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Robust Luenberger observers for microalgal cultures

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ABSTRACT

The advanced control of microalgal cultures usually requires the knowledge of several component concentrations, which are however not always measurable on-line. In this context, state estimation plays an important role, and software sensors should be robust to model uncertainties and measurement noise. In this study, two software sensors are designed in the form of extended Luenberger observers, using Lyapunov arguments and linear matrix inequalities (LMI). These observers are based on Droop model and a few available on-line sensors. The first observer design estimates the intracellular quota and substrate concentrations considering a linear differential inclusion modeling technique and a constant observer gain. On the other hand, the second one estimates only the intracellular quota concentration assuming uncertainties in the model parameters and a quasi-Linear Parameter Varying (quasi-LPV) representation of the nonlinear system. The results are presented considering simulated and experimental data from *Dunaliella tertiolecta* culture.

1. Introduction

In the last two decades, microalgal cultivation has received an ever increasing attention in relation to the large panel of potential applications ranging from biofuels to pigments, cosmetics, nutrients and wastewater treatment [1,2]. To achieve continuous production, the use of monitoring and control techniques is of paramount importance but is hampered by the lack of on-line instrumentation. To alleviate this difficulty, observers, or software sensors ([3–6] and the references therein) are an appealing alternative to costly on-line hardware probes. State estimation techniques blend the predictive capability of a dynamic model of the process under consideration, and the corrective action that available on-line information can provide.

The first component of a software sensor is therefore a dynamic process model. Several dynamic models describing microalgal growth as a function of environmental variables such as nutrients and light can be found in the literature (see for instance [7] for a nice overview of the subject). In this work, a simple, yet representative, model proposed by Droop [8] is considered. This model is one of the earliest and most accepted microalgal growth models describing the ability of microalgae to store nutrients and the decoupling between substrate uptake and biomass growth. Nutrient storage is represented by an intracellular variable called quota Q, which is defined as the concentration of internal nutrient per concentration of biomass. Even tough the model was original developed considering a limitation in vitamin B_{12}, it has since then demonstrated its large applicability for other limiting substrates such as nitrate, phosphate or silicate [9,10]. Nitrate depletion is of particular interest in applications related to the production of biofuels.

The second component is a nonlinear state estimation technique. According to Ref. [3], two main categories of observers can be applied to bioprocesses: the asymptotic observers and the exponential observers. The first ones do not require the knowledge of the kinetics, but their speed of convergence cannot be adjusted by the user. In contrast, exponential observers require a good-quality model, but their rate of convergence toward the real state can be adjusted via some tuning parameters. The extended Kalman filter [11], the extended Luenberger observer [12] and the high gain observer [14] are examples of exponential observers. However, the main drawback of these observers regards the strong dependency on the model quality and consequently the high sensitivity to parameter uncertainties [15].

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To deal with parameter uncertainties while guaranteeing bounded estimation errors, several robust estimation techniques were proposed in the literature in the last decade. Especially, interval observers [16], which provide lower and upper bounds of the state trajectory based on the knowledge of guaranteed intervals for the uncertain parameters (as well as possible uncertain initial conditions and inputs), have been applied to bioprocesses. In particular, these observers have been applied to microalgal cultures in Refs. [17,18] with satisfactory performance. However, the design of controllers based on these interval observers is more delicate than with conventional (single-valued) observers.

The intent of this study is to consider another class of robust state estimation methods, namely robust extended Luenberger observers (ELO) as proposed in Refs. [19–22], which make use of Lyapunov stability theory and convex optimization techniques to ensure an upper bound on the norm of the estimation error.

More specifically, two observers are designed:

- An ELO for the estimation of the extracellular substrate concentration and the intracellular quota from the measurement of biomass only. This nonlinear observer uses the Lyapunov theory to ensure stability and linear differential inclusion (LDI) modeling of the state error dynamics [24]. The design conditions are expressed in terms of linear matrix inequality (LMI) constraints, and lead to the determination of a static correction gain.
- A second ELO for the estimation of the intracellular quota from the measurement of the extracellular substrate and biomass concentrations. The design not only considers the model nonlinearities, but also takes model uncertainties into account in a way similar to [19]. To deal with system nonlinearities, Droop model is represented as a quasi-Linear Parameter Varying (quasi-LPV) system [25]. In other words, the system nonlinearities are viewed as bounded time-varying parameters. The advantage of this representation is that the nonlinearities are hidden into bounded parameters allowing the application of well-established robust control theory. In addition, for designing a gain scheduling mechanism, the bounded parameters are split into two groups depending on whether they can be measured online or not. The non-measurable parameters are considered as model uncertainties, whereas the measurable parameters are used to schedule the observer gain. Moreover, an $\mathcal{H}_\infty$ design is applied to attenuate modeling errors on the norm of the estimation error [26].

Prior to the observer design an observability analysis is achieved following [27]. Finally, the observers are tested in simulation and with experimental data collected from a lab-scale photobioreactor.

This paper is organized as follows. The next section presents Droop model and the lab-scale experimental set-up used for microalgal cultivation. The two robust observers are designed in Section 3, and tested both in simulation and real-case situations in Section 4. Finally, Section 5 is dedicated to conclusions and perspectives.

2. Process description and Droop model

The Droop model [9] describes the growth of microalgae cultivated in a photobioreactor, under constant temperature and illumination conditions. This model uncouples the microalgae growth from substrate uptake and describes the growth rate as a function of the internal quota concentration of a limiting nutrient. This latter nutrient is essential for growth, can be stored in periods of abundance, and limits growth in periods of scarcity. Originally, Droop considered vitamin B_{12} as the limiting nutrient, but more recent works [9,10] have demonstrated the model adequacy when, for instance, nitrogen, phosphate or silicate play the role of limiting nutrients. In this work, nitrogen is the limiting nutrient as considered, for instance, in Ref. [7]. This situation is particularly interesting when studying the production of biofuels, where the accumulation of lipids within the microalgae can be triggered by nitrogen depletion.

Fig. 1. Lab-scale flat-panel photobioreactor.

Droop model is often the corner stone of more elaborate models, including additional effects such as temperature, light irradiance, photoacclimation and inhibition [7,28].

The following differential equation model, Eq. (1), expresses the mass balances in a continuous bioreactor. It includes three state variables, i.e., the concentration of biomass X, the concentration of substrate S, and the intracellular quota Q.

$$\begin{aligned}\dot{X} &= \mu(Q)X - DX\\ \dot{S} &= -\rho(S)X - DS + DS_{in}\\ \dot{Q} &= \rho(S) - \mu(Q)Q\end{aligned} \tag{1}$$

The dilution rate $D = F_{in}/V$ is the ratio between the inlet flow rate and the volume of the culture. Here, we assume continuous operation with constant volume, i.e., a chemostat. The uptake rate $\rho(S)$ is defined by the following Monod law:

$$\rho(S) = \rho_m \frac{S}{S + K_s} \tag{2}$$

where K_s is the half saturation constant of substrate and ρ_m is the maximum inorganic nitrogen uptake rate of limiting substrate.

Droop proposed that the microalgal growth rate depends on the intracellular quota as shown in Eq. (3) instead of the external substrate concentration. Hence, microalgae can still grow when the external substrate is exhausted, but reserves are available in the internal pool.

$$\mu(Q) = \mu_m \left(1 - \frac{Q_0}{Q}\right) \tag{3}$$

In this latter expression, Q_0 is the minimum cell quota identified empirically by Droop under which microalgae do no longer grow, and μ_m is the maximum growth rate.

In order to investigate the performance of state estimation techniques in realistic conditions, an experimental system has been set-up at the University of Mons, which is shown in Fig. 1.

This system consists of a 13 L flat-panel photobioreactor (PBR), illuminated from one side by a set of six fluorescent tubes placed vertically and parallel to the front side of the reactor, with the same height and width as the reactor. These fluorescent tubes of 18 W each are dimmable and used generally in horticulture applications (Fluora 18 W/77, Osram). The main emitted wavelengths are located in the visible spectrum (blue (430 nm) and red