful to note that at time t the information available at the estimator site, given by Equation (5), can be written as the output of the following system:

$$x_{k+1} = Ax_k + w_k \tag{9}$$
$$\tilde{y}^t_{k+1} = C^t_{k+1} x_{k+1} + \tilde{v}^t_{k+1}, \quad k = 0, \ldots, t-1 \tag{10}$$

where $C^t_k = \gamma^t_k C$, and the random variables $\tilde{v}^t_k = \gamma^t_k v_k$ are uncorrelated, zero mean white noise with covariance $R^t_k = \mathbb{E}[\tilde{v}^t_k(\tilde{v}^t_k)^T] = \gamma^t_k R$. For any fixed t this system can be seen as a linear time-varying system with respect to time k, where the only time-varying elements are the observation matrix C^t_k and measurement noise covariance R^t_k.

We can now state the main theorem of this section:

Theorem 1: Let us consider the stochastic linear system given in Equations (1)-(2), where $R > 0$. Also consider the arrival process defined by Equation (3), and the mean square estimator defined in Equation (6). Then we have:

(a) The optimal mean square estimator is given by $\hat{x}_{t|t} = \hat{x}^t_{t|t}$ where:

$$\hat{x}^t_{0|0} = \bar{x}_0, \quad P^t_{1|0} = P_0 \tag{11}$$
$$\hat{x}^t_{k|k} = A\hat{x}^t_{k-1|k-1} + \gamma^t_k K^t_k(\tilde{y}^t_k - CA\hat{x}^t_{k-1|k-1}), \qquad k = 1, \ldots, t \tag{12}$$
$$K^t_k = P^t_{k|k-1} C^T (CP^t_{k|k-1} C^T + R)^{-1} \tag{13}$$
$$P^t_{k+1|k} = AP^t_{k|k-1}A^T + Q - \gamma^t_k AP^t_{k|k-1} C^T (CP^t_{k|k-1}C^T + R)^{-1} CP^t_{k|k-1} A^T \tag{14}$$

(b) The optimal estimator $\hat{x}_{t|t}$ can be computed iteratively using a buffer of finite length N if and only if $\gamma^t_k = \gamma^{t-1}_k, \forall k \geq 1, \forall t \geq k + N$. If this property is satisfied, then $\hat{x}_{t|t} = \hat{x}^t_{t|t}$ where $\hat{x}^t_{t|t}$ is given by Equations (11)-(14) for $t = 1, \ldots, N$ and as follows for $t > N$:

$$\hat{x}^t_{t-N|t-N} = \hat{x}^{t-1}_{t-N|t-N}, \tag{15}$$
$$P^t_{t-N+1|t-N} = P^{t-1}_{t-N+1|t-N} \tag{16}$$

Equations (12),(13),(14) $\qquad k = t - N + 1, \ldots, t$ (17)

Proof: (a) Since the information available at the estimator site at time t is given by the time-varying linear stochastic system of Equations (9)-(10) , then the optimal estimator is given by its corresponding time-varying Kalman filter:

$$\begin{aligned}
\hat{x}^t_{k|k} &= A\hat{x}^t_{k-1|k-1} + K^t_k(\tilde{y}^t_k - C^t_k A\hat{x}^t_{k-1|k-1}) \\
K^t_k &= P^t_{k|k-1}C^{t^T}_k(C^t_k P^t_{k|k-1}C^{t^T}_k + R^t_k)^{-1} \\
P^t_{k+1|k} &= AP^t_{k|k-1}A^T + Q - AP^t_{k|k-1}C^{t^T}_k(C^t_k P^t_{k|k-1}C^{t^T}_k + R^t_k)^{-1}C^t_k P^t_{k|k-1}A^T \\
\hat{x}^t_{0|0} &= \bar{x}_0, \quad P^t_{1|0} = P_0
\end{aligned}$$

whose derivation can be found in any standard textbook on stochastic control [33] [34]. By substituting $C^t_{k+1} = \gamma^t_{k+1}C$ and $R^t_k = \gamma^t_k R$ into the previous equations and after performing some simplifications[3] we obtain optimal estimator Equations (11)-(14).

(b)($\Longrightarrow$) Let us consider $t > N$. If $\gamma^t_k = \gamma^{t-1}_k, \forall k \geq 1, \forall t \geq k+N$, then also $P^t_{k+1|k} = P^{t-1}_{k+1|k}$ and $\hat{x}^t_{k|k} = \hat{x}^{t-1}_{k|k}$ hold under the same conditions on the indices. In particular it holds for $k = t-N$ which implies $P^t_{t-N+1|t-N} = P^{t-1}_{t-N+1|t-N}$ and $\hat{x}^t_{t-N|t-N} = \hat{x}^{t-1}_{t-N|t-N}$. Therefore, it not necessary to compute $P^t_{t+1|t}$ and $\hat{x}^t_{t|t}$ at any time step t starting from $k = 1$, but it is sufficient to use the values $\hat{x}^{t-1}_{t-N|t-N}$ and $P^{t-1}_{t-N+1|t-N}$ precomputed at the previous time step $t-1$, as in Equations (15) and (16), and then iterate Equations Equations (12)-(14) for the latest N observations.

($\Longleftarrow$) Using a contradiction argument suppose that there exists N for which estimator defined by Equations (15)-(17) is optimal. Now consider an arrival sequence for which $\gamma^t_1 = 0$ for $t = 1, \ldots, N$ and $\gamma^{N+1}_1 = 1$, and also $P_0 > 0$. Then $P^{N+1}_{2|1} < P^N_{2|1}$ which does not satisfy Equation (16) for $t = N+1$. As a consequence, the estimator with finite memory buffer cannot be optimal, thus contradicting the initial hypothesis. ∎

If there is no packet loss and no packet delay, i.e. $\gamma^t_k = 1, \forall (k,t)$, then Equations (11)-(14) reduce to the standard Kalman filter equations for a time-invariant system. However, there are some differences between the standard Kalman filter and the optimal filter when random packet delay is allowed.

The first difference is that the optimal estimator under our framework jumps between an open loop estimate when $\gamma^t_k = 0$ and closed loop estimate when $\gamma^t_k = 1$. In fact, when $\gamma^t_k = 0$ the value stored in the buffer is not used and the error covariance increases, while when $\gamma^t_k = 1$ the observation measurement is used according to the usual Kalman equations and the error covariance decreases. Therefore, the optimal estimator and its error covariance are strongly time-varying and stochastic. Differently, in standard Kalman filtering the error covariance $P_{t|t}$ and the optimal gain K_t, under standard observability and controllability hypotheses, converge to finite steady-state values, P_∞ and K_∞ respectively, as time progresses. Moreover, it is possible to achieve the same steady-state error P_∞ by simply using a constant filter with the steady-state gain $K_t = K_\infty$, which is very valuable from a implementation point of view since it does not require any on-line matrix inversion.

The second difference is that the standard Kalman filter does not need to store all past observations and to compute $\hat{x}_{t|t}$ starting from $k = 1$, but the optimal estimate can be computed incrementally by storing only the current observation y_t, the past state estimate $\hat{x}_{t-1|t-1}$ and the past error covariance $P_{t|t-1}$. Differently, the optimal estimator subject to random packet delay requires the storing of all past packets and the inversion of up to t matrices at any time step t to calculate the optimal estimate, as shown in Theorem 1(b). The optimal estimator can be implemented incrementally according to Equations (15)-(17) using a buffer of finite length N only if all successfully received observations have a delay smaller than N time step, i.e. $\gamma^t_k = \gamma^{t-1}_k, \forall k \geq 1, \forall t-k \geq N$ (see Fig. 4). This does not mean that *all* packets arrive at the receiver within N time steps, but only that if a packet arrives then it does within N time steps. In other words, this is equivalent of stating that the packet delay belongs to the finite set $\tau_k \in \{0, \ldots, N-1, \infty\}, \forall k \geq 1$.

[3]In particular, we employed the fact that the Kalman filter equations can be generalized to the case $R \geq 0$ by using pseudoinverse rather than the inverse in the computation of the posterior error covariance.

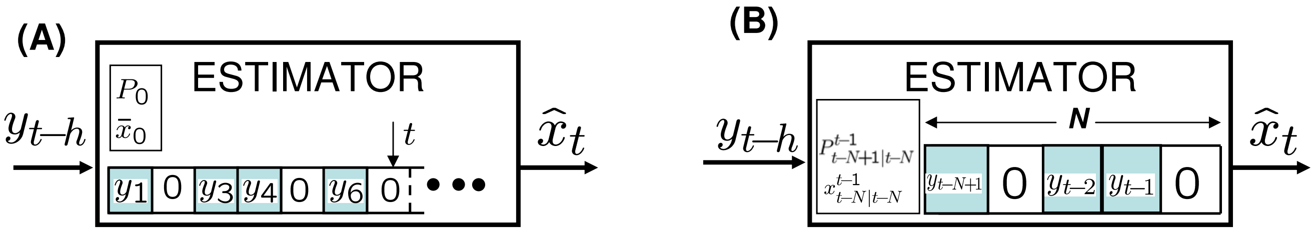

Fig. 4. Optimal estimator for general packet arrival processes (*left*). Optimal estimator with finite memory buffer for packet arrival processes with bounded delay *(right)*.

The previous condition is rather common in DSNs since they can hardly guarantee correct delivery of all transmitted packets, while they often implement mechanisms to drop packets that are too old.

Up to this point we made no assumptions on the packet arrival process which can be deterministic, stochastic or time-varying. However, from an engineering perspective it is important to determine the performance of the estimator, which is evaluated based on the error covariance $P_{t+1|t}$. If the packet arrival process is stochastic, then also the error covariance is stochastic. In this scenario a common performance metric is the expected error covariance, i.e. $\mathbb{E}_\gamma[P_{t+1|t}]$, where the expectation is performed with respect to the arrival process γ_k^t. However, other metrics can be considered, such as the probability that the error covariance exceeds a certain threshold, i.e. $\mathbb{P}[P_{t+1|t} > P_{max}]$ [35]. In this work we will consider only the expected error covariance $\mathbb{E}_\gamma[P_{t+1|t}]$. It has been shown in [24] that computing $\mathbb{E}_\gamma[P_{t+1|t}]$ analytically it is not possible even for a simple Bernoulli arrival process, and only upper and lower bounds can be obtained. Rather than extending those results by trying to bound performance of the time-varying optimal estimator, we will focus on filters with constant gains and with a finite buffer dimension, i.e. we will consider $K_{t-h}^t = K_h$ for all $t \in \mathbb{N}, h = 0, \ldots, N-1$. The gains K_h will then be optimized to achieve the smallest error covariance at steady-state. The advantage of using constant gains is that it is not necessary to invert up to N matrices at any time step t, thus making it attractive for on-line applications. Moreover, filters with constant gains are necessarily suboptimal, therefore their error covariance provides an upper bound for the error covariance of the true optimal minimum error covariance filter given by Equations (11)-(14).

V. Optimal estimation with constant gains

In this section we will study minimum error covariance filters with constant gains under stationary i.i.d arrival processes.

Assumption: The packet arrival process at the estimator site is stationary and i.i.d. with the following probability function:

$$\mathbb{P}[\tau_t \leq h] = \lambda_h \tag{18}$$

where $t \geq 0$, and $0 \leq \lambda_h \leq 1$ is a non-decreasing in $h = 0, 1, 2, \ldots$, and τ_t was defined in Equation (4).

Equation (18) corresponds to the probability that a packet sampled h time steps ago has arrived at the estimator. Obviously, λ_h must be non-increasing since $\lambda_h = \mathbb{P}[\tau_t \leq h-1] + \mathbb{P}[\tau_t = h] = \lambda_{h-1} + \mathbb{P}[\tau_t = h]$.

Also, we define the packet loss probability as follows:

$$\lambda_{loss} \triangleq 1 - \sup\{\lambda_h | \; h \geq 0\} \tag{19}$$

The arrival process defined by Equation (18) can be also be defined with respect to the probability density of packet delay. In fact, by definition we have $\mathbb{P}[\tau_k = 0] = \lambda_0$, $\mathbb{P}[\tau_k = h] = \lambda_h - \lambda_{h-1}$ for $h \geq 1$, and $P[\tau_k = \infty] = \lambda_{loss}$.

Finally, we define the maximum delay of arrived packets as follows:

$$\tau_{max} \triangleq \begin{cases} \min\{H | \, \lambda_H = \lambda_{H+1}\} & \textit{if } \exists H \textit{ such that } \lambda_h = \lambda_H, \forall h \geq H \\ \infty & \textit{otherwise} \end{cases} \tag{20}$$

Fig. 5 shows some typical scenarios that can be modeled under the previous hypotheses. Scenario (A) corresponds to a deterministic process where all packets are successfully delivered to the estimator with a constant delay. This scenario is typical of wired systems. Scenario (B) models a DCN that guarantees delivery of all packets within a finite time window τ_{max}, but the delay is not deterministic. This is a common scenario in drive-by-wire systems. Scenario (C) represents a DCN which drops packets that are older than τ_{max} and consequently a fraction $\lambda_{loss} > 0$ of observations is lost. This scenario is often encountered in wireless sensor networks. Scenario (D) corresponds to a DCN with no packet loss but with unbounded random packet delay. One example of such a scenario is a DCN that continues to retransmit a packet till it is not delivered.

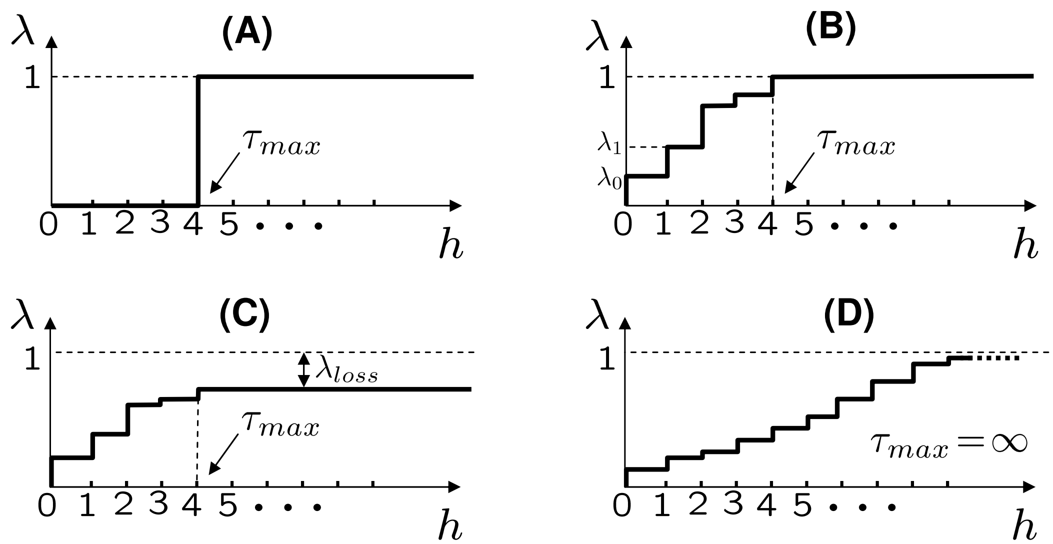

Fig. 5. Probability function of arrival process $\lambda_h = \mathbb{P}[\tau_k \leq h]$ for different scenarios: deterministic packet arrival with fixed delay (A); bounded random packet delay with no packet loss (B); bounded random packet delay with packet loss (C); unbounded random packet delay with no packet loss (D).

In the rest of the paper we will use the following definition of stability for an estimator.

Definition: Let $\tilde{x}_{t|t} = f(\tilde{\mathbf{y}}_t, \boldsymbol{\gamma}_t)$ be a generic estimator, where f is a measurable function, and $\tilde{e}_{t|t} = x_t - \tilde{x}_{t|t}$ and $\tilde{P}_{t|t} = \mathbb{E}[\tilde{e}_{t|t}\tilde{e}_{t|t}^T | \tilde{\mathbf{y}}_t, \boldsymbol{\gamma}_t]$ its error and error covariance, respectively. We say that the estimator is mean-square stable stable if and only if $\lim_{t\to\infty} \mathbb{E}[\tilde{e}_{t|t}] = 0$ and $\mathbb{E}[\tilde{P}_{t|t}] \leq M$ for some $M > 0$ and for all $t \geq 1$.

The previous definition can be rephrased in terms of the moments of the estimator error. In fact the conditions above are equivalent to $\lim_{t\to\infty} \mathbb{E}[||\tilde{e}_{t|t}||] = 0$ and $\mathbb{E}[\,||\tilde{e}_{t|t}||^2] \leq \mathrm{trace}(M)$.

Let us consider the following constant-gain estimator $\tilde{x}_{t|t} = \tilde{x}^t_{t|t}$ with finite-buffer of dimension N, where $\tilde{x}^t_{t|t}$ is computed as follows:

$$\tilde{x}^t_{t-k|t-k} = A\tilde{x}^t_{t-k-1|t-k-1} + \gamma^t_{t-k} K_k (\tilde{y}^t_{t-k} - CA\tilde{x}^t_{t-k-1|t-k-1}), \quad k = N-1, \ldots, 0 \tag{21}$$

$$\tilde{x}^t_{t-N|t-N} = \tilde{x}^{t-1}_{t-N|t-N} \tag{22}$$

$$\tilde{x}^t_{-k|-k} = \bar{x}_0, \quad \gamma^t_{-k} = 0, \quad \tilde{y}^t_{-k} = 0 \tag{23}$$

where the last line include some dummy variables necessary to initialize the estimator for $t = 1, \ldots, N$. Note that constant-gain estimator structure is very similar to the optimal estimator structure given by Equation (12) as the estimate is corrected only if the observation has arrived, i.e. $\gamma^t_{t-k} = 1$, otherwise the open loop estimate is considered. However, differently from Equation (12), the gains $K_k, k = 0, \ldots, N-1$

are constant and independent of t, and the computation of the estimate $\tilde{x}_{t|t}$ does not require any on-line matrix inversion differently from $\hat{x}_{t|t}$ as indicated by Equations (12)-(14).

We also define the following variables that will be useful to analyze the performance of the estimator:

$$\tilde{x}^t_{k+1|k} = A\tilde{x}^t_{k|k} \quad (24)$$
$$\tilde{e}^t_{k+1|k} = x_{k+1} - \tilde{x}^t_{k+1|k} \quad (25)$$
$$\widetilde{P}^t_{k+1|k} = \mathbb{E}[\tilde{e}^t_{k+1|k}\tilde{e}^{t^T}_{k+1|k} \,|\, \tilde{\mathbf{y}}_t, \boldsymbol{\gamma}_t] \quad (26)$$
$$\overline{P}^t_{k+1|k} = \mathbb{E}[\tilde{e}^t_{k+1|k}\tilde{e}^{t^T}_{k+1|k}] = \mathbb{E}[\widetilde{P}^t_{k+1|k}] \quad (27)$$

where $t \geq k \geq 1$. From these definitions we get:

$$\begin{aligned}\tilde{e}^t_{k+1|k} &= Ax_k + w_k - A\big(\tilde{x}_{k|k-1} + \gamma^t_k K_{t-k}(\gamma^t_k C x_k + v_k - C\tilde{x}_{k|k-1})\big)\\ &= A(I-\gamma^t_k K_{t-k}C)\tilde{e}^t_{k|k-1} + w_k - \gamma^t_k A K_{t-k} v_k \quad (28)\end{aligned}$$
$$\widetilde{P}^t_{k+1|k} = A(I-\gamma^t_k K_{t-k}C)\widetilde{P}^t_{k|k-1}(I-\gamma^t_k K_{t-k}C)^T A^T + Q + \gamma^t_k A K_{t-k} R K^T_{t-k} A^T \quad (29)$$
$$\overline{P}^t_{k+1|k} = \lambda_{t-k} A(I-K_{t-k}C)\overline{P}^t_{k|k-1}(I-K_{t-k}C)^T A^T + (1-\lambda_{t-k})A\overline{P}^t_{k|k-1}A^T + Q + \lambda_{t-k}A^T K_{t-k} R K^T_{t-k} A^T \quad (30)$$

where $I \in \mathbb{R}^{n\times n}$ is the identity matrix. To obtained the previous equations we employed independence of γ^t_k, v_k, w_k, and $\tilde{e}^t_{k|k-1}$, and the fact that v_k and w_k are zero mean. For ease of notation let us define the following operator:

$$\mathcal{L}_\lambda(K,P) = \lambda A(I-KC)P(I-KC)^T A^T + (1-\lambda)APA^T + Q + \lambda AKRK^T A^T \quad (31)$$

If we substitute $k = t - N$ into Equation (30), and noting that from Equation (22) follows that $\widetilde{P}^t_{t-N+1|t-N} = \widetilde{P}^{t-1}_{t-N+1|t-N}$ and $\overline{P}^t_{t-N+1|t-N} = \overline{P}^{t-1}_{t-N+1|t-N}$, we obtain:

$$\overline{P}^t_{t-N+2|t-N+1} = \mathcal{L}_{\lambda_{N-1}}(K_{N-1}, \overline{P}^{t-1}_{t-N+1|t-N}) \quad (32)$$
$$\overline{P}^t_{t-k+1|t-k} = \mathcal{L}_{\lambda_k}(K_k, \overline{P}^t_{t-k|t-k-1}), \qquad k = N-2, \ldots, 0 \quad (33)$$

Observe that Equation (32) and (33) define a set of linear deterministic equations for fixed λ_k and K_k. In particular, if we define $S_t = P^{t-1}_{t-N+1|t-N}$, then Equations (32) can be written as

$$S_{t+1} = \mathcal{L}_{\lambda_{N-1}}(K_{N-1}, S_t) \quad (34)$$

Since all matrices $\overline{P}^t_{t-k+1|t-k}, k = 0, \ldots, N-1$ can be obtained from S_t it follows that stability of estimator can be inferred from the properties of the operator $\mathcal{L}_\lambda(K,P)$. The following theorem provides these properties:

Theorem 2: Consider the operator $\mathcal{L}_\lambda(K,P)$ as defined in Equation (31). Assume also that $P \geq 0$, (A,C) is observable, $(A,Q^{1/2})$ is controllable, $R > 0$, and $0 \leq \lambda \leq 1$. Also consider the following operator:

$$\Phi_\lambda(P) = APA^T + Q - \lambda\, APC^T(CPC^T+R)^{-1}CPA^T \quad (35)$$

and the gain $K_P = PC^T(CPC^T+R)^{-1}$.

Then the following statements are true:

(a) $\mathcal{L}_\lambda(K,P) = \Phi_\lambda(P) + \lambda A(K-K_P)(CPC^T+R)(K-K_P)^T A^T$.

(b) $\mathcal{L}_\lambda(K,P) \geq \Phi_\lambda(P) = \mathcal{L}_\lambda(K_P,P), \quad \forall K$

(c) $(P_1 \geq P_2) \Longrightarrow \big(\Phi_\lambda(P_1) \geq \Phi_\lambda(P_2)\big)$.

(d) $(\lambda_1 \geq \lambda_2) \Longrightarrow \big(\Phi_{\lambda_1}(P) \leq \Phi_{\lambda_2}(P)\big), \quad \forall P$.

(e) If there exists P^* such that $P^* = \mathcal{L}_\lambda(K,P^*)$, then $P^* > 0$ and it is unique. Consequently this is true also for $K = K_{P^*}$, where $P^* = \Phi_\lambda(P^*)$.

(f) If $(\lambda_1 \geq \lambda_2)$ and there exist P^*_1, P^*_2 such that $P^*_1 = \Phi_{\lambda_1}(P^*_1)$ and $P^*_2 = \Phi_{\lambda_2}(P^*_2)$, then $P^*_1 \leq P^*_2$.

(g) Let $S_{t+1} = \mathcal{L}_\lambda(K, S_t)$ and $S_0 \geq 0$. If $S^* = \mathcal{L}_\lambda(K, S^*)$ has a solution, then $\lim_{t\to\infty} S_t = S^*$, otherwise the sequence S_t is unbounded.

(h) If there exists S^*, K such that $S^* = \mathcal{L}_\lambda(K, S^*)$, then also $P^* = \Phi_\lambda(P^*)$ exists and $P^* \leq S^*$.

(i) If A is strictly stable, then $P^* = \Phi_\lambda(P^*)$ has always a solution. Otherwise, there exist λ_c such that $P^* = \Phi_\lambda(P^*)$ has a solution if and only if $\lambda > \lambda_c$. Also $\lambda_{min} \leq \lambda_c \leq \lambda_{max}$, where $\lambda_{min} = 1 - \frac{1}{\prod_i |\sigma_i^u|^2}$, $\lambda_{max} = 1 - \frac{1}{\max_i |\sigma_i^u|^2}$, and $|\sigma_i^u| \geq 1$ are the unstable eigenvalues of A. In particular $\lambda_c = \lambda_{min}$ if *rank*$(C) = 1$, and $\lambda_c = \lambda_{max}$ if C is square and invertible.

(j) The critical probability λ_c and the fixed point $P^* = \Phi_\lambda(P^*)$ for $\lambda > \lambda_c$ can be obtained as the solutions of the following semi-definite programming (SDP) problems: $\lambda_c = \inf\{\lambda \,|\, \Psi_\lambda(Y, Z) > 0, 0 \leq Y \leq I, \text{for some } Z, Y \in \mathbb{R}^{n\times n}\}$, and $P^* = \operatorname{argmax}\{\textit{trace}(P) \,|\, \Theta_\lambda(P) \geq 0, P \geq 0\}$ where:

$$\Psi_\lambda(Y,Z) = \begin{bmatrix} Y & \sqrt{\lambda}(YA + ZC) & \sqrt{1-\lambda}YA \\ \sqrt{\lambda}(A'Y + C'Z') & Y & 0 \\ \sqrt{1-\lambda}A'Y & 0 & Y \end{bmatrix} \quad (36)$$

$$\Theta_\lambda(P) = \begin{bmatrix} APA' - P & \sqrt{\lambda}APC' \\ \sqrt{\lambda}CPA' & CPC' + R \end{bmatrix} \quad (37)$$

(k) If there exist $P^* > 0$ and K such that $P^* = \mathcal{L}_\lambda(K, P^*)$, then the matrix $A_c = A(I - \lambda KC)$ is strictly stable.

Proof: Some of these statements can be found in [24] or can be derived along similar lines, therefore only a brief sketch is reported here for those ones.

(a) This fact can be verified by direct substitution

(b) This statement follows from previous fact and $\lambda A(K - K_P)(CPC^T + R)(K - K_P)^T A^T \geq 0$.

(c) From previous fact $\Phi_\lambda(P_1) = \mathcal{L}_\lambda(K_{P_1}, P_1) \geq \mathcal{L}_\lambda(K_{P_1}, P_2) \geq \mathcal{L}_\lambda(K_{P_2}, P_2) = \Phi_\lambda(P_2)$.

(d) From Equation (35) we have $\Phi_{\lambda_1}(P) - \Phi_{\lambda_2}(P) = -(\lambda_1 - \lambda_2)APC^T(CPC^T + R)^{-1}CPA^T \leq 0$.

(e) Uniqueness and strictly positive definiteness of P^* follows from the assumption that $(A, Q^{1/2})$ is controllable [24].

(f) Consider $P_{t+1} = \Phi_{\lambda_1}(P_t)$ and $S_{t+1} = \Phi_{\lambda_2}(S_t)$ where $P_0 = S_0 = 0$. From fact (c) and (e) it follows that $P_t \leq S_t$. Also $P_t \leq P_1^*$ and $S_t \leq P_2^*$, therefore $\lim_{t\to\infty} P_t = \bar{P}$, $\lim_{t\to\infty} S_t = \bar{S}$, and $\bar{P} \leq \bar{S}$. From fact (e) it follows that $\bar{P} = P_1^*$ and $\bar{S} = P_2^*$, and thus $P_1^* \leq P_2^*$

(g-h) Let consider $P_{t+1} = \Phi_\lambda(P_t)$ and $S_{t+1} = \mathcal{L}_\lambda(K, S_t)$ where $P_0 = S_0 = 0$. From fact (c) and monotonicity of operator $\mathcal{L}_\lambda(K, P)$ with respect to P we have $P_{t+1} \geq P_t$, $S_{t+1} \geq S_t$, and $P_t \leq S_t \leq S^*$ for all t. Since both sequences are monotonically increasing and bounded, then $\lim_{t\to\infty} P_t = \bar{P}$, $\lim_{t\to\infty} S_t = \bar{S}$, $\bar{P} = \Phi_\lambda(\bar{P})$, $\bar{S} = \mathcal{L}_\lambda(K, \bar{S})$, and $\bar{P} \leq \bar{S}$. From fact (e) it follows that $\bar{P} = P^*$ and $\bar{S} = S^*$. A complete proof for convergence from any initial condition can be obtained along the lines of Theorem 1 in [24], thus it is not reported here.

(i) The proof for existence of a critical probability λ_c was given in [24] and it is based on observability of (A, C) and monotonicity of $\Phi_\lambda(P)$ with respect to λ. The proof for $\lambda_c = \lambda_{min}$ when *rank*$(C) = 1$ can be found in [37][23] although it was not explicitly derived for the operator Φ_λ. The proof for $\lambda_c = \lambda_{max}$ when C is square and invertible was first proved in [38].

(j) The proof can be found in [24].

(k) Let us consider the linear operator $\mathcal{F}(P) = \lambda A(I - KC)P(I - KC)^T A^T + (1-\lambda)APA^T$. Clearly $\mathcal{L}_\lambda(K, P) = \mathcal{F}(P) + D$, where $D = Q + \lambda AKRK^T A^T \geq 0$. Consider the sequences $S_{t+1} = \mathcal{L}_\lambda(K_{P^*}, S_t)$, $T_{t+1} = \mathcal{L}_\lambda(K_{P^*}, T_t)$ with initial condition $S_0 = 0$, then $T_0 \geq 0$. Note that $S_t = \sum_{k=0}^{t-1} \mathcal{F}^k(D)$ and $T_t = \mathcal{F}^t(T_0) + \sum_{k=0}^{t-1} \mathcal{F}^k(D)$ for $t \geq 1$, where we define $\mathcal{F}^0(D) = D$ and $\mathcal{F}^{k+1}(D) = \mathcal{F} \circ \mathcal{F}^k(D)$. Therefore $\mathcal{F}^t(T_0) = T_t - S_t$. From fact (g) it follows $\lim_{t\to\infty} S_t = \lim_{t\to\infty} T_t = P^*$, therefore $\lim_{t\to\infty} \mathcal{F}^t(T_0) = 0$, for all $T_0 \geq 0$, i.e. the linear operator $\mathcal{F}()$ is strictly stable. Now consider the system $A_c = A(I - \lambda KC)$. The system is strictly stable if and only if $\lim_{t\to\infty} A_c^t x_0 = 0$, for all x_0. This is equivalent to $\lim_{t\to\infty} A_c^t x_0 x_0^T (A_c^T)^t = \mathcal{G}^t(X_0) = 0$, where $X_0 = x_0 x_0^T \geq 0$ and $\mathcal{G}^t(X_0) = A_c^t X_0 (A_c^T)^t$. Note that $\mathcal{G}(X_0) = AX_0A^T - 2\lambda AX_0(AKC)^T + \lambda^2 AKCX_0(AKC)^T = \mathcal{F}(X_0) + \lambda(\lambda - 1)AKCX_0(AKC)^T \leq$

$\mathcal{F}(X_0)$ since $\lambda(\lambda-1)AKCX_0(AKC)^T \leq 0$. Since we just proved that $\lim_{t\to\infty}\mathcal{F}^t(X_0)=0$ for all $X_0 \geq 0$, then also $\lim_{t\to\infty}\mathcal{G}^t(X_0) \leq \mathcal{F}^t(X_0)=0$ for $X_0 = x_0x_0^T$, i.e. the system A_c is strictly stable. ■

The previous theorem provides all tools necessary to analyze and design the optimal estimator with constant gains. In particular, fact (g) indicates that the constant gain K^* that minimizes the steady state error covariance P^* can be derived from the unique fixed point of the nonlinear operator Φ_λ, where $K^* = K_{P^*}$. If the optimal gain K^* is used, then the expected error covariance converges to P^* regardless of the initial conditions $(P_0, \bar{x}_0)$, as follows from fact (f). Fact (i) shows that if the system A is unstable the arrival probability λ needs to be sufficiently large to ensure stability, and that the critical value λ_c is a function of the unstable eigenvalues of A. Finally, although λ_c and the the fixed point $P^* = \Phi_\lambda(P^*)$ cannot be computed analytically, from fact (j) follows that they can be computed efficiently using numerical optimization tools. Finally fact (k) will be used to show that if the error covariance is bounded then the estimator is asymptotically strictly stable, therefore estimator stability reduces to finiteness of steady state error covariance.

The following theorem shows how compute the optimal estimator with constant gains.

Theorem 3: Let us consider the stochastic linear system given in Equations (1)-(2), where (A, C) is observable, $(A, Q^{1/2})$ is controllable, and $R > 0$. Also consider the arrival process defined by Equations (18)-(20), and the set of estimators with constant gains $\{K_k\}_{k=0}^N$ defined in Equations (21)-(23). If A is not strictly stable and $\lambda_{loss} \geq 1-\lambda_c$, where λ_c is defined in Theorem 2(j), then there exist no stable estimator with constant gains. Otherwise, let N such that $\lambda_N > \lambda_c$ and consider the optimal gains $\{K_k^N\}_{k=0}^N$ defined as follows:

$$K_k^N = V_k^N C^T (C V_k^N C^T + R)^{-1}, \quad k = 0, \ldots, N \tag{38}$$

$$V_{N-1}^N = \Phi_{\lambda_{N-1}}(V_{N-1}^N) \tag{39}$$

$$V_k^N = \Phi_{\lambda_k}(V_{k+1}^N), \quad k = N-1, \ldots, 0 \tag{40}$$

Also consider $\overline{P}^t_{k+1|k}$ as defined in Equation (27), then $\lim_{t\to\infty}\overline{P}^t_{t-k+1|t-k} = V_k^N$, independently of initial conditions $(P_0, \bar{x}_0)$. For any other choice of gains $\{K_k\}_{k=0}^N$ for which the following equations exist:

$$T_N^N = \mathcal{L}_{\lambda_N}(K_N, T_N^N) \tag{41}$$

$$T_k^N = \mathcal{L}_{\lambda_k}(K_k, T_{k+1}^N), \quad k = N-1, \ldots, 0 \tag{42}$$

then $\lim_{t\to\infty}\overline{P}^t_{t-k+1|t-k} = T_k^N$, and $V_k^N \leq T_k^N$ for $k = 0, \ldots, N$. Also $V_0^{N+1} \leq V_0^N$. Finally, if $\tau_{max} < \infty$, then $V_0^N = V_0^{\tau_{max}}$ for all $N \geq \tau_{max}$.

Proof: First we prove by contradiction that there is no stable estimator with constant gains if A is not strictly stable and $\lambda_{loss} \geq 1-\lambda_c$. Suppose such an estimator exists, i.e. there exist N and $\{K_k\}_{k=0}^{N-1}$ such that $\overline{P}^t_{t|t}$ is bounded for all t. Since $\overline{P}^t_{t+1|t} = A\overline{P}^t_{t|t}A^T + Q$ also $\overline{P}^t_{t+1|t}$ must be bounded for all t. From Equations (32) and (33) it follows that $\overline{P}^t_{t+1|t}$ is bounded if and only if $\overline{P}^t_{t-k+1|t-k}$ for $k = 0, \ldots, N-1$ are bounded for all t. Therefore, since the bounded sequence $S_t = \overline{P}^t_{t-N+1|t-N}$ needs to satisfy Equation (34), from Theorem 2(g) follows that $S^* = \mathcal{L}_{\lambda_{N-1}}(K_{N-1}, S^*)$ has a solution. From Theorem 2(h) follows that also $P^* = \Phi_{\lambda_{N-1}}(P^*)$ has a solution. However, by hypothesis $\lambda_{N-1} \leq \sup\{\lambda_h \,|\, h \geq 0\} = 1-\lambda_{loss} \leq \lambda_c$. Consequently, according to Theorem 2(i), $P^* = \Phi_{\lambda_{N-1}}(P^*)$ cannot have a solution, which contradicts the hypothesis that a stable estimator exists.

Consider now the case when N is such that $\lambda_N > \lambda_c$. From Theorem 2(h) it follows that Equations (38)-(40) are well defined and have a solution. From Theorem 2(g) it follows that $\lim_{t\to\infty}\overline{P}^t_{t-k+1|t-k} = V_k^N$ for the optimal gains $\{K_k^N\}_{k=0}^{N-1}$, and $\lim_{t\to\infty}\overline{P}^t_{t-k+1|t-k} = T_k^N$ when using generic gains $\{K_k\}_{k=0}^{N-1}$. From Theorem 2(h) it follows that $V_{N-1}^N \leq T_{N-1}^N$. From Theorem 2(c) we have $V_{N-2}^N = \Phi_{\lambda_{N-2}}(V_{N-1}^N) \leq \mathcal{L}_{\lambda_{N-2}}(K_{N-2}, V_{N-1}^N) \leq \mathcal{L}_{\lambda_{N-2}}(K_{N-2}, T_{N-1}^N) = T_{N-2}^N$. Inductively, it is easy to show that $V_k^N \leq T_k^N$ for all $k = 0, \ldots, N-1$.

Now we want to show that $V_0^{N+1} \leq V_0^N$. From Theorem 2(f) and the property $\lambda_{N+1} \geq \lambda_N$ follow also that $V_{N+1}^{N+1} = \Phi_{\lambda_{N+1}}(V_{N+1}^{N+1}) \leq V_N^N = \Phi_{\lambda_N}(V_N^N)$. Therefore $V_N^{N+1} = \Phi_{\lambda_N}(V_{N+1}^{N+1}) \leq \Phi_{\lambda_N}(V_N^N) = V_N^N$ and inductively $V_k^{N+1} \leq V_k^N$ for all $k = N, \ldots, 0$ which proves the statement.

Finally, if τ_{max} is finite, then $\lambda_k = \lambda_{\tau_{max}}$ for all $k \geq \tau_{max}$. Assume $N > \tau_{max}$, then $V_N^N = \Phi_{\lambda_N}(V_N^N) = \Phi_{\lambda_{N-1}}(V_N^N) = V_{N-1}^N = \Phi_{\lambda_{N-1}}(V_{N-1}^N) = \Phi_{\lambda_{N-2}}(V_{N-1}^N) = V_{N-2}^N = \ldots = V_{\tau_{max}}^N = \Phi_{\lambda_{\tau_{max}}}(V_{\tau_{max}}^N)$. Since $V_{\tau_{max}}^{\tau_{max}} = \Phi_{\lambda_{\tau_{max}}}(V_{\tau_{max}}^{\tau_{max}})$, then by Theorem 2(e) we have that $V_{\tau_{max}}^{\tau_{max}} = V_{\tau_{max}}^N$. According to Equation (40) we also have $V_k^{\tau_{max}} = V_k^N$ for $k = \tau_{max}, \ldots, 0$, which concludes the theorem. ■

The previous theorems shows that the optimal gains can be obtained by finding the fixed point of a modified algebraic Ricatti Equation (39) and then iterating N time an operator with the same structure but with different λ_k. The theorem also demonstrates that a stable estimator with constant gains exists if and only if the optimal estimator with constant gains exists, therefore the optimal estimator design implicitly solves the problem of existence of stable estimators. If the system to be estimated is unstable, then the estimator is stable if and only if the packet loss probability λ_{loss} is sufficiently small. This is a remarkable result since it implies that stability of estimators does not depend on the packet delay τ_{max} as long as most most of the packets eventually arrive. Another important result is that the performance of the estimator, i.e. its steady state error covariance $\lim_{t\to\infty} P_{t+1|t} = \lim_{t\to\infty} \mathbb{E}[e_{t+1|t}e_{t+1|t}^T] = V_0^N$, improves as the buffer length N is increased. However, if the maximum packet delay is finite $\tau_{max} < \infty$, then the performance of the estimator does not improve for $N > \tau_{max}$. This is consistent with Theorem 1(b) since if a measurement packet has not arrived within τ_{max} time steps after it was sampled, then it will never arrive and it is useless to wait longer.

From a practical perspective, the designer can evaluate the tradeoff between the estimator performance V_0^N and buffer length N which is directly related to computational requirements. To this respect, the following theorem provides some useful bounds on the ultime performance achievable with an estimator with constant gains:

Theorem 4: Let A strictly stable or $\lambda_{loss} < 1 - \lambda_c$ otherwise. Let the sequence V_0^N with respect to N be defined as in Theorem 3, where $N \geq N_{min} \stackrel{\Delta}{=} \min\{N \,|\, \lambda_N > \lambda_c\}$ if A is unstable, or $N \geq 0$ otherwise. Also consider the sequence S_k^N defined similarly to V_k^N but for the following modified arrival statistic $\lambda_k^N = \lambda_k, k = 0, \ldots, N-1$ and $\lambda_k^N = \sup\{\lambda_h \,|\, h \geq 0\}, k \geq N$. Then V_0^N is a monotonically decreasing sequence and S_0^N is a monotonically increasing sequence. Also there exists P^* such that

$$S_0^N \leq P^* \leq V_0^N, \quad \forall N \geq N_{min} \tag{43}$$

$$P^* = \lim_{N\to\infty} S_0^N = \lim_{N\to\infty} V_0^N \tag{44}$$

Finally, if $\tau_{max} < \infty$, then $P^* = V_0^{\tau_{max}} = S_0^{\tau_{max}}$.

Proof: From assumption $\lambda_{loss} < 1 - \lambda_c$ it follows that N_{min} is well defined and exists. From Theorem 3 it also follows that V_k^N and S_k^N are well defined and exist. Since V_0^N is monotonically decreasing and bounded from below $V_0^N \geq 0$ then $\lim_{N\to\infty} V_0^N = V^*$. Since $\lambda_N^N \geq \lambda_N$, from Theorem 2(f) we have that $S_N^N \leq V_N^N$, and since $\lambda_k^N = \lambda_k, k = N-1, \ldots, 0$ we inductively have $S_0^N \leq V_N^0$. Moreover since by definition $\lambda_N^N = \lambda_{N+1}^{N+1} = 1 - \lambda_{loss}$, then $S_N^N = S_{N+1}^{N+1}$. Also by definition $\lambda_N^{N+1} = \lambda_N \leq \lambda_N^N$, therefore $S_N^{N+1} = \Phi_{\lambda_N^{N+1}}(S_{N+1}^{N+1}) = \Phi_{\lambda_N^{N+1}}(S_N^N) \geq \Phi_{\lambda_N^N}(S_N^N) = S_N^N$ where we used Theorem 2(d). Once again, since $\lambda_k^N = \lambda_k^{N+1}, k = N-1, \ldots, 0$ inductively it follows that $S_0^{N+1} \geq S_0^N$. Therefore the sequence $\{S_0^N\}$ is monotonically increasing and bounded from above since $S_0^N \leq V_0^{N_{min}}, N \geq N_{min}$, from which it follows that $\lim_{N\to\infty} S_0^N = S^*$. Since $S_0^N > 0$ for all N, then also $S^* > 0$. Now it is left to prove that $S^* = V^*$. If $\tau_{max} < \infty$, this is trivial since $S_0^N = V_0^N = P^*, N \geq \tau_{max}$. Otherwise if $\tau_{max} = \infty$ note that S_0^N and V_0^N are continuous function of the sequences $\{\lambda_k^N\}_{k=0}^\infty$ and $\{\lambda_k\}_{k=0}^\infty$, respectively. Since $\lim_{N\to\infty}\{\lambda_k^N\}_{k=0}^\infty = \{\lambda_k\}_{k=0}^\infty$ with respect to any norm defined on sequences, for example $||\{\lambda_k\}_{k=0}^\infty|| \stackrel{\Delta}{=} \sup\{\lambda_k \,|\, k \geq 0\}$, then by continuity also $\lim_{N\to\infty} S_0^N = \lim_{N\to\infty} V_0^N = P^*$ which concludes the theorem. ■

The positive definite matrix P^* defined in the previous theorem correspond to the ultimate limit of performance of any estimator with constant gains, i.e. it is not possible to reduce the steady state error covariance below P^* when using only constant gains. This is useful since the designer can evaluate the loss of performance when using an estimator with a short buffer, i.e. $N < \tau_{max}$, which is more advantageous from computational point of view. The theorem also provides a tool to compute P^* to any arbitrary precision when $\tau_{max} = \infty$. In fact, we have $V_0^N - P^* \leq V_0^N - S_0^N = \Delta P^N \geq 0$ for all N, where ΔP^N can be easily computed and has the property $\lim_{N\to\infty} \Delta P^N = 0$.

VI. Optimal estimation with co-located smart sensors

In this section we describe an alternative coding at the sensor location which improves the overall performance of the estimator at the receiver side. This scheme was independently proposed in [39] and [27] where it was suggested to compute and transmit the state estimate rather than the raw measurement. As will be shown shortly, this approach gives an estimator with a better performance, however it is applicable only if some computational resources are available on the sensor, commonly known as “smart sensor”, and when all entries of the observation vector y_t are collected from sensors which are co-located. For example, this scenario is rarely the case in applications running over sensor networks where sensors are distributed and have very limited computation resources [36]. Nonetheless, this scheme is useful per se since it provides a computable lower bound for the performance of the optimal time-varying filter proposed in Section IV.

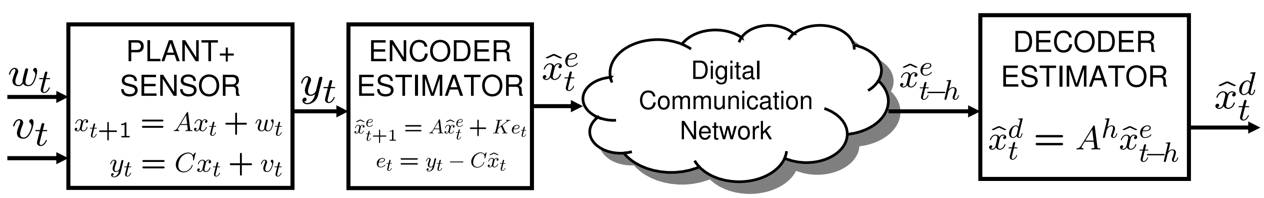

Fig. 6. Smart sensor with state estimator at encoder site before transmission.

Rather than sensing the raw measurements y_t over the DCN the sensor compute the optimal state estimate as follows:

$$\hat{x}_t^e = A\hat{x}_{t-1}^e + K_t^e(y_t - A\hat{x}_{t-1}^e) \quad (45)$$

$$K_t^e = P_t^e C^T (C P_t^e C^T + R)^{-1} \quad (46)$$

$$P_{t+1}^e = A P_t^e A^T + Q - A P_t^e C^T (C P_t^e C^T + R)^{-1} C P_t^e A^T = \Phi_1(P_t) \quad (47)$$

$$P_0^e = P_0, \quad \hat{x}_0^e = \bar{x}_0 \quad (48)$$

These are the equations for the standard Kalman filter, i.e. the minimum error covariance estimator $\hat{x}_t^e = \mathbb{E}[x_t \,|\, y_t, \ldots, y_1]$ whose estimation error $e_t^e = x_{t+1} - A\hat{x}_t^e$ has covariance $cov(e_t^e) = \mathbb{E}[e_t^e e_t^{e^T} \,|\, y_t, \ldots, y_1] = P_t^e$. The state estimate computed by the sensor encoder is then transmitted over the DCN to the decoder estimator. Using the same notation of Equation (5) the value stored at the buffer can be written as follows:

$$\tilde{y}_k^t = \gamma_k^t \hat{x}_k^e \quad (49)$$

Let us define the delay of the most recent packet arrived at the decoder estimator as $\kappa_t = t - \max\{k \,|\, \gamma_k^t = 1\}$ if $\exists \gamma_k^t = 1$, or $\kappa_t = t$ otherwise. The estimate of current state at the decoder estimator $\hat{x}_t^d$ is computed as follows:

$$\hat{x}_t^d = A^{\kappa_t} \tilde{y}_{t-\kappa_t}^t = A^{\kappa_t} \hat{x}_{t-\kappa_t}^e \quad (50)$$

Note that the decoder estimate is equivalent to $\hat{x}_t^d = \mathbb{E}[x_t \,|\, y_{t-\kappa_t}, \ldots, y_1]$ and that the its error $e_t^d = x_{t+1} - A\hat{x}_t^d$ has covariance:

$$cov(e_t^d) = \mathbb{E}[e_t^d e_t^{d^T} \,|\, y_{t-\kappa_t}, \ldots, y_1] = \Phi_0^{t-\kappa_t}(\mathbb{E}[e_{t-\kappa_t}^d e_{t-\kappa_t}^{d^T} \,|\, y_{t-\kappa_t}, \ldots, y_1]) = \Phi_0^{t-\kappa_t}(P_{t-\kappa_t}^e) = \Phi_0^{t-\kappa_t} \circ \Phi_1^{\kappa_t}(P_0),$$

where the superscript of $\Phi_\lambda^n(P)$ indicates $\Phi_\lambda \circ \cdots \circ \Phi_\lambda(P)$ composed n-times. Therefore, the decoder estimator error at any time step t is equivalent to the optimal estimator that one would obtain if all observations up to time $t-\kappa_t$ were successfully delivered. This estimation architecture is superior to the estimation architecture proposed in Section IV, in fact the estimator obtained in Theorem 1 has error covariance $cov(x_{t+1} - A\hat{x}_{t|t}^t) = P_{t+1|t}^t$, where $P_{t+1|t}^t$ is given by Equations (13)-(14) and can be written as:

$$\begin{aligned}
P_{t+1|t}^t &= \Phi_{\gamma_t^t} \circ \ldots \circ \Phi_{\gamma_1^t}(P_0) \\
&= \Phi_0^{t-\kappa_t} \circ \Phi_{\gamma_{\kappa_t}^t} \circ \ldots \circ \Phi_{\gamma_1^t}(P_0) \\
&\geq \Phi_0^{t-\kappa_t} \circ \Phi_{\gamma_{\kappa_t}^t} \circ \ldots \circ \Phi_1(P_0) \\
&\geq \Phi_0^{t-\kappa_t} \circ \Phi_1 \circ \ldots \circ \Phi_1(P_0) \\
&= \Phi_0^{t-\kappa_t} \circ \Phi_1^{\kappa_t}(P_0) \\
&= cov(e_t^d)
\end{aligned}$$

where we used the facts $\gamma_k^t = 0$ for $k > \kappa_t$, $\gamma_k^t \leq 1$ for $k \leq \kappa_t$, and Theorem 2(d). Therefore, the error covariance of the estimator proposed in this section is smaller than the error covariance of estimator proposed in Section IV. We can summarize the previous result in the following theorem:

Theorem 5: Let us consider the stochastic linear system given in Equations (1)-(2), where $R > 0$. Also consider the packet arrival process defined by Equation (3). Let $\hat{x}_t^y = \hat{x}_{t|t}^t$ the optimal estimator given by Equations (11)-(14) when raw measurements y_t are transmitted over the network. Let $\hat{x}_t^d$ the estimator given by Equation (50) where the state estimate $\hat{x}_t^e$ defined by Equations (45)-(48) is pre-computed by the sensor and then transmitted over the network. Then the estimation error covariance of $\hat{x}_t^e$ is always smaller than the estimation error covariance of $\hat{x}_t^t$, i.e.

$$cov(x_t - \hat{x}_t^d) \leq cov(x_t - \hat{x}_t^y), \quad \forall t.$$

Besides having a better performance, the estimator proposed in this section requires very limited computational requirements at the receiver side, in fact it suffices to store the most recent packet arrived at the receiver and then to compute the best state estimate at current time by pre-multiplying the packet data with a matrix which depend on the packet delay. Moreover, as for the estimator of Section IV, also the estimator based on co-located smart sensors does not require any statistical a-priori knowledge of the arrival process.

However, if the packet arrival statistics are stationary and i.i.d, then it is possible to give stability criteria and to compute the expected error covariance as shown in the following theorem:

Theorem 6: Let us consider the stochastic linear system given in Equations (1)-(2), where (A, C) is observable, $(A, Q^{1/2})$ is controllable, and $R > 0$. Also consider the arrival process defined by Equations (18)-(20), and the estimator architecture given by Equations (45)-(50). Then the estimator is stable if and only if A is stable, or $\lambda_{loss} < \frac{1}{|\sigma_{max}^u(A)|^2}$, where $\sigma_{max}^u(A)$ is the largest eigenvalue of the matrix A. If the estimator is stable then the covariance of the estimation error defined as $e_t^d = x_{t+1} - Ax_t^d$ has the following property:

$$\lim_{t\to\infty} \mathbb{E}[e_t^d e_t^{d^T}] = D^\infty = \lim_{N\to\infty} D_0^N \tag{51}$$

where the matrix D_0^N is computed as follows:

$$D_N^N = (1-\lambda_N)AD_N^N A^T + (1-\lambda_N)Q + \lambda_N P_\infty^e \tag{52}$$

$$D_k^N = (1-\lambda_k)AD_{k+1}^N A^T + (1-\lambda_k)Q + \lambda_k P_\infty^e, \quad k = N-1, \ldots, 0 \tag{53}$$

and P_∞^e is the unique positive definite solution of the Ricatti Equation $P_\infty^e = \Phi_1(P_\infty^e)$. If $\tau_{max} < \infty$, then $D^\infty = D_0^{\tau_{max}} = D_0^N$, for all $N \geq \tau_{max}$.

Proof: The proof follows along the same lines of Theorems 1 and 3. Let us consider the following estimator:

$$\begin{aligned} \breve{x}^t_{t-N|t-N} &= (1-\gamma^t_{t-N})A\breve{x}^{t-1}_{t-N-1|t-N-1} + \gamma^t_{t-N}\hat{x}^s_{t-N} \\ \breve{x}^t_{t-k|t-k} &= (1-\gamma^t_{t-k})A\breve{x}^t_{t-k-1|t-k-1} + \gamma^t_{t-k}\hat{x}^s_{t-k}, \quad k = N-1,\ldots,0 \\ \breve{x}^t_{-k|-k} &= \bar{x}_0, \ \gamma^t_{-k} = 0, \ \hat{x}^s_{-k} = 0 \end{aligned}$$

It should be clear that by construction $\hat{x}^d_t = \breve{x}^t_{t|t}$ if and only if $N \geq \tau_{max}$. If $N < \tau_{max}$, then the estimator $\hat{x}^d_t$ cannot be optimal. Let us consider the estimator error defined as $\breve{e}^t_{k+1|k} = x_{k+1} - A\breve{x}^t_{k|k}$ that can be written as:

$$\begin{aligned} \breve{e}^t_{k+1|k} &= x_{k+1} - A\big((1-\gamma^t_k)A\breve{x}^t_{k-1|k-1} + \gamma^t_k\hat{x}^s_k\big) = (1-\gamma^t_k)(x_{k+1} - AA\breve{x}^{t-1}_{k-1|k-1}) + \gamma^t_k(x_{k+1} - A\hat{x}^s_k) \\ &= (1-\gamma^t_k)(A(x_k - A\breve{x}^{t-1}_{k-1|k-1}) + w_k) + \gamma^t_k e^s_k = (1-\gamma^t_k)(A\breve{e}^t_{k|k-1} + w_k) + \gamma^t_k e^s_k \end{aligned}$$

and its error covariance $\breve{P}^t_{k+1|k} = \mathbb{E}[\breve{e}^t_{k+1|k}\breve{e}^{tT}_{k+1|k} \,|\, \gamma^t_k,\ldots,\gamma^t_1]$ is then given by:

$$\begin{aligned} \breve{P}^t_{t-N+1|t-N} &= (1-\gamma^t_{t-N})(A\breve{P}^{t-1}_{t-N|t-N-1}A^T + Q) + \gamma^t_{t-N}P^e_{t-N} \\ \breve{P}^t_{t-k+1|t-k} &= (1-\gamma^t_{t-k})(A\breve{P}^t_{t-k|t-k-1}A^T + Q) + \gamma^t_{t-k}P^e_{t-k}, \quad k = N-1,\ldots,0 \\ \breve{P}^t_{-k|-k} &= P_0, \ \gamma^t_{-k} = 0 \end{aligned}$$

The error covariance $\breve{P}^t_{t+1|t}$ is then stochastic and depends on the arrival sequence. However since it is linear in the arrival sequence γ^t_k, it is possible to compute the expected error covariance $\mathbb{E}[\breve{P}^t_{k+1|k}] = \widehat{P}^t_{k+1|k}$ as follows:

$$\begin{aligned} \widehat{P}^t_{t-N+1|t-N} &= (1-\lambda_N)A\widehat{P}^{t-1}_{t-N|t-N-1}A^T + (1-\lambda_N)Q + \lambda_N P^s_{t-N} \\ \widehat{P}^t_{t-k+1|t-k} &= (1-\lambda_k)A\widehat{P}^t_{t-k|t-k-1}A^T + (1-\lambda_k)Q + \lambda_k P^s_{t-k}, \quad k = N-1,\ldots,0 \\ \widehat{P}^t_{-k|-k} &= P_0, \ \gamma^t_{-k} = 0 \end{aligned}$$

Since $\lim_{t\to\infty} P^e_{t-k} = P^e_\infty$ where $P^e_\infty = \Phi_1(P^e_\infty)$, then $\lim_{t\to\infty}\widehat{P}^t_{t-N+1|t-N} = D^N_N$ exists and it is finite if and only if $\sqrt{1-\lambda_N}A$ is stable, i.e. $\sqrt{1-\lambda_N}\,|\sigma^u_{max}(A)| < 1$. This is equivalent to $\lambda_N > 1 - \frac{1}{|\sigma^u_{max}(A)|^2}$. Such λ_N exists if and only if $\lambda_{loss} < \frac{1}{|\sigma^u_{max}(A)|^2}$. If this condition holds then Equations (52)-(53) follow. Also it is simple to show that $\{D^N_0\}^\infty_{N=0}$ is a decreasing function of N and bounded from below, therefore $\lim_{N\to\infty} D^N_0 = D^\infty$. Moreover, since $\mathbb{E}[e^d_t e^{d^T}_t] = \lim_{N\to\infty}\widehat{P}^t_{t+1|t}$, then it follows $\lim_{t\to\infty}\mathbb{E}[e^d_t e^{d^T}_t] = D^\infty$. Following Theorem 3, it is easy to show that if $\tau_{max} < \infty$, then $D^\infty = D^{\tau_{max}}_0 = D^N_0$, for all $N \geq \tau_{max}$, which concludes the theorem. ■

The previous theorem shows that performance of the smart optimal estimator under the assumption of i.i.d. packet arrival process, can be obtained by solving the Lyapunov Equation (52) and then iterating $N = \tau_{max}$ linear equations (53), if τ_{max} is finite. Otherwise if $\tau_{max} = \infty$, then D^∞ cannot be computed exactly, however upper and lower bounds can be obtained similarly to Theorem 4.

VII. Numerical Examples

In this sections we illustrate the use of the tools developed in the previous sections with the aid of some numerical examples.

Let us consider the following probability function of packet delay:

$$\lambda_h = \begin{cases} 0.05\,h, & h = 0,\ldots,15 \\ 0.75, & h > 15 \end{cases} \tag{54}$$

which is depicted in Fig. 7.

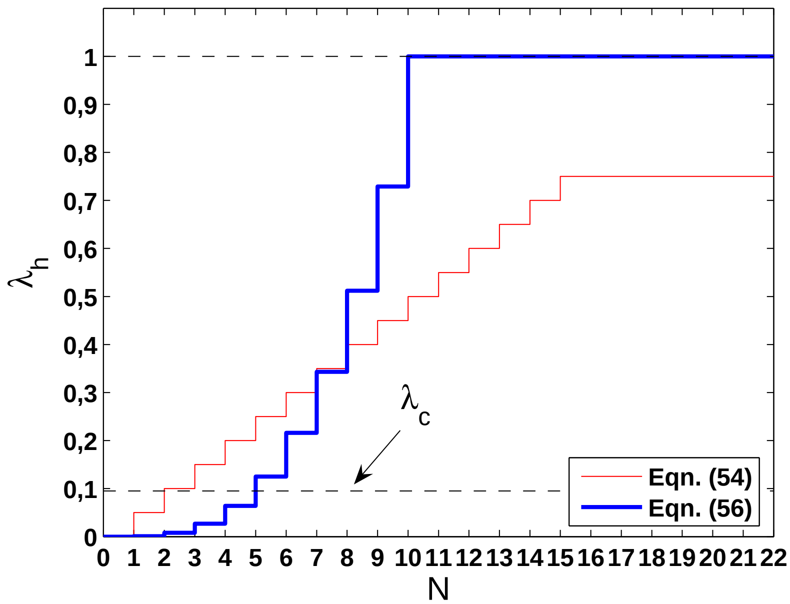

Fig. 7. Probability function of packet delay for different scenarios and critical probability λ for dynamical systems (55).

Let us consider the following discrete time system:

$$A = \begin{bmatrix} 1.001 & 0.05 \\ 0.05 & 1.001 \end{bmatrix}, \quad C = [\, 1 \quad 0 \,], \quad R = 0.01, \quad Q = \begin{bmatrix} 0 & 0 \\ 0 & 0.01 \end{bmatrix} \tag{55}$$

which corresponds to the discretization with sampling period $T = 0.05$ of the continuous time system $\ddot{x} - x = 0$. This system has one stable pole and one unstable pole, and it is the model for the discrete time dynamics of an inverted pendulum. The discrete time eigenvalues of the matrix A are $eig(A) = (1.05, 0.95)$, which give the critical probability $\lambda_c = 1 - 1/1.05^2 = 0.095$, as stated in Theorem 2(i). According to Theorem 3 and 6 the estimator is stable if and only if $N \geq 2$, in fact $\lambda_1 = 0.05 < \lambda_c$ and $\lambda_2 = 0.01 > \lambda_c$.

The trace of the covariance of the estimator error with constant gains, V_0^N, and the estimator error for smart sensors, D_0^N are shown in Fig. 8. As mentioned in Section IV, the error covariance for time-varying optimal estimator of Theorem 1 cannot be computed explicitly but it is upperbounded and lowerbounded by V_0^N and by D_0^N, respectively. It is interesting to compare the performance of these estimators with the error covariance $P_\infty^e = \Phi_1(P_\infty^e)$, shown in the same figure, corresponding to the ideal case when there is no packet loss and no delay, since this gives an idea of the degradation due the communication network. It is also relevant to evaluate the performance of an estimator with constant gains designed without exploiting the prior knowledge about the packet arrival statistics. A natural choice is to use the standard Kalman gain $K_\infty^e = P_\infty^e C^T (C P_\infty^e C^T + R)^{-1}$, i.e. $K_k = K_\infty^e, k = 0, \ldots, N$ rather than the optimal constant gains K_k^N defined in Theorem 3. The corresponding expected error covariance T_0^N can be obtained by Equations (41)-(42) and it is shown in Fig. 8. From this example it is clear that the tools developed in this paper can help to substantially reduce the degradation of performance when statistics of packet arrival are available.

Now, we illustrate how these tools can be also used to compare two different communication protocols. Let us consider a protocol giving rise to arrival statistics of Equation (54) and a protocol giving rise to the following arrival statistics:

$$\lambda_h = \begin{cases} (\frac{h}{10})^3, & h = 0, \ldots, 10 \\ 1, & h > 10 \end{cases} \tag{56}$$

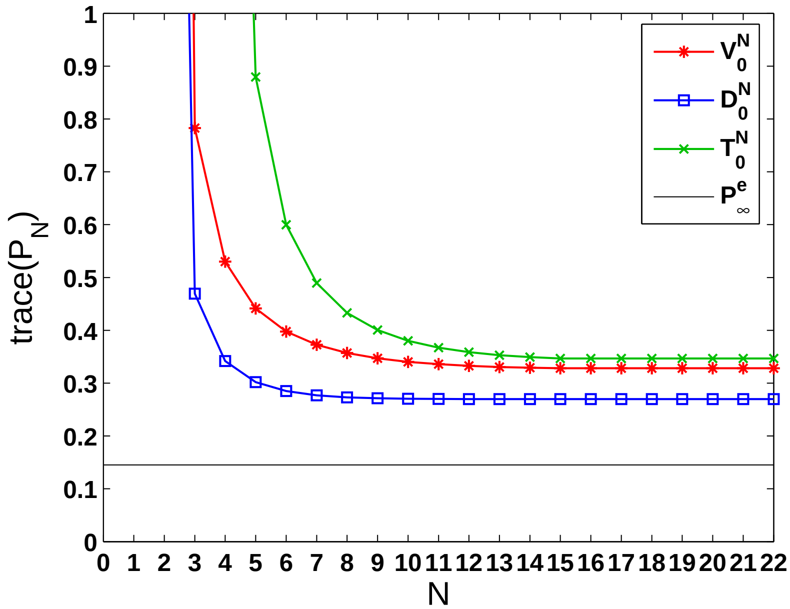

Fig. 8. Trace of the steady state error covariance for the optimal estimator with constant gains (V_0^N), for the optimal estimator with a smart sensor (D_0^N). The horizontal line P_∞^e corresponds to the trace of the error covariance in the ideal scenario with no delay and no packet loss, i.e. $\lambda_h = 1$ for all h, while T_0^N is the actual steady state error when using the Kalman gain K_∞^e. The error covariances V_0^N, D_0^N are unbounded for $N < 2$, while the covariance P_∞^e is unbounded for $N < 4$, and they are all cosnstant constant for $N \geq \tau_{max} = 15$.

for which $\tau_{max} = 10$, and it is graphically shown in Fig. 7. These two protocols are substantially different: the first protocol has larger packet delivery with small delay, but also larger overall packet loss than the first protocol, therefore it is difficult to evaluate which one is better suited for a real-time control application. In Fig. 9 it is shown the trace of the error covariance V_0^N for the two protocols with respect to the system dynamics of Equation (55). For a buffer with a short memory the first protocol performs better, but for a buffer of length $N = 10$ the second protocol starts performing better as the larger packet delivery can compensate for a larger delay of arrived packets. If buffer length is further increased, then the first protocol returns to perform better. This example clearly shows how optimal estimation design can be used to evaluate and compare the performance of different communication protocols with respect to a specific real-time application, which currently it is based only on heuristics and designer experience, and therefore prone to errors.

VIII. Conclusions

In this work we proposed a framework to optimally design and analyze the performance of estimators in networked control system subject to simultaneous random packet delay and packet dropped. We showed that the optimal estimator is time-varying, stochastic, and does not depend on the specific communication protocols adopted as long as measurements are time-stamped and can be re-ordered at the estimator site. Also two alternative optimal estimator designs based on finite memory buffers and constant gains were described and it was shown that if packet arrival is i.i.d., then the estimators are mean square stable if and only if the packet loss probability is below a critical value. Therefore, implicitly we also provided necessary and sufficient conditions about existence of stable estimators. Finally, we presented numerical algorithms for the computation of the expected estimator error covariance of all the proposed estimators.

The tools developed in this paper are useful both from a control system design perspective and from a communication design perspective. In fact, from a control perspective they can help to evaluate the tradeoffs between performance (error covariance), memory requirements (buffer length), and the hardware complexity ("smart" sensor). In particular, the knowledge of the packet arrival statistics can be used

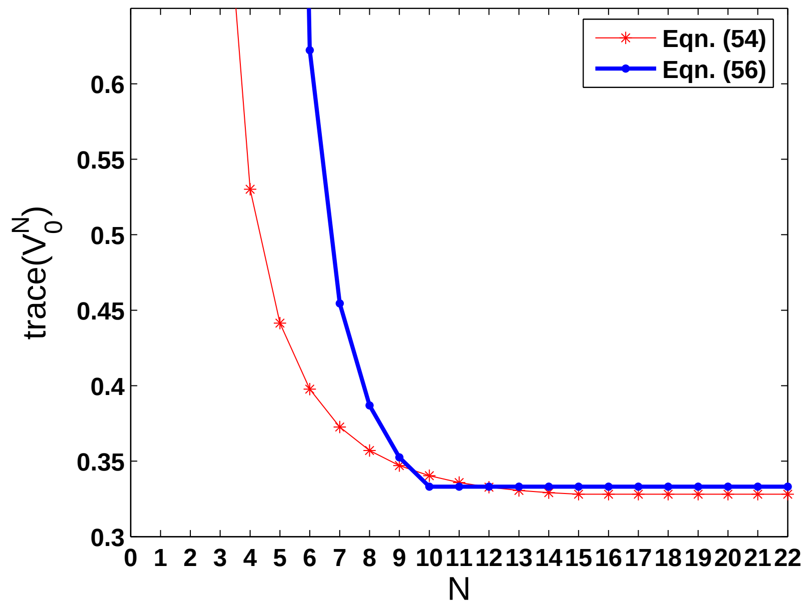

Fig. 9. Trace of the steady state error covariance for the optimal estimator with constant gains (V_0^N) for two different communication protocols whose packet arrival statistics is given by Equations (54) and (56).

to find the optimal constant gains $\{K_k^N\}_{k=0}^N$ and thus improving performance. From a communication perspective, these tools can be used to aid communication protocol design for real-time applications. In fact, as mentioned in Section I, when designing communication protocols, in particular for wireless systems, there is tradeoff between packet loss and packet delay. At the moment, the choice between favoring reduction of overall packet delay or reduction of packet loss is based on heuristics and experience, and it is not tailored to the specific real-time applications. Therefore, being able to quantitatively measure performance of different protocols can improve cross-layer design of complex networked control systems.

A possible future avenue of research is the extension of this work to the design of optimal LQG-like controller design. This is not a trivial step as many important assumptions in standard LQG control, like the separation principle, do not always hold for NCSs [26]. Another research direction is the application of these tools to real-time control applications in wireless sensor networks. A preliminary attempt has already been successfully applied to multiple target tracking [4], but extensive experimental work is still needed.

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