Automatica 91 (2018) 54–60

Contents lists available at ScienceDirect

Automatica

journal homepage: www.elsevier.com/locate/automatica

Brief paper

Transmission scheduling for remote state estimation and control with an energy harvesting sensor[☆]

Alex S. Leong[a,*], Subhrakanti Dey[b], Daniel E. Quevedo[a]

[a] Department of Electrical Engineering (EIM-E), Paderborn University, Paderborn, Germany
[b] Institute for Telecommunications Research, University of South Australia, Adelaide, Australia

ARTICLE INFO

Article history:
Received 11 August 2016
Received in revised form 11 October 2017
Accepted 7 December 2017

ABSTRACT

This paper studies a remote state estimation problem where a sensor, equipped with energy harvesting capabilities, observes a dynamical process and transmits local state estimates over a packet dropping channel to a remote estimator. The objective is to decide, at every discrete time instant, whether the sensor should transmit or not, in order to minimize the expected estimation error covariance at the remote estimator over a finite horizon, subject to constraints on the sensor's battery energy governed by an energy harvesting process. We establish structural results on the optimal scheduling which show that, for a given battery energy level and a given harvested energy, the optimal policy is a threshold policy on the error covariance. Similarly, for a given error covariance and a given harvested energy, the optimal policy is a threshold policy on the current battery level. An extension to the problem of transmission scheduling and control with an energy harvesting sensor is also considered.

1. Introduction

The harvesting of energy from the surrounding environment, such as solar, thermal, mechanical vibrations, or electromagnetic radiation, has attracted significant research interest, due to its potential for enabling self-sustaining and environmentally friendly devices. In wireless communications, transmission strategies for optimizing communication objectives such as maximizing throughput or minimizing transmission delay have been extensively studied, see e.g. Ho and Zhang (2012), Ozel, Tutuncuoglu, Yang, Ulukus, and Yener (2011) and Sharma, Mukherji, Joseph, and Gupta (2010). In the control literature, power/energy allocation strategies for optimizing state estimation (Li, Quevedo, Lau, Dey, & Shi, 2017; Nourian, Leong, & Dey, 2014) and control (Knorn & Dey, 2017) objectives have also received recent attention.

In event triggered estimation, a sensor will transmit to a remote estimator only when certain events occur, e.g. if the estimation quality has deteriorated sufficiently, with different transmission strategies proposed (Li, Lemmon, & Wang, 2010; Trimpe & D'Andrea, 2014; Wu, Jia, Johansson, & Shi, 2013; Xia, Gupta, & Antsaklis, 2013). A probabilistic triggering mechanism has also been recently studied in event triggered estimation with an energy harvesting sensor (Huang, Shi, & Chen, 2017).

In this paper we will study a transmission scheduling problem for remote state estimation, that minimizes the expected estimation error covariance at the remote estimator. The scheduling is subject to the constraint that the sensor is equipped with energy harvesting capabilities, and transmission over a packet dropping channel can only occur if there is sufficient energy in the sensor battery. Note that one can regard the situation where there is insufficient battery energy for transmission as a sensor failure. Other related work on sensor failures include Chen, Yu, Zhang, and Liu (2013), Hounkpevi and Yaz (2007), Qu and Zhou (2013), Wang, Ho, and Liu (2003), to mention a few.

We will derive structural results on the optimal transmission policy. Namely, for a given battery energy level and a given harvested energy, we will show that the optimal policy is a threshold policy on the estimation error covariance. Similarly, for a given error covariance and a given harvested energy, the optimal policy is a threshold policy on the battery level. This is reminiscent of the threshold based policies often considered in event triggered estimation. We then extend our results to the problem of transmission scheduling and control with an energy harvesting sensor, where one can show that this problem is separable into an LQG-type control problem and a transmission scheduling problem, with the optimal transmission schedule having threshold-type behaviour.

Optimality of threshold-type policies has been shown in other contexts. For the case of noiseless measurements and no packet

[☆] The material in this paper was partially presented at the 24th EUSIPCO 2016, 29 August–2 September, 2016, Budapest, Hungary. This paper was recommended for publication in revised form by Associate Editor Shreyas Sundaram under the direction of Editor Christos G. Cassandras.

* Corresponding author.
E-mail addresses: alex.leong@upb.de (A.S. Leong), Subhra.Dey@unisa.edu.au (S. Dey), dquevedo@ieee.org (D.E. Quevedo).

https://doi.org/10.1016/j.automatica.2018.01.027
0005-1098/

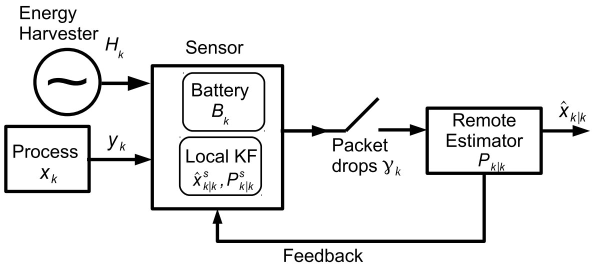

Fig. 1. Remote state estimation with an energy harvesting sensor.

drops, Lipsa and Martins (2011) showed a threshold behaviour in the difference between the current state and most recently transmitted state, with Nayyar, Başar, Teneketzis, and Veeravalli (2013) also considering energy harvesting. In event triggered control, optimality of threshold policies have been shown in Molin and Hirche (2010). For variance based triggering (where transmit decisions depend on the estimation error covariance) with no energy harvesting, it was shown in Leong, Dey, and Quevedo (2017) (see also Mo, Sinopoli, Shi, & Garone, 2012; Ren, Cheng, Chen, Shi, & Zhang, 2014) that threshold-type policies are optimal, in the sense that it minimizes a linear combination of the expected estimation error covariance and expected energy usage of the sensors.

The paper is organized as follows. Section 2 describes the system model. The optimal transmission scheduling problem is formulated in Section 3. Structural results for the optimal transmission schedule are derived in Section 4. The problem of transmission scheduling for control with an energy harvesting sensor is considered in Section 5. Numerical studies are presented in Section 6.

2. System model

A diagram of the system model is shown in Fig. 1. Consider a discrete time process

$$x_{k+1} = Ax_k + w_k \tag{1}$$

where $x_k \in \mathbb{R}^{n_x}$ and w_k is i.i.d. Gaussian with zero mean and covariance $Q \geq 0$.[1] There is a sensor taking measurements

$$y_k = Cx_k + v_k, \tag{2}$$

where $y_k \in \mathbb{R}^{n_y}$ and v_k is Gaussian with zero mean and covariance $R > 0$. The noise processes $\{w_k\}$ and $\{v_k\}$ are assumed to be mutually independent.

The sensor has some computational capabilities and can run a local Kalman filter. The local state estimates and estimation error covariances

$$\hat{x}^s_{k|k-1} \triangleq \mathbb{E}[x_k|y_0,\dots,y_{k-1}],\ \hat{x}^s_{k|k} \triangleq \mathbb{E}[x_k|y_0,\dots,y_k]$$
$$P^s_{k|k-1} \triangleq \mathbb{E}[(x_k-\hat{x}^s_{k|k-1})(x_k-\hat{x}^s_{k|k-1})^T|y_0,\dots,y_{k-1}]$$
$$P^s_{k|k} \triangleq \mathbb{E}[(x_k-\hat{x}^s_{k|k})(x_k-\hat{x}^s_{k|k})^T|y_0,\dots,y_k]$$

can be computed at the sensor using the standard Kalman filtering equations. We assume that the pair (A, C) is detectable and the pair $(A, Q^{1/2})$ is stabilizable, with the local Kalman filter operating in steady state,[2] i.e. $P^s_{k|k} = \bar{P}, \forall k$, where $\bar{P}$ is the steady state value of $P^s_{k|k}$, which exists by the detectability assumption.

Let $\nu_k \in \{0, 1\}$ be decision variables such that $\nu_k = 1$ if and only if $\hat{x}^s_{k|k}$ is to be transmitted[3] by the sensor to the remote estimator at time k. Let B_k denote the battery level of the sensor at time k, with $B_{\max}$ the maximum capacity of the sensor's battery. There is an energy usage of E for each scheduled transmission. Transmission at time k can only occur if there is sufficient energy in the battery, i.e. $\nu_k = 1$ is possible only when $B_k \geq E$. The sensor is equipped with energy harvesting capabilities, with the energy harvested by the sensor between the discrete time instants $k-1$ and k denoted by H_k. Similar to Ho and Zhang (2012), the evolution of the battery level is modelled as

$$B_{k+1} = \min\{B_k - \nu_k E + H_{k+1}, B_{\max}\}, \tag{3}$$

with $\nu_k = 0$ if $B_k < E$. The harvested energy process $\{H_k\}$ can in general be temporally correlated, e.g. the amount of solar energy harvested may differ significantly depending on the time of day and weather conditions (Ho & Zhang, 2012). In this paper we will assume that $\{H_k\}$ is Markovian. We denote the support of $\{H_k\}$ by $\mathbb{H}$, and that of B_k by $\mathbb{B} \subseteq [0, B_{\max}]$.

At time instances when $\nu_k = 1$, the sensor transmits its local state estimate $\hat{x}^s_{k|k}$ over a packet dropping channel, see Fig. 1. Let $\gamma_k \in \{0, 1\}$ be random variables such that $\gamma_k = 1$ if and only if the transmission at time k is successfully received by the remote estimator. We will assume that $\{\gamma_k\}$ is i.i.d. Bernoulli with

$\mathbb{P}(\gamma_k = 1) = \lambda \in (0, 1)$.

At instances where $\nu_k = 1$, it is assumed that the remote estimator knows whether the transmission was successful or not, i.e., the remote estimator knows the value γ_k, with dropped packets discarded. Define

$$\mathcal{I}_k \triangleq \{\nu_0,\dots,\nu_k,\nu_0\gamma_0,\dots,\nu_k\gamma_k,\nu_0\gamma_0\hat{x}^s_{0|0},\dots,\nu_k\gamma_k\hat{x}^s_{k|k}\}$$

as the information set available to the remote estimator at time k. Denote the state estimates and error covariances at the remote estimator by:

$$\hat{x}_{k|k} \triangleq \mathbb{E}[x_k|\mathcal{I}_k],\ \ P_{k|k} \triangleq \mathbb{E}[(x_k-\hat{x}_{k|k})(x_k-\hat{x}_{k|k})^T|\mathcal{I}_k]. \tag{4}$$

Given that the decision variables ν_k depend on $P_{k-1|k-1}$, H_k and B_k, but not on the state x_k, the optimal remote estimator can be shown to have the following form, similar to Xu and Hespanha (2005):

$$\hat{x}_{k|k} = \begin{cases} A\hat{x}_{k-1|k-1}, & \nu_k\gamma_k = 0 \\ \hat{x}^s_{k|k}, & \nu_k\gamma_k = 1 \end{cases}$$
$$P_{k|k} = \begin{cases} f(P_{k-1|k-1}), & \nu_k\gamma_k = 0 \\ \bar{P}, & \nu_k\gamma_k = 1, \end{cases} \tag{5}$$

where

$$f(X) \triangleq AXA^T + Q. \tag{6}$$

We assume that γ_k is fed back to the sensor before the transmission decision at the next time instant $k+1$. Thus, the remote estimate $P_{k|k}$ can be reconstructed at the sensor with this acknowledgement mechanism.[4]

Define the countable set

$$\mathcal{S} = \{\bar{P}, f(\bar{P}), f^2(\bar{P}), \dots\}, \tag{7}$$

where $f^n(.)$ is the n-fold composition of $f(.)$, with the convention that $f^0(X) = X$. Then it is clear from (5) that $\mathcal{S}$ consists of all

[1] For a symmetric matrix X, we say that $X > 0$ if it is positive definite, and $X \geq 0$ if it is positive semi-definite. Given two symmetric matrices X and Y, we say that $X \leq Y$ if $Y - X$ is positive semi-definite, and $X < Y$ if $Y - X$ is positive definite.

[2] The local Kalman filter in general converges to steady state at an exponential rate.

[3] When there are packet drops, sending state estimates generally gives better estimation performance than sending measurements (Xu & Hespanha, 2005).

[4] The case of imperfect feedback acknowledgements can also be considered, using similar ideas as in Nourian et al. (2014).