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Journal of Process Control



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

# An adaptive high-gain observer for wastewater treatment systems

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#### ARTICLE INFO

Article history: Received 5 October 2010 Received in revised form 31 January 2011 Accepted 14 March 2011 Available online 9 April 2011

*Keywords:* Nonlinear observer and filter design Wastewater treatment processes

#### ABSTRACT

The purpose of this paper is twofold: (1) we apply the adaptive observer developed in Boizot et al. [1] to a wastewater system, following two cascade steps. First, we apply it to a simplified model of the system. Second, we use this "simplified" estimation as a measurement for the full system. (2) Although the observability analysis is trivial, the equations contain rather complicated terms. Therefore, it is not reasonable to change coordinates for those of the required observability canonical form. Hence, we have to establish and work with the "unusual" equations of the observer in natural coordinates.

Let us point out that the simulations are done taking into account the small number of measurements (three) available in practice.

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### 1. Introduction

The present work deals with the observer design of non linear dynamical systems, and application to a wastewater treatment system.

The need to develop observers or "software sensors" for Activated Sludge Processes in perspective of on-line monitoring is due to the following facts, among others:

- (1) Although sensors for measuring chemical and biological variables are widespread and very advanced, such measurements are still unreliable and noisy.
- (2) The implementation and maintenance costs of these advanced sensors are high.

A lot of work has been developed on the synthesis of nonlinear observers for (bio)chemical processes [2–13]. Here, we have chosen an adaptive high-gain observer as proposed in the paper [1] for the following reasons. This observer is high-gain, but it is also extended-Kalman-filter based: first, in the context of large transitions, it is an high-gain (HG) observer which guarantees theoretical convergence with arbitrary rate, under certain observability assumptions. Second, for small enough initial estimation error, it behaves like a classical extended Kalman filter (EKF), i.e. it is more or less optimal w.r.t. noise. Moreover, in a deterministic setting, it has good convergence properties [14].

Here, transition from HG mode to EKF mode is performed via an adaptation procedure based upon the level of innovation (i.e. the

level of new information appearing through the "recent" observations).

For the general theory of high-gain nonlinear observers (see [15,1,7,16]).

The EKF is widely used and works rather well in practice. The main disadvantage for the EKF algorithm is that it requires an approximate knowledge of the initials conditions. Conversely, the HG-EKF algorithm converges whatever the initial guess but is rather sensitive with respect to noise. Then, the idea is to switch between the EKF and the HG-EKF algorithm. If the estimation error of the HG-EKF becomes sufficiently small then the EKF is used. The switching between these two modes can be done by having the high-gain parameter  $\theta$  evolving between 1 and  $\theta_{max}$ . The adaptation is made by using a differential equation driven by the "innovation".

Usually this method is applied by previously changing coordinates in order to put the system under a certain observability canonical form. In our case, we prefer to write our observer in the natural coordinates in order that it is not necessary to realize online the inverse coordinates change. The counterpart of this choice is that the Riccati equation of the Kalman filter has not the standard form. Detailed computations are provided in Appendix A.

Moreover here, in order to simplify the computations, we use cascade observers (reduced and complete): a first observer of the type above is used on a simplified model to provide an intermediate estimate of the state, this estimation being itself used as the output of the non simplified system.

Actually, for the complete observer with the three practical outputs, the computations are very heavy, even working in natural coordinates.

In Section 2 we recall the structure of our observer, which is just the multi-output version of the one developed in the paper [1]. Section 3 is devoted to the crucial concept of innovation, which

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<sup>0959-1524/\$ -</sup> see front matter © 2011 Elsevier Ltd. All rights reserved. doi:10.1016/j.jprocont.2011.03.006