Chapter 15
Recurrent Higher Order Neural Observers for Anaerobic Processes

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ABSTRACT

In this chapter we propose the design of a discrete-time neural observer which requires no prior knowledge of the model of an anaerobic process, for estimate biomass, substrate and inorganic carbon which are variables difficult to measure and very important for anaerobic process control in a completely stirred tank reactor (CSTR) with biomass filter; this observer is based on a recurrent higher order neural network, trained with an extended Kalman filter based algorithm.

INTRODUCTION

Anaerobic digestion is a bioprocess developed in oxygen absence by different populations of bacteria; these micro-organisms degrade progressively complex organic molecules. One of the most important applications of this process is the wastewater treatment, and it is very efficient to treat substrates with high organic load; besides the treated water, this process produces biogas, which is mainly composed of methane and carbon dioxide and it is considered as an alternative energy. However, anaerobic digestion process is very sensitive to changes on operating conditions and parameters, such as hydraulic and organic overloads, pH, temperature, etc. Then, control strategies are required in order to guarantee an
adequate operation of the process. Moreover, methane production, biomass growth and substrate degradation are good indicators of biological activity inside the reactor. These variables can be used for monitoring the process and to design control strategies. Some biogas sensors have been developed in order to measure methane production in bioprocesses. However, substrate and biomass measures are more restrictive. The existing biomass sensors are quite expensive, are designed from biological viewpoint and then, they are not reliable for control purposes. Besides, substrate measure is done off-line by chemical analysis and it requires at least two hours. Then, state observers are an interesting alternative in order to deal with this problematic. This chapter deals with the neural estimation of variables hard to measure in anaerobic process.

Nowadays, artificial neural networks are a useful tool for modelling, identification, state estimation and control of a wide variety of processes. Feedforward neural networks are a good option for simple dynamics; however, for complex nonlinear systems, higher order recurrent neural networks (RHONN) are a better alternative due to their excellent approximation capabilities, requiring fewer units (Rovithakis & Christodoulou, 2000). These kind of neural networks, compared to the first order ones, are more flexible and robust when faced with new and or noisy data patterns (Ghosh & Shin, 1992). Besides RHONN performed better than the multilayer first order ones using a small number of free parameters (Ghazali, Hussain & Merabti, 2006; Rovithakis & Christodoulou, 2000). Furthermore, different authors have demonstrated the feasibility and the advantages of using these architectures in applications for system identification and control (Ge, Zhang & Lee, 2004; Narendra & Parthasarathy, 1990; Rovithakis & Christodoulou, 2000; Sanchez & Ricalde, 2003; Yu & Li, 2004).

The best known training approach for recurrent neural networks (RNN) is the back propagation through time learning (Williams & Zipser, 1989). However, it is a first order gradient descent method and hence its learning speed could be very slow (Leunga & Chan, 2003). Recently, the extended Kalman filter (EKF) based algorithms has been introduced to train neural networks (Feldkamp, Prokhorov & Feldkamp, 2003), in order to improve the learning convergence (Leunga & Chan, 2003). The EKF training for neural networks, both feedforward and recurrent ones, has proven to be reliable and practical in many applications over the past fifteen years (Feldkamp, Prokhorov & Feldkamp, 2003; Haykin, 2001; Leunga & Chan, 2003; Williams & Zipser, 1989; Yu & Li, 2004).

On the other hand, many of the nonlinear control publications assume complete accessibility for the system state; this is not always possible (Poznyak, Sanchez & Yu, 2001). For this reason, nonlinear state estimation is a very important topic for nonlinear control (Poznyak, Sanchez & Yu, 2001). State estimation has been studied by many authors, who have obtained interesting results in different directions. Most of those results need the use of a special nonlinear transformation (Nicosia & Tornambe, 1989) or a linearization technique (Grover & Hwang, 1992; Krener & Isidori, 1983). Such approaches can be considered as a relatively simple method to construct nonlinear observers; however, they do not consider uncertainties (Li & Zhong, 2005; Liu, Wang & Liu, 2007; Wang, Ho & Liu, 2005). In practice, there exist external and internal uncertainties. Observers which have a good performance even in presence of model and disturbance uncertainties, are called robust; their design process is quite complex (Chen & Dunnigan, 2002; Coutinho & Pereira, 2005; Huang, Feng & Cao, 2008; Walcott & Zak, 1987). All the approaches mentioned above need the previous knowledge of the plant model, at least partially. Recently, other kind of observers has emerged: neural observers (Kim & Lewis, 1998; Levin & Narendra, 1996; Marino, 1990; Poznyak, Sanchez & Yu, 2001; Sanchez & Ricalde, 2003), for unknown plant dynamics. However (Kim & Lewis, 1998; Marino, 1990; Poznyak, Sanchez & Yu, 2001; Sanchez & Ricalde, 2003), are analyzed for continuous-time unknown nonlinear systems, besides for (Marino, 1990; Poznyak, Sanchez & Yu,
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