ELEKTROTEHNIŠKI VESTNIK 91(5): 265-271, 2024
ORIGINAL SCIENTIFIC PAPER

Fixed-Time Observer for a Specific Growth Rate and Substrate in a Bioreactor

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Abstract. The paper provides an online estimation of state variables in a bioreactor using a fast and straightforward nonlinear observer with an unknown specific growth rate. The fixed time observer is based on a known biomass concentration instead of a known substrate concentration. The observer design is based on the sliding mode approach. A Fixed-time stability of the resulting error system is proven. Computer simulations show the performance and robustness of the proposed nonlinear observer, which ensures a robust performance in the presence of a model uncertainty and measurement noise.

Keywords: Bioreactor, Fixed-time observer, nonlinear system, robust observer, specific growth rate.

Opazovanje stanja s stalnim časovnim korakom v bioreaktorju na osnovi koncentracije biomase

V prispevku obravnavamo oceno spremenljivk stanja v bioreaktorju z uporabo hitrega in enostavnega nelinearnega opazovanja z neznano specifično hitrostjo rasti. Opazovanje s fiksnim časom temelji na znani koncentraciji biomase namesto na znani koncentraciji substrata. Zasnova opazovanja temelji na pristopu drsnega načina. Razvili smo programe za računalniško simulacijo, ki prikazujejo zmogljivost in robustnost predlaganega pristopa ob prisotnosti merilnega šuma.

1 INTRODUCTION

Among the most frequent and important challenges in the control of bioprocesses is finding adequate and reliable sensors to measure all the important state variables of the plant. Even if a number of online sensors providing the state information are available today on an industrial scale, they are still very expensive, and their maintenance usually consumes significant time. Moreover, the reaction rate functions are unknown, and complex experimental procedures must be engaged to estimate these functions. The specific growth rate is an important parameter in bioreactors as it indicates the rate at which microorganisms are growing, and is used to optimize the bioprocess. The substrate concentration is also a critical parameter in bioreactors, as it affects the growth rate of microorganisms and is used to control the feeding rate of the bioreactor. Therefore, to estimate the states and parameters of a system, it is necessary to use observers, also called software sensors. The estimated states and parameters can then be used only for supervising the process [1], or they can be incorporated into a control loop [2].

In recent years, observation has been extensively studied [3], and various design methods for nonlinear observer strategies have been proposed. The design of robust observers occurs in many practical applications, such as systems with unknown parameters, fault and identification problems, cryptography [4, 5], Asymptotic observers [6,7], observers based on the extended Kalman filter (EKF) [8], high gain observers [9], adaptive observers [10], H∞ hybrid observers [11]. Different kinds of sliding mode observers [12,13, 14, 15], first-order [16, 17], and second-order [18, 19] have been successfully tested on this class of the bioprocess model. Two nonlinear observers-based sliding mode controllers are proposed in [20] to perform an accurate tracking of the temperature and concentration in the reactor. The sliding mode strategy has been widely used in the design of controllers and observers for nonlinear systems. This approach is well known for its stability in finite time and its excellent robustness properties with respect to parametric uncertainties and external disturbances [21].

The problem of both the state observation and parameter identification has already been extensively investigated in the literature [22, 23]. An adaptive observer to simultaneously estimate the state and the unknown parameters is proposed in [24].

The majority of these observers are asymptotic or exponential, which means that the estimation error converges to zero and reaches zero towards an infinite time. A Finite-time control and finite-time observation of uncertain non-linear systems have been intensively

Received 5 February 2024
Accepted 30 September 2024

studied for many years [25, 26, 27, 28, 29]. An observer that achieves both the state and parameter estimation in a finite time is designed in [30]. The terminal time admits a uniform upper bound regardless of the initial conditions [31].

[32] addresses the problem of determining the input excitation for a data-driven model identification appropriate for cell culture bio-processes in general and for an industrial bioreactor used for the production of monoclonal antibodies in particular.

[33] presents the design of a high-gain nonlinear observer for bilinear systems in the block form. We also study and simulate two examples of observers for bioreactor systems in two and three dimensions.

Anaerobic digestion processes are proposed to be monitored using an observer for estimating the status and unknown inputs [34]. The three sub-observers that make up this estimator are (a) a gramian-based fixed-time convergent observer for the inlet chemical oxygen demand (COD) and the acidogenic bacteria population, (b) an asymptotic observer for the methanogenic bacteria population, and (c) a super-twisting observer for systems with time-varying parameters to estimate the inlet volatile fatty acid (VFA) concentration [34]. The estimator is based on a dynamic model that takes acidogenesis and methanogenesis into account. The unknown influent concentration is estimated using a sliding mode observer, but the unknown states and kinetics are also estimated using state observers and parameter estimators [35]. In [36], the Sonnleitner bottleneck model is used to solve the observer design problem for state estimation in a continuous (or semi-continuous) yeast fermentation and a methane bioconversion process using an observer and controller structure [37].

[38] investigates the challenge of fixed-time observation for nonlinear dynamic systems with unknown parameters and inputs.

Few studies deal with the problem of fixed-time estimation for bioreactors with unknown specific growth rates. The problem is challenging due to the non-linear and complex dynamics of the system, uncertainties in measurements, and time-varying parameters. Therefore, developing accurate and robust estimation techniques is important for an efficient and reliable bioprocess control and optimization.

For example, in [39], a specific growth rate and substrate concentration of microorganisms in a fed-batch bioreactor used to produce monoclonal antibodies are estimated using a fixed-time observer. [40] investigates a fixed-time distributed estimate issue for a class of second-order nonlinear systems with an uncertain input, unknown nonlinearity, and matching perturbations. To provide stable and limited estimates of the respiration rate, the problem of the respiration rate estimation employing two new non-linear observers for a wastewater treatment plant, namely a non-linear adaptive Luenberger-like observer and a super twisted sliding mode observer, are derived [41]. [42] provides a unique extended super-twisting technique for a class of nonlinear systems that converges on the estimate of uncertain parameters, unknown internal dynamics, and external disturbances in a finite period or a neighbourhood around their nominal values. [43] combines the study of non-asymptotic convergence rates (finite and fixed-time) with the input-to-state stability condition.

In most approaches, the substrate concentration is the measured variable. However, many practical and economical reasons render the measurement with a good precision of the substrate concentration very difficult, particularly when they are in low concentrations. In our case, we address a mathematically challenging estimation issue when only a biomass concentration is available for an online measurement and propose a sliding mode observer to estimate the substrate concentration and the unknown specific growth rate parameters. The fixed-time observer is found to be effective in estimating these parameters and maintaining stable operating conditions.

The main contribution of the paper is the design of a fixed-time observer based on a sliding mode technique to estimate states and the unknown specific growth rate of the bioreactor. The estimation is based on online measurements of a biomass concentration. The fixed-time convergence of the observer is proven using the Lyapunov technique.

This paper is structured as follows. Section 2 presents the bioreactor model and the formulation of the necessary assumptions. The construction of the fixed-time observer to estimate the concentrations and the unknown specific growth rate is the subject of Section 3. Section 4 is reserved for the development of computer simulations to illustrate the effectiveness of the proposed approach. The paper is concluded with some remarks.

2 EXPLANATION OF PROCESSES IN A BIOREACTOR FROM A CHEMICAL, BIOLOGICAL/PHYSICAL POINT OF VIEW

A bioreactor is an engineered system or device that supports a biologically active environment [44]. It serves as a vessel in which chemical processes involving organisms or their bioactive substances occur, which can be either aerobic or anaerobic. Bioreactors come in various sizes, from a few litters to several cubic meters, and are usually made of stainless steel. They are also used to grow cells or tissues in cell culture systems. The technology of bioreactors is continually evolving, particularly for the use in tissue engineering and biochemical engineering processes.

Bioreactors operate in distinct modes, namely batch, fed-batch, or continuous, exemplified by a continuous stirred-tank reactor model. The chemostat stands out as a type of a continuous bioreactor. Within these bioreactors, organisms or biochemically active substances can thrive either submerged in a liquid medium or anchored to the surface of a solid medium. The submerged cultures may be free-floating or immobilized. The suspension bioreactors are versatile, supporting a wide variety of organisms without special attachment surfaces and offering a greater scalability compared to immobilized cultures. However, in continuous operations, organisms exit the system with the outflow. Immobilization encompasses techniques for securing cells or particles [45] and is integral to all biocatalysis forms, including enzymes, cellular organelles, cells and organs from animals and plants [46], [47]. While immobilization enhances continuous processes by keeping organisms inside the reactor, it faces limitations in the scale due to the confinement of microbes to the reactor internal surfaces.

The main function of a bioreactor is to enhance the interaction between contaminants within the target matrix and the microorganisms that break them down. Essentially, a bioreactor is a vessel or apparatus where cells or microbes are cultivated in a controlled setting to create particular compounds. It ensures a consistent physicochemical milieu for the cells and supports the cell attachment when needed.

Figure 1. Operation of the bioreactor.

3 MATHEMATICAL MODEL OF THE BIOREACTOR

Let us consider the following two-dimensional system that describes the dynamical behavior of a Continuous Stirred Tank Bioreactor [48],

$$\begin{cases} \dot{X} &= \mu(S)X - DX \\ \dot{S} &= -k_1\mu(S)X + D(S_i - S) \end{cases} \quad (1)$$

where the state variables S and X are the substrate and biomass concentrations respectively, D=q/V is the dilution rate with V the volume of the bioreactor and q the volumetric flow rate, k_1 the yield coefficient, S_i is the inlet substrate concentration and μ(S) is the specific growth rate.

The formulation of a precise model for the specific growth rate μ(S) is the most critical problem in solving Eq.(1). As presented in [49], many analytical expressions have been proposed to describe these functions. Here, we assume that function μ(S) is unknown and is considered as a function of the substrate concentration.

We make the following Theorem and assumptions:

Assumption 1 : Let $\xi = [X, S]^T$ is the state vector of the system (1),
$\forall \xi \in R^2$, $0 < X < X_{max}$ and $0 < S < S_i$

Assumption 2 : Function $\mu(S)$ is non-negative and bound such that $\exists S^* \in]0\ S_i[,\ \mu(S) \leqslant \mu(S^*) = \bar{\mu}$ where $\bar{\mu}$ is the upper bound of $\mu(S)$.

Assumption 3 : Let's define the time-derivative of $\mu(S)$ as:

$$\dot{\mu} = \frac{d\mu(S)}{dt} = \rho(S) \quad (2)$$

$\rho(S)$ is an unknown non-negative function and bound as: $\rho(S) \leq \bar{\rho}$, ($\bar{\rho}$ is positive known constant)

Assumption 4 : Dilution rate D is known and uniformly bound.

Theorem 1 [50] *Suppose that Lyapunov function $V(x)$ defines the neighborhood at the origin in $U \in R^n$, if the time derivative of $V(x)$ satisfies :*

$$\dot{V} \leq -aV^p - bV^q - cV$$

where $a, b, c > 0$, $0 < p < 1$ and $q > 1$. It can be said that $V(x)$ can reach $V(x) \equiv 0$ in a fixed time T_r, where:

$$T_{rmax} = \frac{1}{c(1-p)} ln(1 + \frac{c}{a}) + \frac{1}{c(q-1)} ln\left(1 + \frac{c}{b}\right) \quad (3)$$

4 FIXED-TIME OBSERVER DESIGN

An observer to estimate the unknown specific growth rate μ(S) and the whole state vector are introduced. For the observer design, the system (1) can be rewritten as:

$$\begin{cases} \dot{X} &= \mu(S)X - DX \\ \dot{S} &= -k_1\mu(S)X + D(S_i - S) \\ \dot{\mu} &= \rho(S) \\ y &= X \end{cases} \quad (4)$$

The following proposition is introduced:

Proposition 1 Under Assumptions 1 to 4 and based on Theorem 1, the dynamical system given by:

$$\begin{cases} \dot{\hat{X}} = \hat{\mu}\hat{X} - D\hat{X} + \alpha_1|\tilde{X}| + \alpha_2|\tilde{X}|^{\frac{1}{2}} + \beta_1|\tilde{X}|^{\frac{3}{2}}tanh(\tilde{X}) \\ \dot{\hat{S}} = -k_1\hat{\mu}\hat{X} + DS_i - D\hat{S} + \beta_2|\tilde{X}|^{\frac{3}{2}}tanh(\tilde{X}) \\ \dot{\hat{\mu}} = \alpha_3 + \beta_3|\tilde{X}|^{\frac{3}{2}}tanh(\tilde{X}) \end{cases} \quad (5)$$

(with α_i , $\beta_i (i = 1,2,3)$ to be selected later), is a fixed-time dynamic observer for the nonlinear system.

The hyperbolic tangent function changes gradually from a value of -1 to a value of 1. It can be used to represent a phenomenon of a gradual transition, "soft", between two states. On its domain of definition, "tanh" is holomorphic (therefore continuous and even infinitely differentiable.) Unlike the "sign" function which suddenly changes from the value -1 to the value 1, the "tanh" function allows a gradual transition that softens and decreases the transient effect of the signals.

Proof:

Let : $\tilde{X} = X - \hat{X}$, $\tilde{S} = S - \hat{S}$, and $\tilde{\mu} = \mu - \hat{\mu}$. Then we have :

$$\dot{\tilde{X}} = \tilde{\mu}X + (\hat{\mu} - D)\tilde{X} - \varphi_1(\tilde{X}) \tag{6}$$

$$\dot{\tilde{S}} = -k_1\tilde{\mu}X - k_1\hat{\mu}\tilde{X} - D\tilde{S} - \varphi_2(\tilde{X}) \tag{7}$$

$$\dot{\tilde{\mu}} = \rho(S) - \varphi_3(\tilde{X}) \tag{8}$$

with :

$$\varphi_1(\tilde{X}) = \alpha_1|\tilde{X}| + \alpha_2|\tilde{X}|^{\frac{1}{2}} + \beta_1|\tilde{X}|^{\frac{3}{2}}tanh(\tilde{X}) \tag{9}$$

$$\varphi_2(\tilde{X}) = \beta_2|\tilde{X}|^{\frac{3}{2}}tanh(\tilde{X}) \tag{10}$$

$$\varphi_3(\tilde{X}) = \alpha_3 + \beta_3|\tilde{X}|^{\frac{3}{2}}tanh(\tilde{X}) \tag{11}$$

To analyze the closed-loop stability, we introduce the Lyapunov function:

$$V = \frac{1}{2}(\tilde{X}^2 + \tilde{S}^2 + \tilde{\mu}^2) \tag{12}$$

Differentiating V

$$\dot{V} = \tilde{X}\dot{\tilde{X}} + \tilde{S}\dot{\tilde{S}} + \tilde{\mu}\dot{\tilde{\mu}} \tag{13}$$

$$\dot{V} = \tilde{X}\left(\tilde{\mu}X + (\hat{\mu} - D)\tilde{X} - \varphi_1(\tilde{X})\right) + \tilde{\mu}\left(\rho(S) - \varphi_3(\tilde{X})\right) + \tilde{S}\left(-k_1\tilde{\mu}X - k_1\hat{\mu}\tilde{X} - D\tilde{S} - \varphi_2(\tilde{X})\right) \tag{14}$$

$$\dot{V} = (\hat{\mu} - D)\tilde{X}^2 + \tilde{X}\tilde{\mu}X - D\tilde{S}^2 - k_1\tilde{\mu}X\tilde{S} - k_1\hat{\mu}\tilde{X}\tilde{S} + \tilde{\mu}\rho(S) - \varphi_1(\tilde{X})\tilde{X} - \varphi_2(\tilde{X})\tilde{S} - \varphi_3(\tilde{X})\tilde{\mu} \tag{15}$$

By using the assumptions (4), equation (15) becomes

$$\dot{V} \leq (\hat{\mu} - D)\tilde{X}^2 + \tilde{X}\tilde{\mu}X - D\tilde{S}^2 - k_1\tilde{\mu}X\tilde{S} - \varphi_1(\tilde{X})\tilde{X} - \left(k_1\hat{\mu}\tilde{X} + \varphi_2(\tilde{X})\right)\tilde{S} + \left(\bar{\rho} - \varphi_3(\tilde{X})\right)\tilde{\mu} \tag{16}$$

$$\dot{V} \leq -\tilde{\xi}^T\Gamma\tilde{\xi} - \tilde{\xi}^T\Phi(\tilde{X}) \tag{17}$$

with :

$$\tilde{\xi} = [\tilde{X} \quad \tilde{S} \quad \tilde{\mu}]^T \tag{18}$$

$$\Gamma = \begin{bmatrix} (\alpha_1 + D - \hat{\mu}) & k_1\hat{\mu} & -X \\ \varphi_2(\tilde{X}) & D & k_1X \\ -\bar{\rho} + \varphi_3(\tilde{X}) & 0 & 0 \end{bmatrix} \tag{19}$$

and

$$\Phi(\tilde{X}) = \begin{bmatrix} \alpha_2|\tilde{X}|^{\frac{1}{2}} \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} \beta_1|\tilde{X}|^{\frac{3}{2}}tanh(\tilde{X}) \\ 0 \\ 0 \end{bmatrix} \tag{20}$$

$$\dot{V} \leq -\lambda_{min}^{\Gamma} \parallel \tilde{\xi} \parallel^2 - \alpha_2 \parallel \tilde{\xi} \parallel - \beta_1 \parallel \tilde{\xi} \parallel^{\frac{5}{2}} \tag{21}$$

$$\dot{V} \leq -\lambda_{min}^{\Gamma}V - \alpha_2V^{\frac{1}{2}} - \beta_1V^{\frac{3}{2}} \tag{22}$$

Based on Theorem 1, the estimation error is converged to zero in fixed-time T_r :

$$T_{rmax} = \frac{2}{\lambda_{min}^{\Gamma}}ln(1 + \frac{\lambda_{min}^{\Gamma}}{\alpha_2}) + \frac{2}{\lambda_{min}^{\Gamma}}ln(1 + \frac{\lambda_{min}^{\Gamma}}{\beta_1}) \tag{23}$$

Choosing gains $\alpha_1, \alpha_3, \beta_2, and\beta_3$ in the design of the observer ensures positive definite matrix Γ.

This completes the proof of Proposition.

5 SIMULATION RESULTS

Numerical simulations for the closed-loop system show the effectiveness of the proposed scheme. There are many different models for $\mu(S)$ proposed in the literature. As a matter of example, the Monod model $\mu(S) = \frac{\mu_m S}{S+k_s}$ is often used ($\mu_m > 0$ is the maximum growth rate and k_s is the kinetic parameter).

The model and design parameters and the initial states used in the simulation are given in Table 1.

Table 1. Model and design parameters, and initial states used for the simulation

Model parameters	value	Initial conditions	states value
k_s	$0.2g/l$	$X(0)$	$4.75g/l$
S_i	$10g/l$	$S(0)$	$0.5g/l$
μ_m	$1h^{-}1$	$\mu(0)$	$0.75h^{-}1$
k_1	2	$\hat{X}(0)$	$1.5g/l$
		$\hat{S}(0)$	$0.6g/l$
		$\hat{\mu}(0)$	$0.1h^{-}1$

Figures 1-3 display the transient observer performances. It is shown that the observer reconstructs the process state variables (biomass and substrate concentration) as well as the unknown parameter (specific growth rate (S)) with a quick rate of the convergence. Also, the estimated states converge well in a limited and fixed amount of time (less than the theoretical time ‘‘five hours’’).

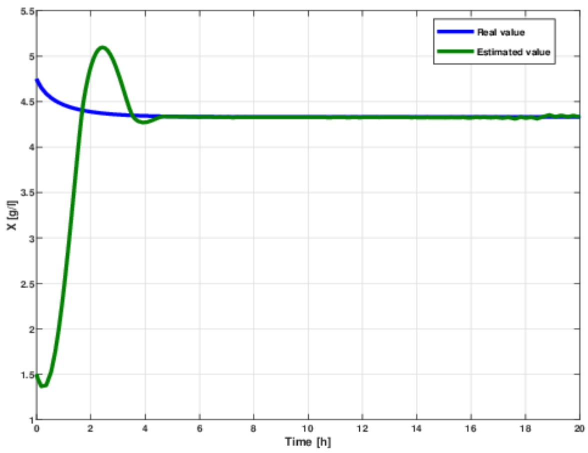

Figure 2. Actual and estimated biomass concentration.

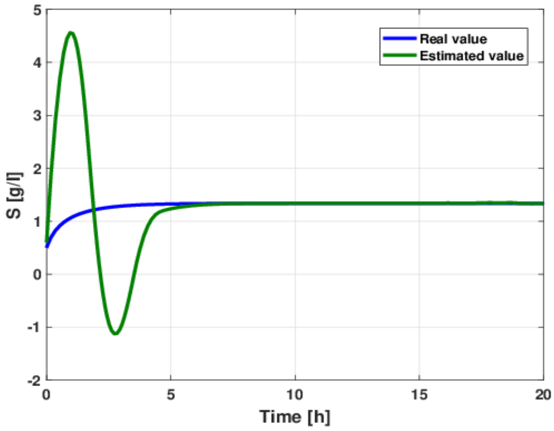

Figure 3. Actual and estimated substrate concentration.

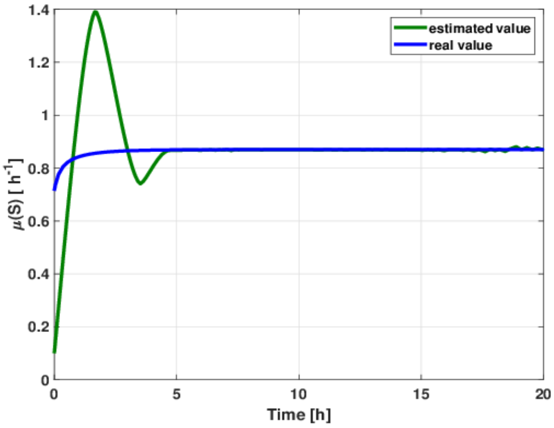

Figure 4. Actual and estimated specific growth rate μ(S).

Observation of the robustness of the proposed observer in the presence of the model uncertainty shows that the major advantage of the variable structure observers and controllers is that they can be made considerably more robust to reject load disturbances and parametric uncertainties. For this purpose, the load disturbance of 20% in the inlet substrate concentration is considered in Figure 4. Simulation results are given in Figures 5-7. The performance is not greatly reduced since the controller effectively rejects the load disturbance.

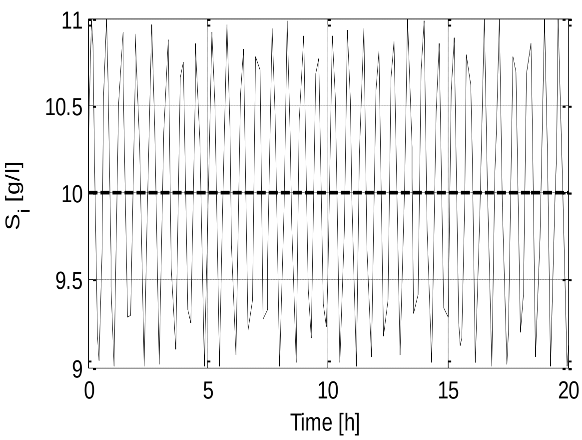

Figure 5. Load disturbance in the inlet substrate concentration.

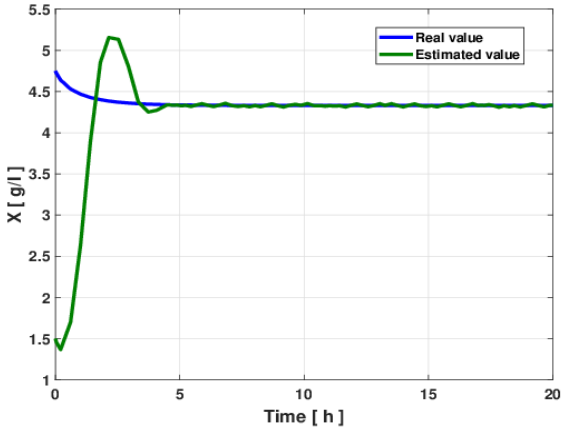

Figure 6. Actual and estimated biomass concentration in the presence of a load disturbance.

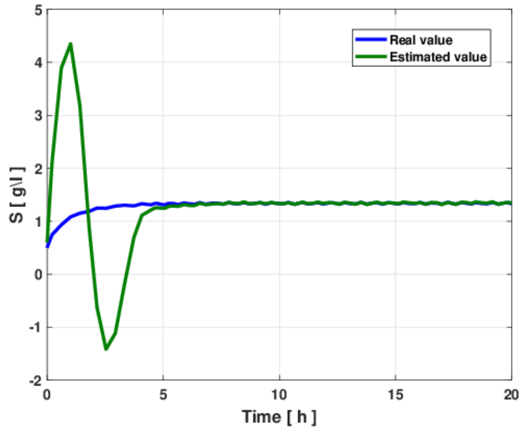

Figure 7. Actual and estimated substrate concentration in the presence of a load disturbance.

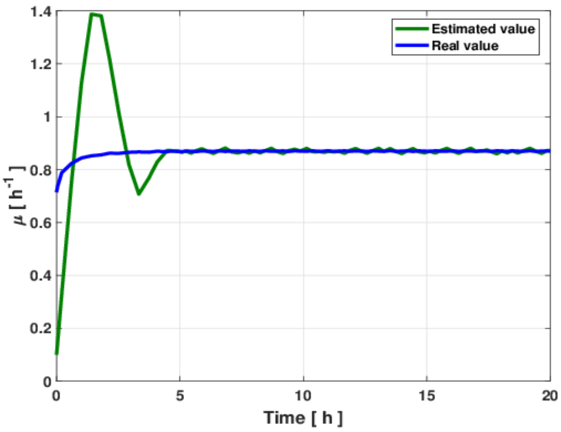

Figure 8. Actual and estimated specific growth rate μ(S) in the presence of a load disturbance.

Figures 1-7 show the three state vectors and their estimate. The figures show the ability of the proposed observer to estimate the states accurately and to cope quite well with a large deviation of the noise.

The results show the high performance of the proposed observer in the CSTR reaction process.

6 CONCLUSION

The paper presents a fixed-time observer for a continuous stirred tank bioreactor with an unknown growth rate. The estimation is made on the bases of a fixed-time convergence observer-based sliding mode technique that robustly guesses the values of the unknown growth rate and the whole state vector from biomass concentration measurements. It is shown that the Fixed Time Observer for a specific growth rate and substrate concentration is effective in estimating the parameters even in the presence of disturbances in the bioreactor system. The observer is robust against the effects of perturbations, and the upper bound of the convergence time is fixed and is determined by the control parameters regardless of the initial conditions. The simulation results show the efficiency of the observer in terms of the convergence speed and robustness against disturbances and uncertainties. The performance does not significantly degrade because the controller can well reject the load disturbance. The numerical simulations illustrate the performance and robustness as well as the feasibility of the designed observer system.

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