Integral Sliding Mode Control of Anaerobic Digestion Process for Improved Biogas Production

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Abstract - The production of biogas via an anaerobic fermentation process is twofold beneficial. Not only does it allow for the production of renewable energy, but it also facilitates organic waste elimination. This process takes place in a continuously stirred tank bioreactor and is described by a highly nonlinear model. The parameters of this model are often uncertain, thereby requiring robust control in any process performance enhancement procedure. Thus, a robust control technique, integral sliding mode control, is proposed to improve the settling time in a fermentation-based biogas production in a simulation study. The simulation study is carried out on a biotechnological process described by a two-step reaction scheme based on a second-order nonlinear model. Genetic Algorithm (GA) optimization is used in the design of control parameters to further enhance the system's overall performance. Finally, a comparative study of the performance of the proposed technique and sliding mode, integral sliding mode control performances, is undertaken, showing the pertinence and the enhancement procured by the proposed methodology.

Keywords – - anaerobic bioreactor; biogas; sliding mode control; Integral sliding mode control, genetic algorithm; nonlinear systems.

I. INTRODUCTION

You Anaerobic Digestion (AD) is a biotechnological process widely used in the chemical industry; it is also a promising field as a renewable energy source and a potential scheme for solving some ecological and environmental problems mainly caused by the agro-industry production remains and waste. In such processes, generally carried out in continuously stirred tank bioreactors, organic substance is decomposed by micro-organisms into biogas (methane and carbon dioxide) and compost in the absence of oxygen [1]. Biogas produced by AD as an additional renewable energy source could eventually replace some fossil fuel sources, thus having an indirect positive effect on greenhouse gas reduction.

Unfortunately satisfactory control of this type of system is not forthright due to its strong nonlinearities and uncertainties; the process is complex, and may become unstable thus requiring more research in both modeling and control. An ongoing active research task is better understanding the dynamics of growth and death of the different populations of the complex community of bacteria acting during AD processes and their impact on biogas production enhancement [2]. Another certainly interesting and complementary approach consist in developing better control procedures; to that effect many approaches have tackled performance enhancement of biotechnological processes through a variety of techniques such as extremum seeking control [3], sliding mode control (SMC) and adaptive SMC [4-6] advocated mainly for their robustness despite chattering inherent to such control technique. Artificial intelligence such as neural network [7] and fuzzy logic [8] have also been applied resulting in appreciable performance enhancement as well as the combination thereof [9]. Enhancing biogas production has thus been sought throughout application of a variety of robust control approaches and remains an up-to-date topic of interest justifying the work in this paper. In view of that a robust control technique for biogas production enhancement is investigated in this paper in which control parameters are optimized using genetic algorithm.

In the following section, a brief description of a prototype continuous anaerobic process is provided, followed by the development of its Integral Sliding Mode Controller. The design of the proposed controller is described in subsequent sections. Details about GA optimization are given in the succeeding segment, which precedes the simulation and results assessments evaluation. The paper concludes with conclusions and perspectives.

II. PROCESS DESCRIPTION

Several mathematical models of the AD process have been proposed [5, 10, 11, 12] consisting in highly nonlinear sets of ordinary differential equations. The prototype model considered in this paper is a second order model based on work such as [5]; model is portrayed by equations (1) and (2):

$$\dot{X} = \mu X - DX \tag{1}$$

$$\dot{S} = -k_1 \mu X - DS + F \tag{2}$$

Where X is the biomass concentration and will be considered as the output [5], S is the substrate concentration , F is the system input is defined as the substrate supply rate to the reactor per unit of volume , D is the dilution rate (h-1), and is the specific growth rate function and k1 a positive constant.

Different models for the specific growth rate exist and depend on the type of microorganisms involved in the reaction. One of the most common models for the specific growth rate is the Monod kinetic model (3) and will be used in this paper:

$$\mu = \mu_m \frac{S}{S + k_S} \tag{3}$$

Values considered for the process parameters:
$k_1 = 12\,; k_S = 10\,g/l\,; D = 0.2\,h^{-1}\,; \mu_m = 2.1\,h^{-1}$

The initial conditions preceding control activation are given as:
$X_0 = 20\,g/l \quad ; \quad S_0 = 40\,g/l$
In papers [10, 12, 13] the gas produced is given by $Q = k_2 \mu X$ thus Q is the main output of interest. It's the biogas flow rate (l/h) where k_2 is a specific positive constant. Therefore, any optimization of X induces an optimization on Q. In reference [5] the authors considered X as the system output.

In this paper a new method based on an integral sliding surface methodology is applied to improve biogas production through reduction of both settling time and steady-state error. Its performance will be compared to Sliding, Integral Sliding Mode control well-established robust control techniques.

III. SLIDING MODE CONTROL

Sliding Sliding mode control theory [14] is well established and only development of SM control law for the process is given in order to support a fair comparison with the proposed controller. Thus SMC of the system is first considered [5,6]. Let a classic sliding surface be chosen as:

$$\sigma = \dot{e} + \gamma_1 e \;\; ; \gamma_1 > 0 \tag{3}$$

Where e stands for the error between the system desired output X_d and its actual value X.
For the class of bioprocess investigated (Selişteanu et al. 2007) this surface translates into (5) :

$$\sigma = \mu X - DX + \gamma_1 X - \gamma_1 X_d \tag{4}$$

For an error e defined as:

$$e = X - X_d \tag{6}$$

SMC development results in the following control law:

$$F_{SMC} = k_1 \mu X + DS - \frac{(\mu - D)^2}{\mu'} + \\ - \frac{1}{\mu' X}\left[\gamma_1 (\mu - D) X + k sgn(\sigma)\right] \tag{7}$$

In which: $\mu' = \mu_m \frac{k_S}{(S + k_S)^2}$; $\gamma_1 = 1$ and $k = 3$

IV. INTEGRAL SLIDING MODE CONTROL

Sliding mode control theory [14] is well established and only development of SM control law for the process is given in order to support a fair comparison with the proposed controller. Thus SMC of the system is first considered [5, 15] Let a classic sliding surface be chosen as:

$$\sigma = \dot{e} + \gamma_1 e \ ; \ \gamma_1 > 0 \tag{8}$$

Where e stands for the error between the system desired output X_d and its actual value X.
For the class of bioprocess investigated [5] this surface translates into (5):

$$\sigma = \mu X - DX + \gamma_1 X - \gamma_1 X_d \tag{9}$$

For an error e defined as:

$$e = X - X_d \tag{10}$$

SMC development results in the following control law [5]:

$$F_{SMC} = k_1 \mu X + DS - \frac{(\mu - D)^2}{\mu'} + \\ - \frac{1}{\mu' X}\left[\gamma_1 (\mu - D) X + ksgn(\sigma)\right] \tag{11}$$

In which: $\mu' = \mu_m \frac{k_S}{(S + k_S)^2}$; $\gamma_1 = 1$ and $k = 3$

As for the integral sliding mode control (ISMC) the sliding surface (8) is selected as to include the error integral as in [16]:

$$sur = a_1 e + a_2 \frac{de}{dt} + a_3 \int e dt \tag{12}$$

Coefficients a_1, a_2 and a_3 are initially selected on base of classical performance indices such as minimum overshoot, adequate damping and sufficient bandwidth. These parameters will later be systematically optimized in GA section.

For interested readers stability issues are detailed in [16].

Taking the time derivative of the new sliding surface leads to:

$$\frac{d(sur)}{dt} = a_1 \frac{de}{dt} + a_2 \frac{d^2 e}{dt^2} + a_3 e = 0 \tag{13}$$

Making use of evident simplifications such as: $\frac{dX_d}{dt} = 0$ and $\frac{d^2 X_d}{dt^2} = 0$ as well as equations (1) and (2) lead to the following equation:

$$a_1 \frac{d(X - X_d)}{dt} + a_2 \frac{d^2(X - X_d)}{dt^2} + a_3 (X - X_d) = 0 \tag{14}$$

$$\frac{d(X - X_d)}{dt} = (\mu_m \frac{S}{S + k_S} - D)X \tag{15}$$

$$\frac{d^2(X - X_d)}{dt^2} = \mu_m k_S \frac{-k_1 \mu X - DS + F_{ISMC}}{(S + k_S)^2} X + \\ + (\mu - D)^2 X \tag{16}$$

where F_{ISMC} is the integral SMC law.
Using (11) and (12) in equation (10) results in (13):

$$a_1 (\mu - D) X + a_2 X k_S \left(k_S \frac{-k_1 \mu X - DS}{(S + k_S)^2} \mu_m + (\mu - D)^2 \right) + \\ + a_3 (X - X_d) = -a_2 \mu_m X \frac{F_{ISMC} k_S}{(S + k_S)^2} \tag{17}$$

Solving (13) for F_{ISMC} leads to (14):

$$F_{ISMC} = B \frac{a_1}{a_2}(D - \mu) + k_1 \mu X + DS + \\ - B(\mu - D)^2 - B \frac{a_3}{a_2}\left(1 - \frac{X_d}{X}\right) \tag{18}$$

in which:

$$B = \frac{(S + k_S)^2}{\mu_m k_S} \tag{19}$$

V. OPTIMIZATION BY GENETIC ALGORITHM

Controller parameters are often chosen on a trial-and-error basis which results in poor performance, remedying to that a systematic optimization through a GA is carried out for all controllers developed in this paper. The GA has been created using the standard GA Matlab toolbox.

An objective function is selected as the sum of absolute error as a criterion for the performance of controlled closed-loop systems. GA is using as a stopping criterion, with 100 generations and stall generations are 100. Crossover rate used has a value 0.8. Population size is 20. Crossover strategy is scattered. Mutation strategy is adaptive feasible and Selection strategy is roulette.

Stall generation: If the weighted average change in the fitness function value over Stall generations is less than Function tolerance, the algorithm stops

Generations specifies the maximum number of iterations the genetic algorithm performs.

Scattered creates a random binary vector. It then selects the genes where the vector is a 1 from the first parent, and the genes where the vector is a 0 from the second parent, and combines the genes to form the child

Adaptive feasible randomly generates directions that are adaptive with respect to the last successful or unsuccessful generation. A step length is chosen along each direction so that linear constraints and bounds are satisfied.

Roulette simulates a roulette wheel with the area of each segment proportional to its expectation. The algorithm then uses a random number to select one of the sections with a probability equal to its area.

VI. SIMULATION AND RESULTS

A) Sliding Mode Control

Control parameters used in [5] maintained for comparison purpose.

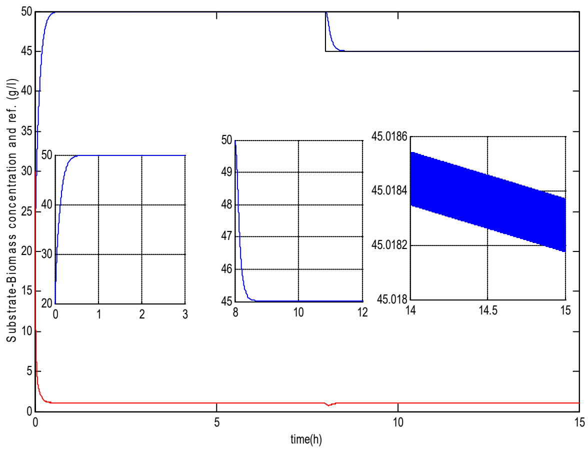

Fig. 1. Biomass-Substrate concentration and reference under SMC [5].

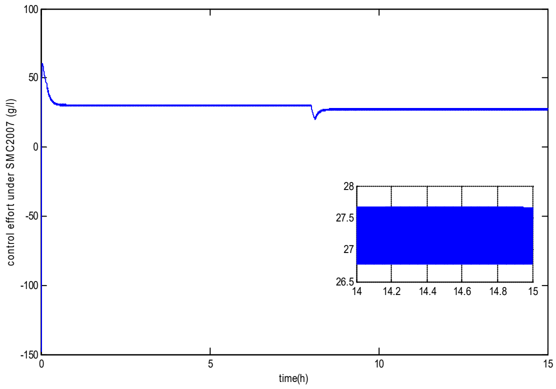

Fig. 2. Control effort under SMC.

B) Integral Sliding mode control

Parameters to be optimized are: a_1, a_2 and a_3 ;used lower bounds [0.0001, 0.0001, 0.0001] and upper bounds [5,2,4];

Optimal values obtained at the iteration 100:

$a_1 = 0.9912$; $a_2 = 0.2650$; $a_3 = 1.0045$

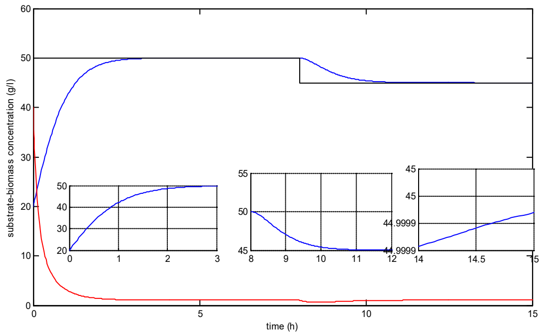

Fig. 3. Biomass- Substrate concentration and reference under ISMC.

Table 1. Simulation summary

	tr1 h	tr2 h	error g/l	u_{final} g/lh
SMC	0.429	0.302	0.018	26.8 27.7

Simulation results for biomass and substrate concentration obtained under the SMC approach are given in Figure 1, showing good overall tracking performance. Figure 2 shows the control effort necessary to achieve the desired tracking.

Table 1 summarizes the simulation results obtained. In evaluating the controllers' time response, a 2% settling time criterion has been selected for the phase before the reference changes from 50 to 45 g/l, referred to as tr1, and afterwards as tr2, as an indication of tracking speed. One can observe that SMC provides an acceptable time response for tr1 (0.429h) and tr2 (0.302h), which is better than both ISMC tr1 (2.518h) and tr2 (1.892h, 1.5h), at the expense of a somewhat larger relative steady-state error (0.0184). It also requires the least amount of control effort, except that it oscillates between 26.8 and 27.7 g/l h, which is not very practical. As can be seen in Table 1, tr2 (0.1h) is faster than SMC at the expense of an increased control effort, reaching a peak of 429.3 g/lh with a steady final value of 108.2 g/lh as in ISMC, and about a nil steady-state error value.

As for the substrate concentration S, the non-trivial equilibrium point S_e is given by :

$$S_e = \frac{k_s D}{\mu_m - D} = 1.05 \tag{20}$$

Table 1 summarize simulation results for the two controllers indicating a Lowest control effort to achieve desired tracking is attained by SMC approach with much slower response time and an oscillate control between 26.8 and 27.7 g/lh which is not practical.

VII. CONCLUSION

Biogas has recently received a lot of attention due to its potential in preserving the environment and as a cost-effective source of renewable energy. However, biogas production requires robust control techniques, primarily due to its strongly nonlinear model. A comparative simulation study was conducted in this paper, demonstrating improved quantitative performance in both transient and steady-state conditions.

VIII. REFERENCES

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