# Hydrogen sensor fault detection in a dark fermenter based on an interval observer and adaptive thresholds

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**Abstract:** In this paper, we propose an interval observer-based fault detection strategy for a hydrogen production bioreactor in occurrence of sensor faults. Based on the dark fermenter model in presence of disturbances, we design a robust interval observer to: (i) estimate the glucose and biomass concentrations from hydrogen flow rate measurements, (ii) attenuate the influence of a disturbance, and (iii) detect the occurrence of the sensor faults by adaptive thresholds. The features of the proposed observer are assessed by numerical simulations.

*Keywords:* Fault detection, adaptive thresholds, interval observer, biohydrogen production.

## 1. INTERVAL OBSERVER-BASED SENSOR FAULT DETECTION STRATEGY

Dark fermentation is a complex hydrogen production process, it involves crucial state variables that can be estimated by state observers (software sensors). Nevertheless, kinds of malfunctions or imperfect behaviors may appear during the normal operation of the sensors used to measure the system output. They can be detected by means of different methods of fault detection.

In this paper, we consider the interval observer structure, reported in (Meslem et al., 2020), for a class of linear systems in presence of perturbations. The interval observer provides the upper and lower bounds for the trajectory of the dark fermenter state. Furthermore, we present a sensor fault detection scheme considering the adaptive thresholds for the output signal.

### *1.1 Interval observer*

In this section we consider the 3-order linear model proposed in (Torres and Avilés, 2021) that satisfies the following Assumptions.

*Assumption 1.* The pair $(A,\, C)$ is detectable.

*Assumption 2.* We know the upper and lower bounds $\left(\overline{x}^{+}\left(t_0\right),\ \overline{x}^{-}\left(t_0\right)\right)$ for the initial condition, satisfying the following inequality

$$\overline{x}^{+}\ (t_0)\ \succeq\ \overline{x}\,(t_0)\ \succeq\ \overline{x}^{-}\ (t_0)\,, \tag{1}$$

and the disturbance $\overline{w}\,(t)$ is also bounded in the following way,

$$\overline{w}^{+}\,(t)\ \succeq\ \overline{w}\,(t)\ \succeq\ \overline{w}^{-}\,(t)\,, \qquad \forall t\geq 0, \tag{2}$$

where $\overline{w}^{+}\,(t)$ and $\overline{w}^{-}\,(t)$ are known bounded.

Based on the formulation in (Meslem et al., 2020), we firstly consider the linear observer with the Luenberger structure for the dark fermenter linear model presented in (Torres and Avilés, 2021), described as follows

$$\Upsilon_{\mathrm{O}_1}:\begin{cases}\dot{\xi}(t)=A\xi(t)+B_u\bar{u}(t)+L(\bar{y}(t)-\hat{\bar{y}}(t)),\\ \hat{\bar{y}}(t)=C\xi(t),\end{cases} \tag{3}$$

where $\xi\,(t)$ represents the estimate of the real state vector $\overline{x}\,(t)$ and the matrix $L$ requires to be selected to ensure the stability property of the observer. If we define the estimation error as $e\,(t)\triangleq\overline{x}\,(t)-\xi\,(t)$, we get the estimation error dynamics in the fault-free case $f_s\,(t)\,=\,0$, which are given by the following equations

$$\Upsilon_{\mathrm{E}}:\begin{cases}\dot{e}(t)=A_Le(t)\,+\,B_w\overline{w}(t)\,,\\ y_e(t)=I_3e(t),\ e\,(t_0)\,=\,e_0,\end{cases} \tag{4}$$

where $\overline{w}\,(t)$ represents the bounded unknown signals and the matrix $A_L\,=\,A-LC$. $I_3$ is the identity matrix of dimensions $3\times 3$. The estimation error behavior can be analyzed using the solution of the linear system $\Upsilon_{\mathrm{E}}$, expressed as follows

$$e(t)=\Phi\,(t,\,t_0)\,e(t_0)\,+\,\sigma\,(t)\,, \tag{5}$$

where

$$\sigma\,(t)=\int_{t_0}^{t}\Phi\,(t,\,\tau)\,B_w\overline{w}(\tau)\,d\tau, \tag{6}$$

with $\Phi\,(t,\,t_0)\,=\,\exp\left(A_L(t-t_0)\right)$ is the state transition matrix of the system $\Upsilon_{\mathrm{E}}$ in (4).

Secondly, the observer (3) in $\Upsilon_{\mathrm{O}_1}$ is combined with the interval predictor, which is given by the following equations

$$\Upsilon_{\mathrm{O}_2}:\begin{cases}\dot{\sigma}^{+}(t)=\Phi^{+}\,(t,\,t_0)\left(B_w^{+}\overline{w}^{+}-B_w^{-}\overline{w}^{-}\right)-\\ \qquad\Phi^{-}\,(t,\,t_0)\left(B_w^{+}\overline{w}^{-}-B_w^{-}\overline{w}^{+}\right),\\ \dot{\sigma}^{-}(t)=\Phi^{+}\,(t,\,t_0)\left(B_w^{+}\overline{w}^{-}-B_w^{-}\overline{w}^{+}\right)-\\ \qquad\Phi^{-}\,(t,\,t_0)\left(B_w^{+}\overline{w}^{+}-B_w^{-}\overline{w}^{-}\right),\end{cases} \tag{7}$$

$$\Upsilon_{O_3}: \begin{cases} \overline{x}^{+}(t) = \xi(t) + \Phi^{+}(t, t_0)\, e^{+}(t_0) + \\ \qquad\qquad \sigma^{+}(t) - \Phi^{-}(t, t_0)\, e^{-}(t_0), \\ \overline{x}^{-}(t) = \xi(t) + \Phi^{+}(t, t_0)\, e^{-}(t_0) + \\ \qquad\qquad \sigma^{-}(t) - \Phi^{-}(t, t_0)\, e^{+}(t_0), \end{cases} \tag{8}$$

where $\overline{x}^{+}(t)$ and $\overline{x}^{-}(t)$ stand for the upper and lower bounds of the state $\overline{x}(t)$. The matrices $B_w^{+}$ and $B_w^{-}$ in (7) comprise the positive decomposition of the matrix $B_w$. $(\Phi^{+}(t, t_0), \Phi^{-}(t, t_0))$ and $(\sigma^{+}(t), \sigma^{-}(t))$ are the positive decompositions of $\Phi(t, t_0)$ and $\sigma(t)$, respectively. Additionally, $e^{+}(t_0) = \overline{x}^{+}(t_0) - \xi(t_0)$ and $e^{-}(t_0) = \overline{x}^{-}(t_0) - \xi(t_0)$ are upper and lower bounds, positive representations, of the initial estimation error $e(t_0)$.

We design the interval observer gain $L$, under fault-free conditions $f_s(t) = 0$, to guarantee that the estimation error $e(t)$ converges to a neighborhood of the origin even if the dark fermenter is in presence of the perturbation $\overline{w}(t)$, as proposed in (Torres and Avilés, 2021).

### *1.2 Adaptive thresholds strategy*

We consider the sensor fault detection using a scheme of adaptive thresholds for the output signal, stated as follows

$$\Upsilon_{\text{Test}}: \begin{cases} \overline{y}(t) \in [\overline{y}^{-}(t),\ \overline{y}^{+}(t)], & \text{if} \quad f_s(t) = 0, \\ \overline{y}(t) \notin [\overline{y}^{-}(t),\ \overline{y}^{+}(t)], & \text{if} \quad f_s(t) \neq 0, \end{cases} \tag{9}$$

where $\overline{y}^{-} = C\overline{x}^{-}$ and $\overline{y}^{+} = C\overline{x}^{+}$. Thus, the plant is fault free when the output signal is inside the set, limited by the adaptive thresholds (the upper and lower estimates), while a fault is indicated in the plant when the output is outside the set, $[\overline{y}^{-}(t), \overline{y}^{+}(t)]$.

## 2. RESULTS AND DISCUSSION

Simulations of the biohydrogen production process and the Luenberger observer $\Upsilon_{O_1}$ combined with the interval predictor $(\Upsilon_{O_2}, \Upsilon_{O_3})$ have been performed in Matlab for the inputs $Q_{in}$ and $Glu_{in}$ used in (Torres and Avilés, 2021).

We set the following conditions for simulations on the dark fermenter in order to analyze the sensor fault detection strategy proposed. The first one considers the case with a noise variation up to $1\%$ on the hydrogen flow rate sensor during the time period from the beginning of the simulations to day 15, from day 25 to day 35, from day 40 to day 50, and from day 60 to the end of the simulations. This condition corresponds to the sensor fault-free condition. Moreover, we take a noise variation of $10\%$ on the measured variable during the time-period from day 15 to day 25 and from day 50 to day 60, while from day 30 to day 40 an offset of $25\%$ is added to the measured output. These last conditions correspond to sensor fault conditions.

Figure 1a shows the glucose concentration in the dark fermenter, Figure 1b shows the biomass concentration in the dark fermenter, while Figure 1c shows the produced hydrogen flow rate. In green lines the bioreactor simulations, in dashed red line the estimation by the Luenberger observer, and in blue line the lower and the upper estimations by the interval predictor. The behavior of the interval observer is shown in the three figures, where the upper and lower estimations preserve the partial ordering with respect of the trajectories of the bioreactor state when there is no occurrence of faults $f_s = 0$, taking an adequate initialization, and reducing the influence of the unknown inlet glucose concentration. In particular, if there is the presence of sensor faults $f_s \neq 0$, the trajectories of the outputs are outside the interval set given by the lower and upper estimations $\overline{y}(t) \notin [\overline{y}^{-}(t),\ \overline{y}^{+}(t)]$. This fact validates the adaptive thresholds strategy to detect sensor faults.

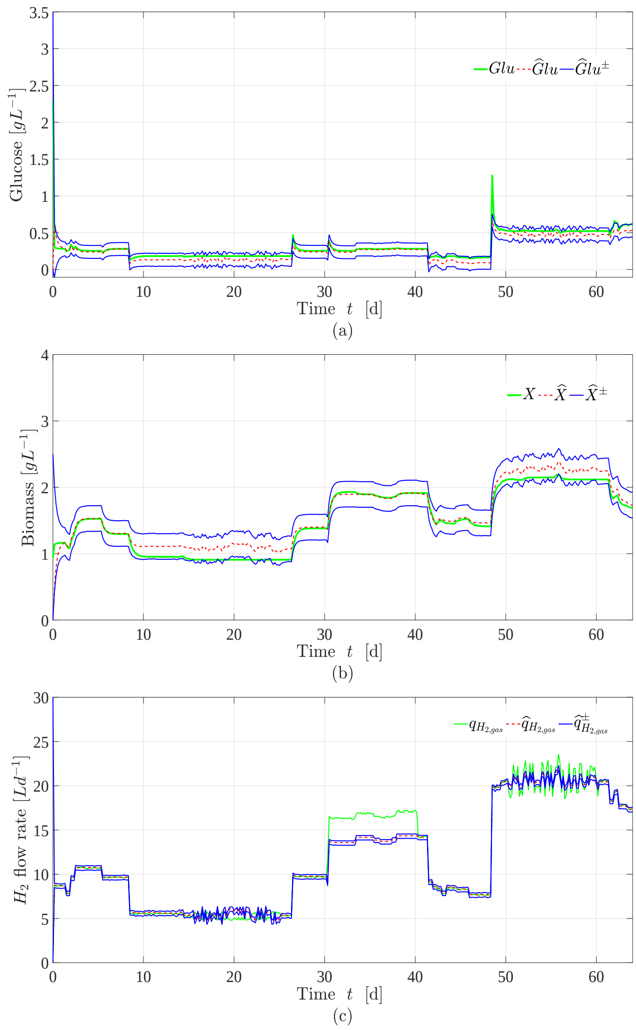


Fig. 1. Biohydrogen production dark fermenter estimations. In green line the bioreactor data, in dotted red line the estimation by the Luenberger observer, and their lower and upper estimations in blue lines. (a) Glucose. (b) Biomass. (c) Hydrogen flow rate.

## 3. CONCLUSIONS

In this paper, an interval observer to detect sensor faults in a hydrogen production bioreactor was presented. The simulation results validated the effectiveness of the proposed method. Besides, its performance guaranteed robustness against measurement noise and the exogenous disturbance.


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