III. BIOAUTOMATICS AND BIOINFORMATICS

EXTREMUM SEEKING BASED COMPOSED RECURSIVE MODEL FREE CONTROL OF TWO-STAGE ANAEROBIC DIGESTION PROCESS

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Abstract. In this paper, a new structure of extremum seeking algorithm is applied to the two-stage anaerobic digestion process to maximize the outflow rate of both hydrogen and methane. The model of the two-stage AD process is presented, which provides the characteristics of the total gas production rate. Based on the original Extremum Seeking Control (ESC), a novel Composed Recursive Model Free Controller (CRMFC) is added for maximum tracking for the gas production in the bioreactors. The proposed controller comprises a recursive model free stabilization term and a recursive time delay compensation term. Standard ESC, Newton-based ESC and Kalman filter (KF) based ESC are respectively combined with the new model-free controller to verify the proposed structure. Numerical simulations illustrate the performance of the proposed controller.

Keywords: two-stage anaerobic digestion, extremum seeking control, composed recursive control

1. INTRODUCTION

Anaerobic digestion (AD) processes are of increasing interest as they are able to produce biogas while treating biodegradable organic waste [Deublein and Steinhauser, 2008]. These processes ensure green energy production, as well as organic waste treatment and environmental protection [Leano and Babe, 2011; Berni et al.,2014; Denchev et al.,2016].

Organic waste, especially lignocellulose is an agricultural waste material with considerable biohydrogen and biomethane potential. Main components of lignocellulose materials are cellulose, hemicellulose and lignin. But complex structure of lignocellulose increase the resistance to anaerobic biodegradation, which leads to the low experimental methane yield compared to theoretical biogas yield [Wickramaarachchi et al., 2019]. Various studies were conducted to enhance the biogas production, such as pretreatment, leachate re-circulation and anaerobic co-digestion [Bisi et al., 2017; Garcia et al., 2015; Nouceiba et al., 2017].

The application of two-stage anaerobic digestion process (TSAD) has been proposed as a promising technology for better process performance and higher energy yields, which consists of hydrogenic process followed by methanogenic process. The resulted overall energy recovery is significantly higher for the TSAD system, as compared to the traditional one-stage CH_4 production process [Pakarinen et al, 2011]. The sub-processes organic matter hydrolysis and its fermentation to organic acids are physically separated from the methane production process in the two-stage AD process. Fast growing acidogens and hydrogen producing microorganisms are developed in the first-stage hydrogenic bioreactor and are involved in the production of VFA and H_2. On the other hand, the slow growing acetogens and methanogens are developed in second-stage methanogenic bioreactor, in which the produced VFA are further converted to CH_4 and CO_2 [Xing and Zhao, 2009].

To increase process efficiency and to maintain optimal conditions, a real-time optimizing control is indispensable in the AD process. Extremum seeking control (ESC) is a well performing method of adaptive feedback control that aims at driving the system to optimal operating conditions corresponding to the extremum of a measurable convex objective function [Krstich and Wang, 2000]. After decades of development, more efficient ES algorithms have been developed, such as sliding mode ESC [Yu and Ozguner, 2003], multivariable Newton-based ESC [Azad et al., 2012], proportional-integral ESC [Guay, 2016], input-output correlation ESC [Salsbury et al., 2017] and fast ESC [Ramirez et al., 2018].

These algorithms can be considered as a useful, practical, and easy-to-implement solution to optimize bioprocesses as long as operating conditions, dithers and controlled variables are carefully selected with respect to system dynamics. However, the classical ES scheme suffers from the time-scale separation between the process and the perturbation signal with respect to the dynamics. Applications with large time constants and long transient phases are more problematic, as is the case for bioprocesses. Undesirable time scale separation will lead to slow convergence of the output.

To overcome the drawbacks of the slow convergence, we integrate ESC with composed recursive model free controller (CRMFC) for output trajectory and disturbance compensation of the two-stage AD process.

doi.org/10.32006/eeep.2022.1.4555

Similar to ESC, CRMFC uses only the output measurement, and is composed of a recursive model free stabilization (RMFS) term and a recursive time delay compensation (TDC) term. The RMFS term is a recursive model free controller based on the theory of Piecewise-Continuous Systems (PCS) which are a special class of hybrid systems with autonomous switching and controlled impulse [Wang et al., 2010]. Then, the TDC term is used to directly compensate the plant unknown dynamics and disturbances employing past observations of the system output response and control inputs. In 2011, CRMFC has been proposed for trajectory tracking of a methane fermentation process in stirred tank bioreactors [Wang et al., 2011]. Then it has been successfully applied to a nonlinear five-order one-stage AD process model [Wang et al., 2013].

The paper is outlined as follows. First, the mathematical modeling of the TSAD process for both hydrogen and methane production is stated and some basic results of the maximum value are reviewed. Then, the Extremum seeking based composed recursive model-free controller is proposed. In Section 4, the proposed optimization strategy is applied into TSAD process with different ESC algorithms and numerical performance is evaluated. Finally, some conclusions about the results are given.

2. PROCESS DESCRIPTION

The application of a TSAD process for simultaneous H_2 and CH_4 production has been proposed as a promising technology for better process performance and higher energy yields as compared to the traditional one-stage CH_4 production process. In the TSAD system, relatively fast growing acidogens and H_2 producing microorganisms are developed in the first-stage hydrogenic bioreactor (BR1 with working volume V1) and are involved in the production of volatile fatty acids (VFA) and H_2. On the other hand, the slow growing acetogens and methanogens are developed in the second-stage methanogenic bioreactor (BR2 with working volume V2) in which the produced VFA are further converted to CH_4 and CO_2 [Borisov et al., 2020]. The scheme of two-stage AD process is shown on Fig. 1.

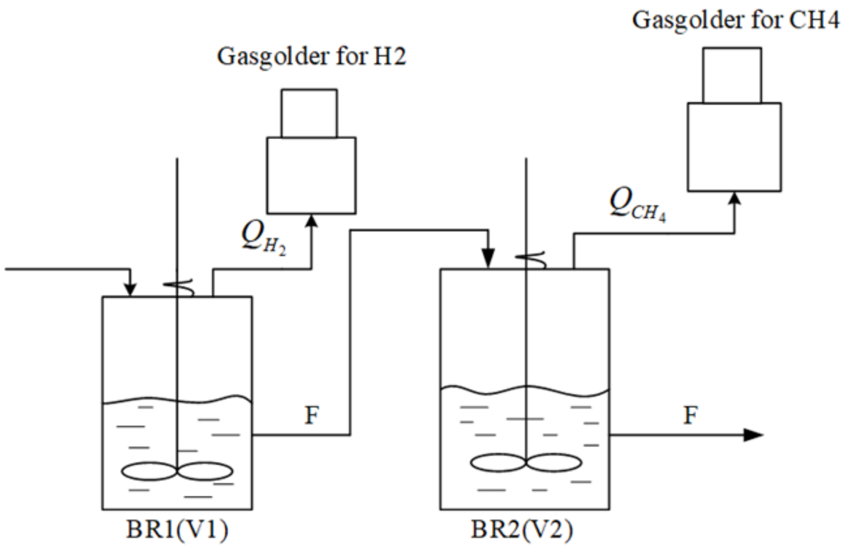

Fig. 1. Scheme of TSAD process for hydrogen and methane production

Assume that the volumes V_1 and V_2 of the bioreactors are constant. Let F_1 and F_2 be the inflows in the first and second bioreactor respectively and let $F_1 = F_2 = F$ be valid. It is well known that the dilution rates D1 and D2 are defined as:

$$D_1 = \frac{F}{V_1}, D_2 = \frac{F}{V_2} \tag{1}$$

Then it can be obtained:

$$\gamma = \frac{V_2}{V_1} = \frac{D_1}{D_2} \tag{2}$$

It is known that the volume V_2 of the second bioreactor for methane production is larger than the volume V_1 of the first bioreactor. Therefore, $\gamma < 1$ should be valid.

It is known that more than 95 % of the working industrial biogas plants operate with the so called continuously stirred thank reactors (CSTRs). In the TSAD process the energy yields are up to 43% more, as compared to the traditional one-stage CH_4 production process [Schievano et al., 2014].

On the basis of the experimental investigations, the following mathematical model of two-stage AD process is proposed [Chorukova and Simeonov, 2020]. The dynamics in BR1 for hydrogen production is described by the following set of nonlinear ordinary differential equations:

$$\frac{dS_0}{dt} = -D_1 S_0 - \beta X_1 S_0 + D_1 Y_P S_0^{in} \quad (3)$$

$$\frac{dS_1}{dt} = -D_1 S_1 + \beta X_1 S_0 - \frac{\mu_1 X_1}{Y_1} \quad (4)$$

$$\frac{dX_1}{dt} = \mu_1 X_1 - D X_1 \quad (5)$$

$$\frac{d\,\mathrm{Pr}_1}{dt} = \frac{\mu_1 X_1}{Y_{\mathrm{Pr}1}} - D_1 \mathrm{Pr}_1 \quad (6)$$

$$\frac{dBut_1}{dt} = \frac{\mu_1 X_1}{Y_{But1}} - D_1 But_1 \quad (7)$$

$$\frac{dAc_1}{dt} = \frac{\mu_1 X_1}{Y_{Ac1}} - D_1 Ac_1 \quad (8)$$

$$Q_{H_2} = Y_{H_2} \mu_1 X_1 \quad (9)$$

Equation (3) and (4) present the balance of the effluent substrate (S_0) - for example cellulose and its transformation into cellobiose (S_1) after hydrolysis. Equation (5) describes the dynamics of the biomass concentration (X_1). Equation (6) - (8) reflect the dynamics of the intermediate products formation - acetate (Ac_1), propionate (Pr_1) and (butyrate But_1). And the algebraic equation (9) presents the flow rate of the hydrogen in the gas phase in BR1. All concentrations in the paper are mass concentrations, not molar concentrations.

For the specific growth rate of the biomass a Monod type function was adopted:

$$\mu_1 = \frac{\mu_{1\max} S_1}{k_{S1} + S_1} \quad (10)$$

A balance model of methane production in the BR2 is adopted consisting of a set of the following equations:

$$\frac{dX_{\mathrm{Pr}}}{dt} = \mu_{\mathrm{Pr}} X_{\mathrm{Pr}} - D_2 X_{\mathrm{Pr}} \quad (11)$$

$$\frac{dX_{But}}{dt} = \mu_{But} X_{But} - D_2 X_{But} \quad (12)$$

$$\frac{dX_{Ac}}{dt} = \mu_{Ac} X_{Ac} - D_2 X_{Ac} \quad (13)$$

$$\frac{d\,\mathrm{Pr}_2}{dt} = -\frac{\mu_{\mathrm{Pr}} X_{\mathrm{Pr}}}{Y_{\mathrm{Pr}2}} + D_2 (\mathrm{Pr}_1 - \mathrm{Pr}_2) \quad (14)$$

$$\frac{dBut_2}{dt} = -\frac{\mu_{But} X_{But}}{Y_{But2}} + D_2 (But_1 - But_2) \quad (15)$$

$$\frac{dAc_2}{dt} = -\frac{\mu_{Ac} X_{Ac}}{Y_{Ac2}} + \frac{\mu_{\mathrm{Pr}} X_{\mathrm{Pr}}}{Y_{\mathrm{Pr}2}} + \frac{\mu_{But} X_{But}}{Y_{But2}} + D_2 (Ac_1 - Ac_2) \quad (16)$$

$$Q_{CH_4} = Y_{CH_4} \mu_{Ac} X_{Ac} \quad (17)$$

Equation (11) describes the dynamics of the propionate degrading population with concentration X_{Pr} , equation (12) - the dynamics of the butyrate degrading population with concentration X_{But} , equation (13) – the dynamics of the methanogenic population X_{Ac} . Equations (14), (15) and (16) present the balances of the corresponding substrates (propionate, butyrate and acetate) with concentrations Pr_2 , But_2 and Ac_2 . The equation (17) reflects the flow rate of the methane in the gas phase of BR2. The specific growth rates of all populations are described as Monod type functions as follows.

$$\mu_{\mathrm{Pr}} = \frac{\mu_{\mathrm{Pr}\max} \mathrm{Pr}_2}{k_{SPr} + \mathrm{Pr}_2} \quad (18)$$

$$\mu_{But} = \frac{\mu_{But\max} But_2}{k_{SBut} + But_2} \quad (19)$$

$$\mu_{Ac} = \frac{\mu_{Ac\max} Ac_2}{k_{SAc} + Ac_2} \quad (20)$$

All the parameters are given in Table 1 [Simeonov et al., 2016]. The volume ratio γ are considered as the constant when analysing the static characteristics.

Nullifying the right hand parts of the equations of the model and after some transformations, using Symbolic toolbox of Matlab, the input-output static characteristic maps (they have the same forms for both bioreactors) of the gas production rates are presented in Fig.2.

From the picture it is evident that the static characteristic of the gas flow *Q = Q(D)* presents a unique extremum (maximum) point, which provides possibility for optimal control. More details are shown in references [Borisov et al.,2020; Chorukova et al., 2021].

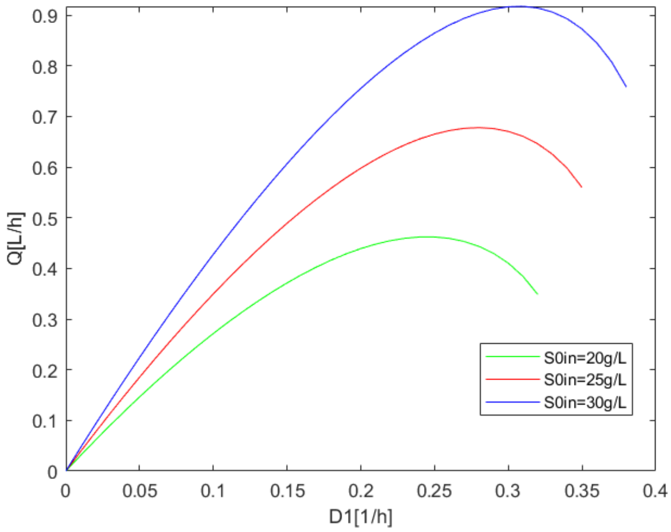

Fig. 2. Static characteristic $Q(D)$ for different values of S_0^{in} in TSAD process.

Table 1: Model parameter value

Notation	Definition of the model parameters	Value
β	coefficient of biodegradability (-)	1
Y_p	coefficient (-)	2
Y_1	yield coefficient for acidogenic bacteria(-)	0.08
$\mu_{1\max}$	maximum specific growth rate of acidogenic bacteria (h^{-1})	0.568
k_{S1}	saturation coefficient of acidogenic bacteria (g/L)	3.914
$Y_{\mathrm{Pr}1}$	yield coefficient for propionate(-)	4.2
Y_{But1}	yield coefficient for butyrate(-)	2.1
Y_{Ac1}	yield coefficient for acetate(-)	1.1
Y_{H_2}	yield coefficient for hydrogen(L/g)	0.22
$Y_{\mathrm{Pr}2}$	yield coefficient for propionate(-)	1.5
Y_{But2}	yield coefficient for butyrate(-)	1.5
Y_{Ac2}	yield coefficient for acetate(-)	0.5
Y_{CH_4}	yield coefficient for methane(L/g)	142
$\mu_{\mathrm{Pr}\max}$	maximum specific growth rate of propionate degrading bacteria(h^{-1})	0.05
k_{SPr}	saturation coefficient of propionate (g/L)	0.22
$\mu_{But\max}$	maximum specific growth rate of butyrate degrading bacteria(h^{-1})	0.05
k_{SBut}	saturation coefficient of butyrate (g/L)	0.22
$\mu_{Ac\max}$	maximum specific growth rate of methanogenic bacteria(h^{-1})	0.025
k_{SAc}	saturation coefficient of acetate (g/L)	0.8

3. EXTREMUM-SEEKING-BASED COMPOSED RECURSIVE MODEL-FREE CONTROL

In this section, a data-driven model free disturbance rejection control is designed to ensure the stable tracking of the optimal value. Composed Recursive Model-free Controller (CRMFC), combined with extremum seeking control, is used for output trajectory tracking and disturbance compensation of the two-stage AD system.

3.1 Overview of Extremum Seeking Control

This section briefly reviews the basic theory of the standard ESC, Newton-based ESC and KF based ESC.

3.1.1. Standard ESC

Consider the nonlinear dynamic system:

$$\begin{cases} \dot{x} = f(x,u) \\ y = h(x) \end{cases} \quad (21)$$

where $x \in R^n, u \in R$ and $y \in R$ are the system state, input and output, and $f : R^n \times R \to R^n$ $h : R^n \to R^n$ are smooth functions.

Suppose that there exists a smooth control law:

$$u = \alpha(x,\theta) \quad (22)$$

parameterized by a scalar parameter θ, for which the closed-loop system has a unique equilibrium. The input-output static function $y = f(\theta)$ of the system has an extremum point (θ^*, y^*), where y^* is the maximum value of the system output. We can select the dilution rate as θ.

The objective of ESC is to search for the input to achieve real-time extremum of a performance index for a nonlinear and possibly slowly time-varying system. It relies on the existence of a measurable and convex objective function but does not require prior knowledge about the process model. One of the earlier forms of model-free ESC is the Standard ESC which is shown in Fig. 3.

The principle of Standard ESC is to estimate the gradient of the objective function and to force this estimate to zero. It is described by the following equations [Krstich and Wang, 2000]:

$$\begin{aligned} \theta &= \hat{\theta} + aS(t) \\ \dot{\hat{\theta}} &= k\hat{b} \\ \dot{\hat{b}} &= -w_l\hat{b} + w_l(y-\eta)S(t) \\ \dot{\eta} &= -w_h\eta + w_h y \end{aligned} \quad (23)$$

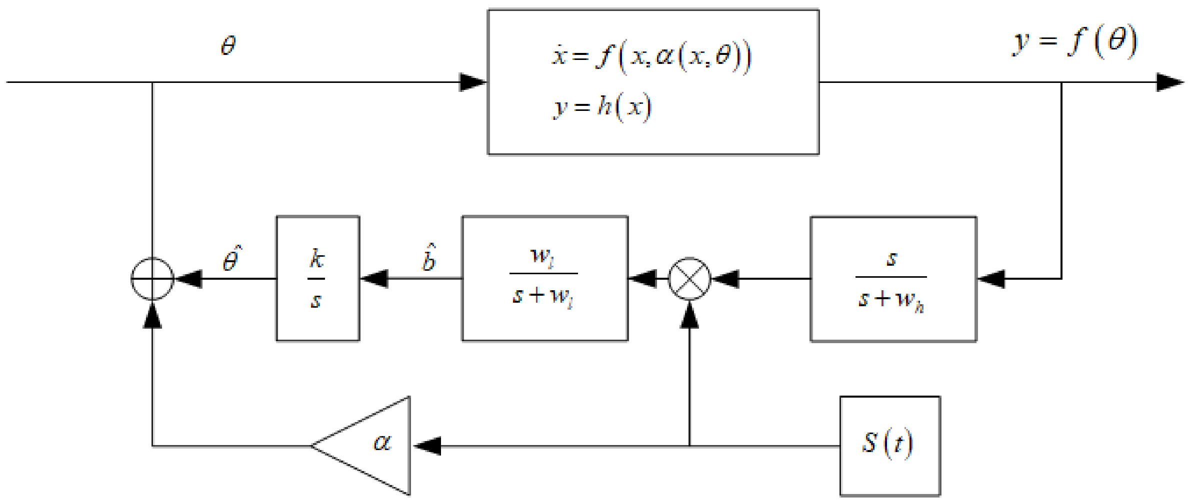

Fig. 3. Structure of standard ESC.

where $\hat{\theta}$ is the estimated input; $S(t)$ is the dither signal, which is set to a sinusoidal signal in this method, $S(t) = a\sin(wt)$; $y-\eta$ is the high-pass filtered output; $\hat{b}$ is the gradient estimation, obtained by the output of an optional low-pass filter, whose input is the demodulated signal resulting from the multiplication of $y-\eta$ by dither signal.

3.1.2. Newton-Based ESC

Unlike the standard ESC, Newton-based ESC includes Hessian estimation and its matrix inversion into the gradient-based ESC loop so as to achieve an effective gain adaptation, and thus make the convergence rate adjustable [Azadet al., 2012].

The elements of the signal $N(t) \in R$ for generating the estimate $\hat{H}$ of the Hessian matrix H are given by:

$$N(t) = -\frac{8}{a^2}\cos(2wt) \qquad (24)$$

The inverse of the Hessian estimation is obtained by solving the Riccati equation:

$$\dot{\Gamma} = w_r\Gamma - w_r\hat{H}\Gamma^2 \qquad (25)$$

This equation has two equilibria: $\Gamma_1^* = 0$ and $\Gamma_2^* = H^{-1}$. The Riccati equation solution $\Gamma(t)$ can thus asymptotically converge to the actual value of the inverse of the Hessian estimate, avoiding inversions that may cross zero during the transient phase.

Besides the plant input is perturbed by dither signal $S(t)$ and the demodulation signal for the gradient information $M(t)$ is defined as

$$S(t) = a\sin(wt)$$
$$M(t) = \frac{2}{a}\sin(wt) \qquad (26)$$

The structure of the Newton-based ESC [Mu et al., 2015] for dynamic systems is shown in Fig. 4.

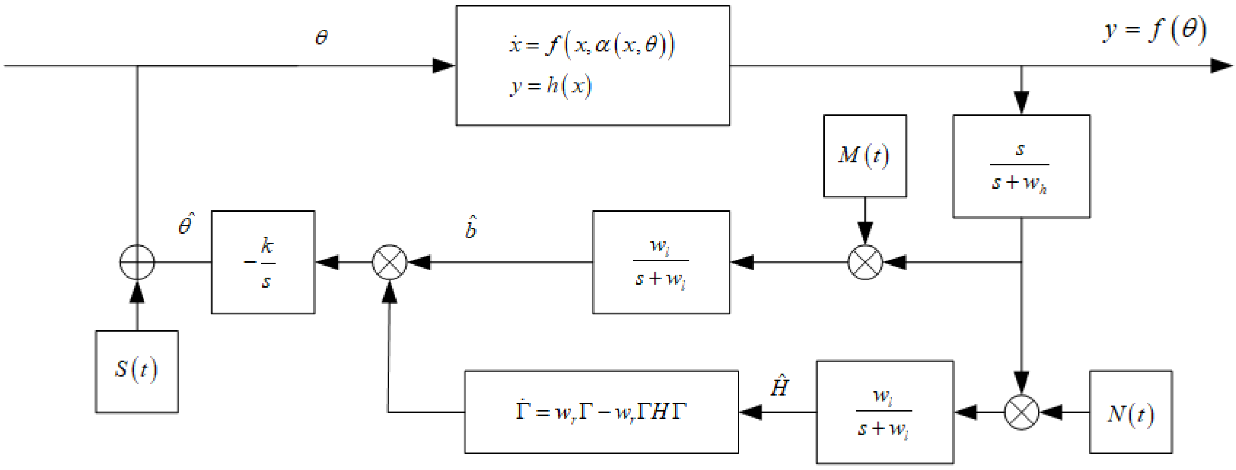

Fig.4. Structure of Newton-based ESC

3.1.3. KF-Based ESC

In this ESC, a Kalman filter is used to replace the classical filter based estimator used in the standard ESC scheme. The use of KF makes possible to obtain faster and more accurate gradient estimation, which can speed up the convergence of the algorithm [Mandi and MiKovi, 2015; Wang et al., 2020]. The structure of the KF-based ESC is shown inFig.5.

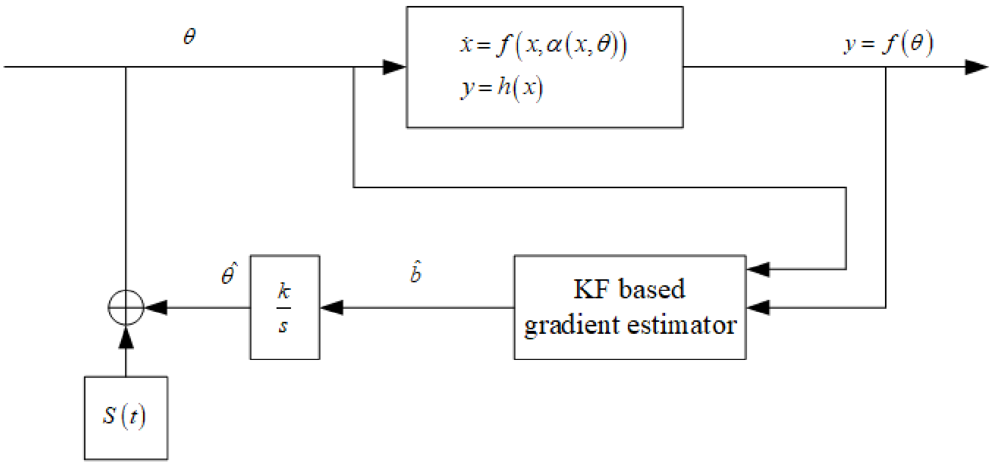

Fig. 5. Structure of KF-based ESC

3.2 Extremum Seeking Based Composed Recursive Model-Free Control

This section describes the novel extremum seeking based composed recursive model free controller (ESCRMFC). The nonlinear model of the two-stage AD processes is not explicitly used in the controller design in the proposed ESCRMFC algorithm. This approach can efficiently reduce the effect of the input disturbance and improve the speed of convergence.

The CRMFC consists of recursive model free stabilization (RMFS) and time delay compensation (TDC) terms, and generates the bioreactor control input D:

$$D(t)=\frac{1}{G}\left(D_c(t)+D_s(t)\right) \qquad (27)$$

where $D_c(t)$ is the TDC term output to compensate unknown system nonlinearities, $D_s(t)$ is the RMFS term output enabling system stabilization, and G is a positive constant.

The compensation control term $D_c(t)$ is determined as:

$$D_c(t) = \dot{Q}_r(t) - P(t-\varepsilon) \qquad (28)$$

Define the kinetic equation

$$\dot{Q}(t) = f(x,t) + g(x,t)D(t) \qquad (29)$$

The term $P(t-\varepsilon)$ is the estimation of

$$P(t) = \dot{Q}(t) - GD(t) \qquad (30)$$

For $\varepsilon \to 0$

$$P(t) \simeq P(t-\varepsilon) = \dot{Q}(t-\varepsilon) - GD(t-\varepsilon) \qquad (31)$$

The optimal dilution rate trajectory $D_{esc}(t)$ generated by ESC block is transformed into the reference trajectory $Q_r(t)$ by using the reference model $M(s)$, and the desired performances of the closed loop are imposed. The choice of $M(s)$ is made based only on the identification using the available input-output data without involving this model in the synthesis procedure. The identification is done considering a fourth order linear model which is a simple presentation of the two-stage AD process. Following the reference [Barbu et al., 2021], the transfer function of the reference model $M(s)$ is chosen as:

$$M(s) \simeq \frac{1}{(0.4s+1)^2} \qquad (32)$$

In turn, $D_s(t)$ is the RMFS control term output, which is computed as

$$\begin{aligned}\lambda(t^+) &= |e(t)|e(t)+\xi(t)\lambda(t)\\ D_s(t) &= C_c\lambda(t)\end{aligned} \qquad (33)$$

where $\lambda(t)$ is the RMFS term state, $e(t)=Q_r(t)-Q(t)$ is the output trajectory error, $Q_r(t)$ is the desired trajectory which is the output of the reference model $M(s)$, C_c is the gain of RMFS output, and $\xi(t)$ is the tracking coefficient. To obtain $e(t)\to 0$, the value of $\xi(t)$ is tuned as

$$\xi(t)=\exp\left(\frac{-e(t)^2}{2\sigma^2}\right) 0<\sigma\le 1 \qquad (34)$$

The structure of the proposed ESCRMFC for dynamic systems is shown in Fig. 6

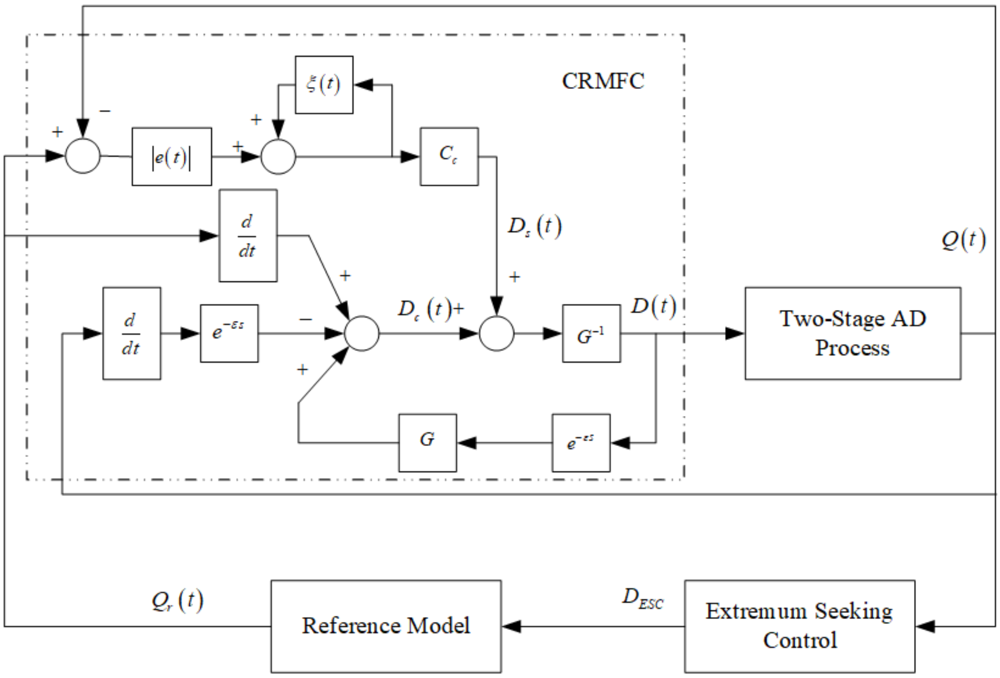

Fig. 6. Structure of ESCRMFC

4. Numerical Results

To test the effectiveness of the ESCRMFC, three types of ES algorithms are used in the proposed ESCRMFC structure: Standard ESC (SESC), Newton-based ESC (NESC) and KF-based ESC (KFESC) respectively. The numerical simulations are realized for initial dilution rate $D_1(0)=0.01h^{-1}$ and inlet organics concentration $S_0^{in}=25g/L$. The performances of the proposed controller have been compared with the performances of the sliding mode ESC (SMESC) [Pan et al., 2003]. The parameters of the controller are selected as $G=1$, $\sigma=0.12$, $C_c=0.2$, $\varepsilon=0.1$. The output trajectory results for SESCRMFC, NESCRMFC and KFESCRMFC are shown in Fig. 7-9.

It can be seen that compared with SMESC, all the proposed methods can get a better convergence performance The combination with CRMFC and ESC algorithms ensures a faster time convergence rate. This structure can be also applicable for some modified ESC methods to increase the convergence rates.

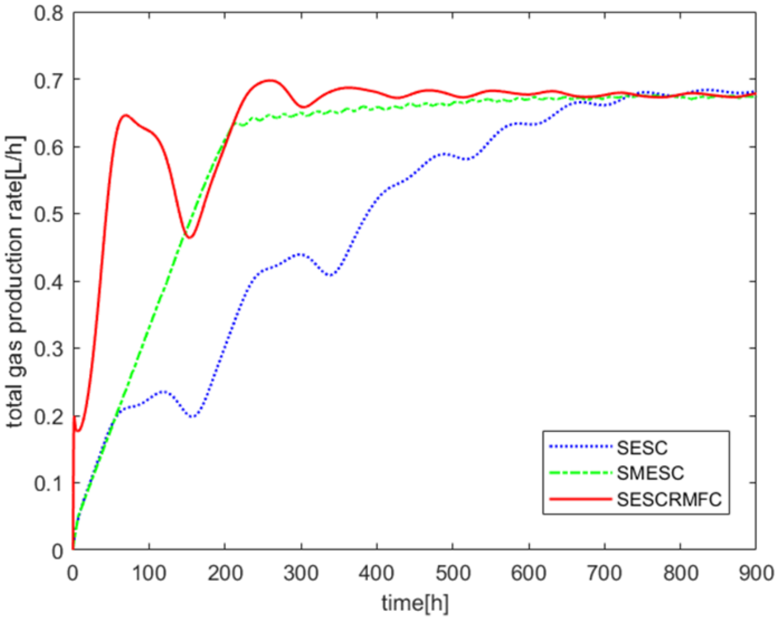

Fig.7. Gas production rate Q using SESCRMFC

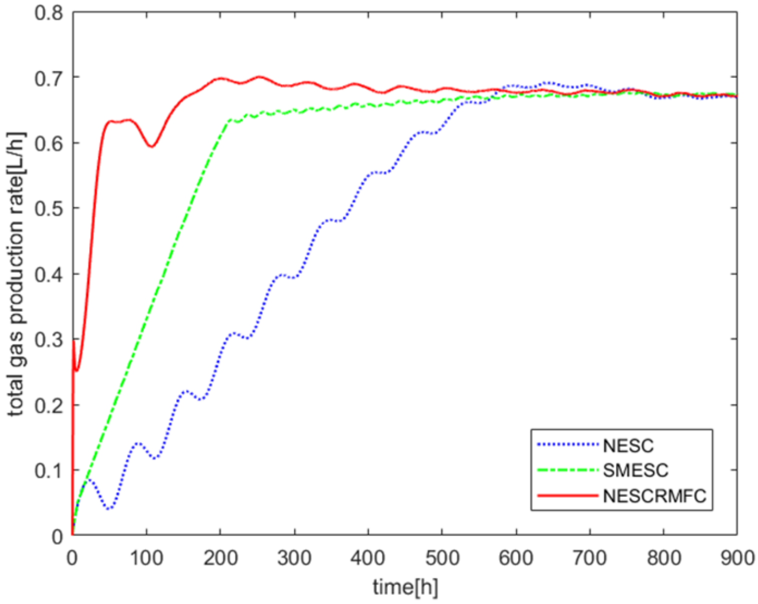

Fig.8. Gas production rate Q using NESCRMFC

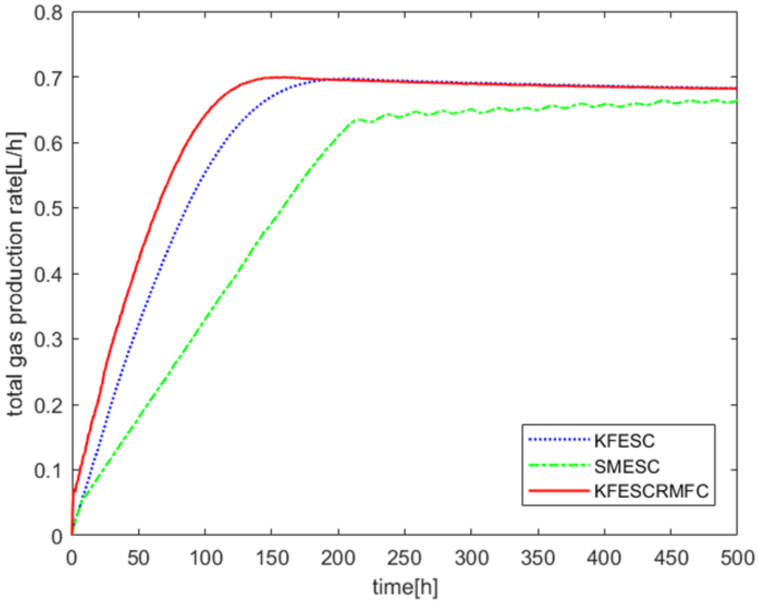

Fig.9. Gas production rate Q using KFESCRMFC

5. CONCLUSION

An extremum seeking based composed recursive model-free controller has been proposed for the TSAD process which can produce simultaneously both hydrogen and methane. In order to achieve maximum total gases production rates, the proposed controller comprises extremum seeking controller, recursive stabilization and time delay compensation terms and does not require any knowledge of the model parameters. Three different extremum seeking algorithms are tested to verify the universality of the proposed control framework. The performances of the proposed extremum seeking control are studied by numerical simulations and compared with those of original ESC and sliding mode ESC. The obtained results show the higher performances of the new controller.

Further studies of the authors are related with optimization of the control structure to reduce steady-state oscillation and parameter identification.

ACKNOWLEDGEMENTS: *This work is partially supported by the Intergovernmental international science and technology innovation cooperation key project of National Key R & D Program of China 2021YFE0102700, and by the Bulgarian National Science Fund under contract No KP-06-IP-CHINA/3.*

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