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Synergetic control of cascade-configured anaerobic digestion bioreactors for enhanced hydrogen production

Control sinérgetico de biorreactores de digestión anaeróbica configurados en cascada para la producción mejorada de hidrógeno

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Abstract

This work introduces, for the first time, a synergetic control law within a cascade control structure tailored to the dynamics of anaerobic bioreactors for hydrogen generation. This novel integration addresses the challenges of biological system nonlinearities, input saturation, and stability under disturbance, offering a promising alternative to traditional PID-based strategies.

To assess the effectiveness of the proposed approach, simulation studies were conducted in the Matlab/Simulink environment using a validated dynamic model from the literature. A comparative analysis with a classical PID controller optimized via genetic algorithms (GA-PID) was also carried out. The proposed synergetic controller achieved the desired hydrogen outflow rate within 1.1 hours, representing a 78.4 % improvement in response time compared to the GA-PID controller (5.1 hours).

Furthermore, the synergetic controller maintained closed-loop stability under input saturation (D_1), effectively handled external disturbances and sensor noise, and provided consistent tracking performance without biomass washout. These results demonstrate the superior precision, robustness, and convergence speed of the proposed method in regulating hydrogen production under realistic constraints.

Keywords: Cascade bioreactors, Synergetic control, Non linear control, Hydrogen, Methane, Waste recycling.

Resumen

Este trabajo presenta, por primera vez, una ley de control sinergetico integrada dentro de una estructura de control en cascada, adaptada a la dinamica de biorreactores anaerobios para la generacion de hidrogeno. Esta novedosa integracion aborda los desafios inherentes a la no linealidad de los sistemas biologicos, la saturacion de entrada y la estabilidad frente a perturbaciones, constituyendo una alternativa prometedora frente a las estrategias tradicionales basadas en controladores PID.

Para evaluar la eficacia del enfoque propuesto, se realizaron estudios de simulacion en el entorno Matlab/Simulink utilizando un modelo dinamico validado disponible en la literatura. Asimismo, se llevo a cabo un analisis comparativo con un controlador PID clasico optimizado mediante algoritmos geneticos (GA-PID). El controlador sinergetico propuesto alcanzo el caudal de salida de hidrogeno deseado en un tiempo de 1.1 horas, lo que representa una mejora del 78.4% en el tiempo de respuesta en comparacion con el controlador GA-PID (5.1 horas).

Ademas, el controlador sinergetico mantuvo la estabilidad en lazo cerrado bajo condiciones de saturacion de entrada (D_1), gestiono eficazmente perturbaciones externas y ruido en los sensores, y garantizo un seguimiento preciso sin provocar el lavado de biomasa. Estos resultados evidencian la superior precision, robustez y velocidad de convergencia del metodo propuesto en la regulacion de la produccion de hidrogeno bajo restricciones realistas.

Palabras clave: Biorreactores en cascada, control sinérgico, control no lineal, hidrógeno, metano, reciclaje de residuos.

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1 Introduction

Anaerobic digestion (AD) is a fundamental process to recycle industrial and domestic agricultural waste. The production of energy in the absence of oxygen will allow to valorize them by ensuring their disintegration. Initially, waste recycling focused solely on methane production, but later it was realized that hydrogen (H_2) could also be produced by combining two bioreactors. With a configuration of two bioreactors arranged in cascade, hydrogen can be obtained from the first bioreactor, in addition to methane from the second. The cascade structure allows for a clear separation between the fast and slow dynamics, enabling independent tuning and improved stability (Braguglia *et al*., 2018; Kuang *et al*., 2020). In such cascade systems, a two-stage configuration is typically employed, consisting of separate reactors for hydrogen and methane production, often implemented as two continuous stirred-tank reactors (CSTRs) (Dareioti and Kornaros, 2014; Li and Li, 2019; Borisov *et al*., 2016; Chorukova *et al*., 2021; Borisov *et al*., 2020; Prapinagsorn *et al*., 2018; Arumugam *et al*., 2015).

Hydrogen is one of the most environmentally friendly energy sources, and its energy density per unit of mass is 2.5 times higher than that of fossil fuels (Khan *et al*., 2016). Among various clean alternative energy resources, hydrogen was considered a potential future energy source to replace the progressive depletion of fossil fuels. Hydrogen energy produces more energy than hydrocarbon energy. It plays a key role in the decarbonization of future energy systems, with strong potential as a clean energy carrier, especially in heating and power generation sectors (Ameli *et al*., 2024). Researchers have devoted significant efforts to advancing hydrogen production technologies. For instance, R. García-Amador et al. (2019) assessed the feasibility of bioelectrohydrogen production using microbial electrolysis cells fed with hydrolysate from agave bagasse, demonstrating its potential as a sustainable substrate for renewable energy generation. Additionally, Buitrón *et al*. (2022) demonstrated that key efficiency parameters, such as current density and cathodic efficiency, are strongly correlated with hydrogen production from volatile fatty acids in microbial electrolysis cells. Therefore, biological processes are being identified as a promising technology for hydrogen production (Abdallah *et al*., 2016; Li and Li, 2019; Borisov *et al*., 2020).

Control is crucial for achieving the desired efficiency in the treatment process of AD plants (Serrano-Meza *et al*., 2020). In order to obtain a maximum yield of biogas and biofuels production, a range of control methods are dedicated to the AD process (Bayen and Gajardo, 2019; Simeonov and Queinnec, 2006; Petre *et al*., 2013; Chaabna and Semcheddine, 2025). Control linearization is frequently used as a stable feeding control strategy in anaerobic digestion. E. Petre *et al*. (2013) implemented robust adaptive linearizing controller to control the pollution level in anaerobic digestion process. Intelligent controllers, such as rule-based expert systems (Barnett and Andrews, 1992), fuzzy control (Ghanavati *et al*., 2021), and neural networks (Holubar *et al*., 2003), serve as effective instruments for stabilizing and regulating the anaerobic digestion process. These controllers eliminate the need for precise mathematical models of the anaerobic digestion process. However, their designs heavily depend on fuzzy rules or intricate neural networks, which can increase computational load. The Proportional–Integral–Derivative (PID) control serves as a straightforward and efficient technique for stabilizing the AD process (García-Diéguez *et al*., 2011). It is often implemented for temperature control (Maurya *et al*., 2024). However, PID controller is known for not being robust and might fail to handle the nonlinearities of complex biological systems. In the control of the AD systems, the dilution rate is commonly utilized as the control action (Antonelli *et al*., 2003). Taking into account the practical operation and the need to prevent the decay of microorganisms, there are always minimum and maximum limits to the dilution rate. Therefore, it is both valuable and necessary to develop a controller that operates within these limits (Grognard and Bernard, 2006). Kolesnikov and coauthors in 2000, have developed a nonlinear control method known as synergetic control, which is a recent technique in which the system's nonlinear component is not compensated, but synthesized based on a system model that forces the system to slide onto a manifold. This method is beneficial for reducing the order of the system. It uses a generalized state-space averaged model to maintain stability, even when there are changes in parameters and disturbances (Santi *et al*., 2004). The synergetic control naturally mitigates the impact of nonlinearities, and uncertainties as well (Hagh *et al*., 2021; Belmouhoub *et al*., 2023). This control approach has been effectively utilized in constant power loads such as converters with constant power load (Santi *et al*., 2004), etc.

This work presents a novel application of synergetic nonlinear control approach to perform the hydrogen outflow rate control. The synergetic control shares robustness characteristics with Sliding Mode Control (SMC), yet it successfully eliminates the issue of chattering (Gao *et al*., 2021; Santi *et al*., 2004). This law requires knowledge of the system model in order to solve a tracking problem (Bouchareb *et al*., 2019). It can be implemented for practical use as it is mentioned in Dong *et al*. (2022) for perspective. The novelty of this work resides in the application of a synergetic approach to control hydrogen production for the first time to date. The proposed approach is

further compared to the classical PID controller. The parameters of the PID were meticulously determined and fine-tuned utilizing the heuristic optimization technique known as Genetic Algorithm (GA). The comparison showed that the proposed approach is more effective in term of robustness and noise rejection.
This paper is organized as follows: an overview of the process is briefly outlined, which is then followed by a concise section on synergetic control. The development of the corresponding control law of a biogas plant is then established. The simulation results are presented and discussed in the following sections. Finally a conclusion and perspectives are presented whose can be developed later.

2 Process model

The Cascade AD system is a promising method to solve some energy problems and recycle organic waste. Production of hydrogen via AD is recently one of the most interesting research topics for different reasons. A nonlinear model expresses the biotechnological process, which is characterized by a two-stage reaction. Various mathematical models for cascade AD have been proposed in the specialized literature (Borisov *et al.*, 2020; Blumensaat and Keller, 2005).
The model adopted in this study was originally proposed in (Chorukova *et al.*, 2021). Hydrogen production takes place in the first bioreactor (BR1) and methane production progress in the second bioreactor (BR2).

The dynamics of a cascade AD system are demonstrated by the following system of first-order differential equations:
BR1:

$$\frac{dS_0}{dt} = -D_1 S_0 - \beta X_1 S_0 + D_1 Y_p S_0^{in} \tag{1}$$

$$\frac{dS_1}{dt} = -D_1 S_1 + \beta X_1 S_0 - \frac{1}{Y_1}\mu_1 X_1 \tag{2}$$

$$\frac{dX_1}{dt} = \mu_1 X_1 - D_1 X_1 \tag{3}$$

$$\frac{dA_{c_1}}{dt} = \frac{1}{Y_2}\mu_1 X_1 - D_1 A_{c_1} \tag{4}$$

$$Q_{H_2} = Y_{H_2}\mu_1 X_1 \tag{5}$$

$$\mu_1 = \frac{\mu_{1max} S_1}{k_{s1} + S_1} \tag{6}$$

BR2:

$$\frac{dX_2}{dt} = \mu_2 X_2 - D_2 X_2 \tag{7}$$

$$\frac{dA_{c_2}}{dt} = -\frac{1}{Y_3}\mu_2 X_2 + D_2(A_{c_1} - A_{c_2}) \tag{8}$$

$$Q_{CH_4} = Y_{CH_4}\mu_2 X_2 \tag{9}$$

$$\mu_2 = \frac{\mu_{2max} A_{c_2}}{k_{s_2} + A_{c_2}} \tag{10}$$

Where the model variables are:

- D_1: Dilution rate for BR1 [h^{-1}];
- D_2: Dilution rate for BR2 [h^{-1}];
- Q_{H_2}: Hydrogen outflow rate [L/h];
- Q_{ch_4}: Methane outflow rate [L/h];
- S_0: Cellulose concentration [g/L];
- S_1: Cellobiose substrate concentration [g/L];
- X_1: Acidogenic bacteria concentration [g/L];
- X_2: Methanogenic bacteria concentration [g/L];
- S_0^{in}: Inlet cellulose concentration in BR1 [g/L];
- A_{c_1}, A_{c_2}: Acetate concentration [g/L];
- μ_1: Specific growth rate for acidogenic bacteria [h^{-1}];
- μ_2: Specific growth rate for methanogenic bacteria [h^{-1}].

And the model parameters:

- μ_{1max}: Maximum specific growth rate for acidogenic bacteria [h^{-1}];
- μ_{2max}: Maximum specific growth rate for methanogenic bacteria [h^{-1}];
- k_{S1}: Saturation coefficient for acidogenic bacteria [g/L];
- k_{S2}:Saturation coefficient for acetogenic bacteria [g/L];
- β: Coefficient of biodegradability [L/(g.h)];
- Y_P: Coefficient [-];
- Y_1: Yield coefficient for acidogenic bacteria [-];
- Y_2: Yield coefficient for acetogenic bacteria [-];
- Y_3: Yield coefficient for methanogenic bacteria [-];
- Y_{H2}: Yield coefficient for hydrogen [L/g];
- Y_{CH4}: Yield coefficient for methane [L/g].

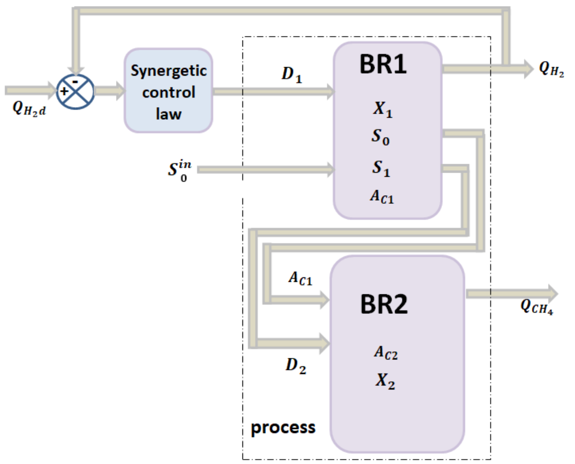

Figure 1. Two-phases process of AD with production of hydrogen and methane under synergetic control law.

3 Synergetic control law design

The concept of synergetic control theory was introduced by Russian researchers in a general manner in the early 2000 (Kolesnikovetal.,2000). The development of synergetic control starts with a judicious choice of macro-variable (Bouchareb *et al.*, 2019). Synergetic control outperforms classical PID by offering inherent robustness to uncertainties and disturbances, ensuring fast convergence with smooth transient responses, and providing a systematic, model-based design suited for complex nonlinear systems. Unlike PID, it guarantees global stability through Lyapunov-based formulations, eliminating the need for frequent gain adjustment.

In a cascade of two interconnected bioreactors, the simplest form of control involves regulating only the first bioreactor (BR1), which produces hydrogen. This control is necessary in the following two cases:

1. To manage disturbances in the influent (inlet organics) of BR1, such as variations in the inlet cellulose concentration, in order to maintain a consistent outflow rate of biohydrogen.

2. To maintain the production of hydrogen and biomethane at a set point level, as required in industrial biogas plants.

Figure 1 presents a cascade system to produce hydrogen and methane under the proposed approach to improve hydrogen production. The process under control appears as a system with two inputs and two outputs where the state vector is: $\begin{pmatrix} S_0 \\ S_1 \\ X_1 \\ A_{c1} \\ X_2 \\ A_{c2} \end{pmatrix}$. The input vector is $\begin{pmatrix} D_1 \\ S_0^{in} \end{pmatrix}$ and the output vector is $\begin{pmatrix} Q_{H_2} \\ Q_{CH_4} \end{pmatrix}$ where D_1 is the synergetic control law and D_2 is the input of the second bioreactor (BR2). D_2 evolves optimally based on A_{c1} following eq. 11 as demonstrated in Simeonov etal.(2018):

$$D_2 = \mu_{2max}(1 - \sqrt{\frac{k_{s_2}}{A_{c1} + k_{s_2}}}) \qquad (11)$$

The system at hand is a Multi Input Multi Output (MIMO). However, only one output is being controlled; The second is influenced by this control. The hydrogen outflow rate is controlled using D_1 to match practical material use. In this paper and for this process, one have a macro-variable defined by the error between the desired output and the real output of the bioreactor. The closed loop system stability under synergetic control was proven in Bouchareb *et al.*(2019).

For the first bioreactor, the macro-variable is given by Eq. 12:

$$\psi = Q_{H_{2d}} - Q_{H_2} \qquad (12)$$

Where $Q_{H_{2d}}$ is the desired hydrogen outflow rate. The macro-variable is then forced to evolve according to a chosen constraint imposing the desired dynamic behavior shown by Eq. 13:

$$T\dot{\psi} + \psi = 0, \; T > 0 \qquad (13)$$

T is the forced convergence speed factor. The desired hydrogen outflow rate being constant, its derivative is null $\dot{Q}_{H_{2d}}$. The derivative of Hydrogen outflow rate is given by Eq. 14 :

$$\dot{Q}_{H_2} = Y_{H_2}(\dot{\mu}_1 X_1 + \mu_1 \dot{X}_1) \qquad (14)$$

The derivative Maximum specific growth rate for acidogenic bacteria is given by Eq. 15:

$$\dot{\mu_1} = \frac{\mu_{1max} k_{s_1} \dot{S}_1}{(k_{s_1} + S_1)^2} \qquad (15)$$

Replacing in the chosen constraint Eq. 13, one gets Eq. 16:

$$-TY_{H_2}X_1 \left[\frac{\mu_{1max} k_{s_1} \dot{S}_1}{(k_{s_1} + S_1)^2} + \mu_1(\mu_1 - D_1) \right] + \psi = 0 \qquad (16)$$

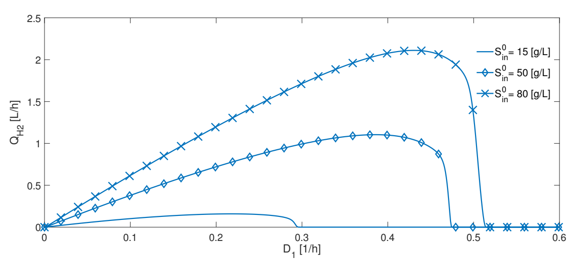

Figure 2. Analysis of the Input-Output response of BR1 Model.

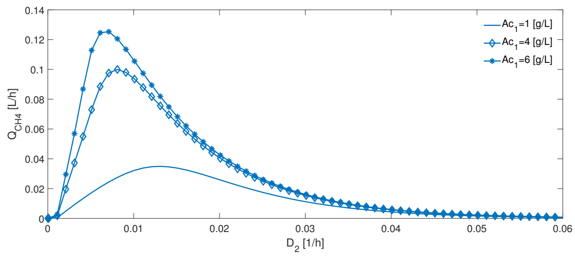

Figure 3. Analysis of the Input-Output response of BR2 Model.

Straightforward steps lead to the controller Eq. 17:

$$D_1 = \frac{k_{s_1}\mu_{1\max}X_1\left(\beta S_0 - \frac{1}{Y_1}\mu_1\right)}{k_{s_1}\mu_{1\max}S_1 + \mu_1(k_{S_1}+S_1)^2} + \frac{\left(\mu_1^2 - \frac{\psi}{X_1 T Y_{H_2}}\right)(k_{s_1}+S_1)^2}{k_{s_1}\mu_{1\max}S_1 + \mu_1(k_{s_1}+S_1)} \quad (17)$$

A major challenge in implementing this approach in real-world plants is the high cost or limited availability of sensors. As a result, unmeasured states can be estimated using software sensors derived from methane or hydrogen measurements (Sbarciog *et al.*, 2020).

4 Introduction of restrictions on the control

Since the practical applicability of the proposed approach is crucial, some static characteristics of both bioreactors need to be defined. Therefore, the authors in (Simeonov *et al.*, 2018) investigate the boundary values of the most important parameters: The boundary value of the dilution rate D_1^{wash} and the optimal value of the dilution rate D_1^{max}. The input-output static characteristic $Q_{H2} = Q_{H2}(D_1)$ for three values of S_0^{in} is shown on Figure 2. D_1^{wash} is approximately 0.28 d^{-1} for S_0^{in}= 15 g/L. If D_1 exceeds the value of 0.28, it leads to biomass washout and complete cessation of biogas production. The input-output static characteristic $Q_{CH4} = Q_{CH4}(D_2)$ for three values of A_{c1} is presented on Figure 3. These figures (2 and 3) were obtained in an open loop. As an optimization objective, it is then natural to consider the maximization of the biogas outflow rate in the first and second bioreactor.

5 Simulation results

The following values of the coefficients of the models in both bioreactors were adopted:

- $S_{\text{in}}^0 = 15$ (g/L);
- $\beta = 1 \left(\frac{\text{L}}{\text{g}\cdot\text{h}}\right)$;
- $Y_p = 1$;
- $Y_1 = 0.08$;
- $Y_2 = 1$;
- $Y_3 = 0.24$;
- $k_{s1} = 3.914$ (g/L);
- $k_{s2} = 0.22$ (g/L);
- $Y_{\text{CH}_4} = 18.7$;
- $Y_{\text{H}_2} = 1$;
- $\mu_{1\max} = 0.568$ (1/h);
- $\mu_{2\max} = 0.0083$ (1/h).

The initial conditions were used for simulations as follows:

- $S_0(0) = 0.11$ g/L;
- $S_1(0) = 1$ g/L;
- $X_1(0) = 0.3$ g/L;
- $X_2(0) = 0.9$ g/L;
- $Ac_1(0) = 0.4$ g/L;
- $Ac_2(0) = 0.7$ g/L.

The gains for the PID controller were optimized using a GA, with the Integral Time Absolute Error (ITAE) serving as the objective function: $k_p = 2.2; k_i = 0.31; k_d = 3.2$.

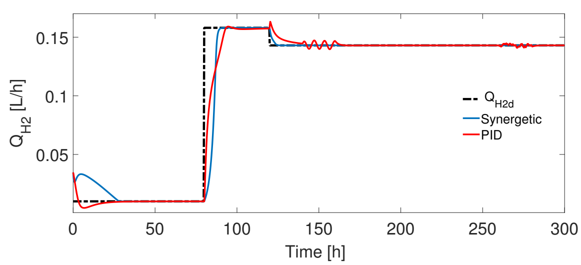

Figure 4. Dynamics of the hydrogen outflow rate Q_{H_2} (BR1) under synergetic and PID.

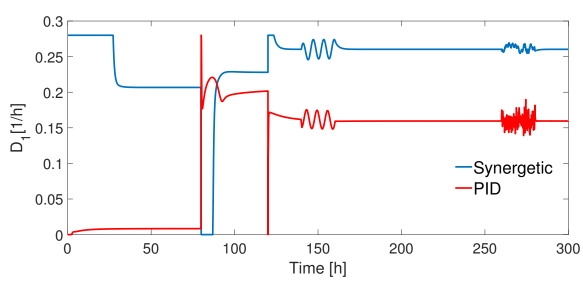

Figure 5. Evolution of the dilution rate (control input D_1) under synergetic and PID.

The GA settings were as follows: Population size: 50 individuals, Number of generations: 100, Selection method: roulette wheel, crossover type and rate: Single-point crossover with rate = 0.8, mutation rate: 0.05, stopping criterion: Maximum number of generations.

In order to evaluate the proposed control law, numerical simulation was carried out under Simulink environment using the block diagram in Figure 1 (ODE45 solver). The solver configuration is as follows: maximum step size: 10^{-2}, minimum step size: 10^{-3}, relative tolerance: 10^{-3}, absolute tolerance: 10^{-3}. The proposed control law is tested by injecting a perturbation between 140h and 160h and a gaussien noise between 260h and 280h in the input S_0^{in} ($S_0^{in} = 15g/L$). The performance of both controller is assessed using three performance indices: ITAE, Integral Squared Error (ISE), Integral Absolute Error (IAE), and the Root Mean Squared Error (RMSE).

- The ITAE is given by the formula :

$$ITAE = \int_0^t t|\psi(t)|dt \tag{18}$$

- The ISE is given by the formula :

$$ISE = \int_0^t \psi(t)^2 dt \tag{19}$$

  where t is the simulation time.

- and IAE is calculated as follows:

$$IAE = \int_0^t |\psi| dt \tag{20}$$

- The RMSE could be calculated as follows:

$$RMSE = \sqrt{\sum_{i=1}^{n} [(\psi_i)^2/n]} \tag{21}$$

  With n is the total number of samples.

The desired hydrogen outflow rate is shown in Eq. 22:

$$Q_{\text{H2 d}} = \begin{cases} 0.01 & 0 \leq t < 80 \\ 0.148 & 80 \leq t \leq 120 \\ 0.015 & 120 \leq t \leq 300 \end{cases} \tag{22}$$

Remark 1. The reaction is assumed to occur under isothermal conditions. Moreover, by assuming hydrogenotrophic methanogenesis as the main hydrogen sink, the conversion of hydrogen and CO_2 to acetate—known as homoacetogenesis—is excluded from the model. Nevertheless, in the experimental setup, homoacetogenesis and other key hydrogen-producing pathways (e.g., lactate-to-acetate) are present, which could significantly affect control performance. However, since the Synergetic controller is designed to be highly robust to uncertainties and nonlinearities, it should, in theory, be capable of mitigating the negative effects caused by these additional hydrogen pathways.

The Synergetic controller has an ITAE value of 74 L/h, while the PID controller has a higher ITAE value of 81.7 L/h. Therefore, the Synergetic controller is more effective at minimizing the product of the absolute error and time, which could indicate faster error correction over time. The ISE value for the Synergetic controller is 0.1 L/h, which is slightly higher than the PID controller's ISE value of 0.05 L/h. Hence, This indicates that the PID controller may be more effective at minimizing large errors, as ISE penalizes larger errors more heavily due to the squaring operation. Figure 4 depicts the dynamics of the output (Q_{H2}) under both controllers. It shows good tracking for both approaches. The convergence of the synergentic controller depends on the parameter T (Bouchareb *et al*., 2019). The lower T, the faster the convergence is. However, The proposed controller is very robust as it can handle disturbances in the range of 140h and 160h and injected noise of the Inlet cellulose concentration in BR1 between 260h and 280h without losing robustness, which makes it reliable. If the proposed approach is compared with the classical PID, the latter is not robust because the disturbance and the noise (S_0^{in}) appear on the output (Hydrogen outflow rate) as shown in Figure 4 and 5. This interprets the constraint in Eq. 13. The disturbance injected into the input S_0^{in} has been compensated for in the control signal D_1 by the synergetic controller, as shown in the input of the controller in Figure 5.

Table 1. Settling Time for Hydrogen Production in Different Phases of Digestion.

Phase	Synergetic	PID
Phase 1 [0h-80h[	27.5 h	24.6 h
Phase 2 [80h-120h[	8 h	11.4 h
Phase 3 [120h-300h]	1.1 h	5.1 h

Table 2. Comparative Analysis of ITAE, ISE and RMSE Performance Metrics for hydrogen production.

Performance index	Synergetic	PID	PG-ULMPC (He *et al.*,2023)
ITAE	74 L/h	81.7 L/h	-
IAE	1.232 L/h	0.9142 L/h	1.4412 L/h
ISE	0.1 L/h	0.05 L/h	0.2275 L/h
RMSE	7.87e-04 L/h	94 L/h	-

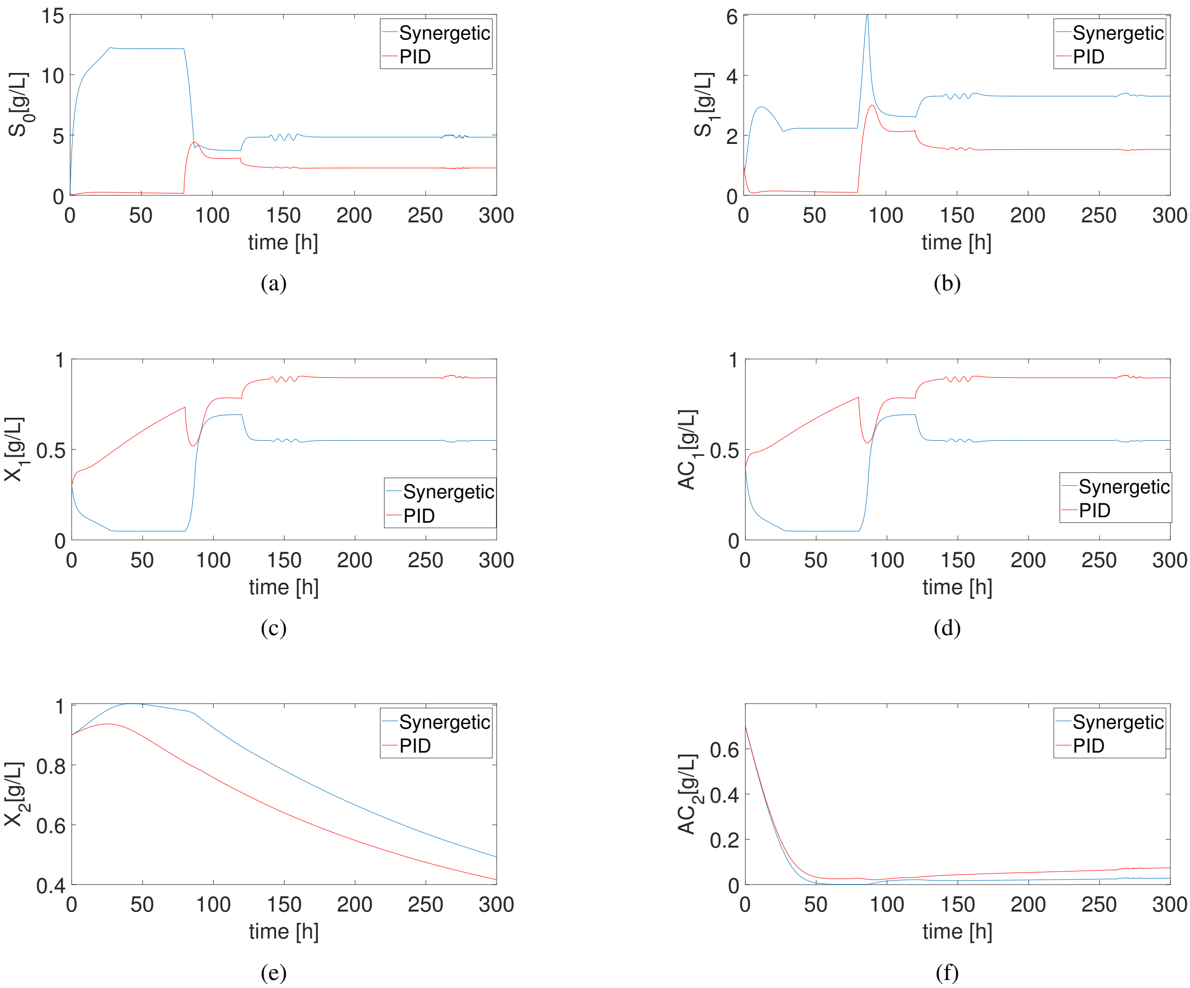

Figure 6. Different concentration of state variables: (a) S_0: Cellulose concentration [g/L], (b) S_1: Cellobiose substrate concentration [g/L], (c) X_1: Acidogenic bacteria concentration [g/L],(d): Ac_1 Acetate concentration [g/L],(e) X_2: Methanogenic bacteria concentration [g/L],(f) Ac_2 :Acetate concentration [g/L]

With this robust control system, the maximum amount of hydrogen Q_{H2} can be extracted, which is 0.16 Liters per day, while staying within the constraint of 0.28 per day for the dilution rate D_1. The results shown in Figure 4 and 5 are consistent with those in Figure 2 and 3, where the limits are well respected.

Figure 6 from a to f show a good evolution of the different concentrations whether with the PID or synergistic controllers. The concentrations always have positive values.

In Figures 6(a) and 6(b), under Synergetic control, S_0 and S_1 reach their steady-state values more rapidly, which demonstrates enhanced disturbance rejection and improved setpoint tracking. In contrast, the PID exhibits slower convergence and notable steady-state deviations, indicating suboptimal substrate utilization efficiency.

In Figures 6(c) and 6(e), the microbial dynamics differ significantly between the two control strategies. Under Synergetic control, X_1 stabilizes efficiently, following a well-defined growth phase, whereas the

PID results in overshoot and prolonged transients. Similarly, X_2 under Synergetic exhibits a more controlled decline, while PID leads to a more abrupt biomass depletion, which may negatively affect system stability and hydrogen yield.

In Figures 6(d) and 6(f), Synergetic ensures a smoother hydrogen accumulation process, effectively minimizing fluctuations and demonstrating superior tracking performance. In contrast, PID introduces oscillations and steady-state discrepancies, which could lead to efficiency losses in practical applications. The improved regulation of AC_1 and AC_2 under Synergetic control contributes to better hydrogen retention and enhanced bioreactor productivity. In Figure 7, it is denoted that the production of methane is greater with the classic PID compared to the proposed controller. However, the objective of the present work is to control the production of hydrogen. Enhancing H_2 production control often compromises CH_4 production due to metabolic competition. Strict control favors hydrogenogenic bacteria but inhibits methanogens, which require low H_2 levels to produce CH_4. Therefore, optimizing H_2 yield typically suppresses CH_4 formation—highlighting a key control conflict in mixed microbial systems.

In other words, the control law is designed to achieve perfect tracking of the desired output, with no deviation from the desired value once the system has reached steady-state. When comparing settling time and ISE, it is observed that the PID controller outperforms during the initial phase, specifically at start-up. However, During the final two phases, the synergetic controller demonstrates superior speed and accuracy.

Table 1 shows the settling times for hydrogen production under different control strategies (Synergetic and PID) across three phases. During the initial phase (0h-80h), the Synergetic controller achieved a settling time of 27.5 h, while the PID controller settled at a slightly faster rate of 24.6 h. In the intermediate phase (80h-120h), the settling times show a notable difference between the two controllers. The Synergetic controller's settling time decreased to 8 h, whereas the PID controller had a higher settling time of 11.4 h. During the final phase (120h-300h), the settling times further diverge. The Synergetic controller demonstrated a significantly lower settling time of 1.1 h compared to the PID controller's 5.1 h. The table 2 presents a comparative analysis of the performance metrics ITAE, IAE, ISE, and RMSE for hydrogen production using different controllers: Synergetic, PID, and another controller from (He *et al.*, 2023) called Performance Guaranteed Ultra Local Model Predictive Controller (PG-ULMPC). The proposed controller outperforms PID and PG-ULMPC in terms of IAE. For the ISE metric, the PID records slightly a lower error than the Synergetic controller with a value of 0.05 L/h compared to 0.1 L/h. The RMSE value for the Synergetic controller is significantly lower (7.87e-04 L/h) than that of the PID controller (94 L/h), suggesting a perfect tracking at the steady state. The PG-ULMPC controller's performance index is only available for the IAE and ISE metrics, where it shows a higher IAE value (1.4412 L/h) and a higher ISE value (0.2275 L/h) compared to both the Synergetic and PID. Overall, the proposed controller achieves superior tracking accuracy, exhibiting minimal error relative to the PID and PG-ULMPC.

Furthermore, the proposed approach enables the controlled system to achieve the target hydrogen outflow rate more rapidly than the PG-ULMPC. Specifically, the system reaches the desired rate in approximately 8 hours with the proposed controller (table 1), compared to around 13 hours with the PG-ULMPC, when a sudden change occurs in the setpoint (He *et al.*, 2023). This rapid response is a critical advantage of the synergetic controller, especially given that abrupt fluctuations in outflow rate frequently occur in industrial bioreactors.

Effective control is essential for optimizing hydrogen production, as it directly impacts both environmental sustainability and energy efficiency. These findings highlight the potential of the proposed controller to enhance hydrogen generation processes, offering a promising solution for improved process stability and performance.

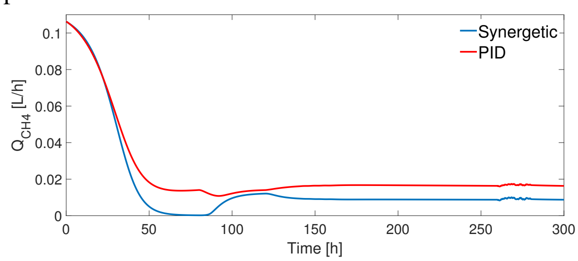

Figure 7. Evolution of methane outflow rate Q_{CH_4}

6 Conclusion

This work has presented a control approach tailored to the nonlinear and highly complex nature of biological hydrogen production via anaerobic digestion. The proposed method has demonstrated its robustness in maintaining system stability and optimizing hydrogen output, even in the presence of dynamic and uncertain process conditions.

A key strength of this approach lies in its simplicity and adaptability, relying on a reduced and well-calibrated model to effectively capture the essential dynamics of the process. Unlike more computationally demanding strategies, this method ensures fast response times and is well-suited for real-time applications.

In comparative analysis, the synergetic controller outperformed classical PID and recent model predictive strategies by achieving improved tracking precision, enhanced transient behavior, and stronger robustness against disturbances. These advantages make it a promising candidate for complex bioprocess control.

However, the control performance is closely tied to the accuracy of model parameters, which must be clearly identified—a limitation that could affect generalizability under varying biological conditions. Moreover, the inherent variability in microbial behavior introduces uncertainty that can impact control accuracy.

Future work will focus on validating the strategy with experimental or real-time data, and exploring its implementation on embedded systems to assess its practical deployment potential. Integrating adaptive mechanisms to account for biological fluctuations may also further improve performance.

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