Methane production from food waste using a feedback control strategy in a sequencing batch reactor

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ABSTRACT

The performance of a feedback control strategy in the operation of a sequencing batch reactor was evaluated. This strategy uses the online biogas flow measurements to define the duration of the reaction phase of each operating cycle, thereby increasing the energy production of the system and maximizing the methane production rate. The reaction phase is ended when the biogas flow rate reaches a sustained value significantly lower than the maximum flow rate achieved, as a consequence of the depletion of the soluble chemical oxygen demand. The implementation of the depletion-time control was successful and reached a maximum methane production rate of 1.22 L CH₄/d, showing an average productivity of 0.73 ± 0.3 L CH₄/d. The reaction phase varied from 1.2 to 6 days with hydraulic retention times from 6 to 30 days. The use of this feedback control strategy increased the methane production and the energy production in 80% of the evaluated cycles (from 10.4 to 43.8%) compared to the operation of conventional AD without a control strategy. Furthermore, the strategy is easy to implement since it does not require complex calculations and uses a readily available biogas flow rate sensor.

Key words: feedback control, food waste, maximum methane production rate, sequencing batch reactor, soluble substrate

HIGHLIGHTS

- A control strategy to optimize methane production rate from organic solid waste was proposed.
- The availability of the soluble substrate was an indicator to define the reaction time.
- The implementation of the depletion-time control maximized the energy production rate.

INTRODUCTION

Food waste (FW) may cause important social and environmental problems associated with its inefficient solid waste management, but it must be included in a circular economy to promote its energy recovery (Alias Meena et al. 2020; Zhou et al. 2020). It is possible to produce up to 110 m³ biogas/ton FW (Bharathiraja et al. 2018), with subsequent energy production of up to 7 kWh/m³ biogas using complementary processes (Panigrahi & Dubey 2019). On the other hand, anaerobic digestion (AD) is a widely used process with social, environmental, and economic advantages that allow the valorization of FW through renewable energy production (Nguyen et al. 2019; Panigrahi & Dubey 2019; Zhang et al. 2019a; Ahmed & Rodríguez 2020). Biogas produced in an AD system, which is mainly composed of methane (CH₄) and carbon dioxide (CO₂), has the potential for 17–25 kJ/L generation of internal energy (Zhang et al. 2019b). However, derived from the physicochemical characteristics and biochemical complexity of FW, the use of AD is challenging (De Gioannis et al. 2017; Vargas et al. 2019), facing several environmental disturbances and scenarios that limit the process optimization and the CH₄ production rate. Feedback control strategies (FCS) are a possible solution to automatically find the optimal operating conditions that lead to an increase in the overall energy production of an AD process, and to make it less sensitive to external and internal disturbances; furthermore, the use of feedback makes the process adapt to changes in the environmental conditions (Jimenez et al. 2015; Gaida et al. 2017). Extremum-seeking control, proportional integral derivative control, adaptive control, fuzzy-logic control, and on/off control have been implemented for AD processes (Jimenez et al. 2015; Nguyen et al. 2015; Gaida et al. 2017). All these control strategies aim to increase the energy production and optimize the process, usually by regulating a critical output variable to some setpoint value that is known beforehand to be adequate for maximum energy production or desired system...
performance. The objective of these control strategies is thus to reach the setpoint and remain there, while rejecting the influence of external disturbances (Jimenez et al. 2015; Nguyen et al. 2015).

Barbu et al. (2017) presented an extremum-seeking control for wastewater treatment. The control strategy was simulated without using a dither signal in the controller for the process optimization. Tawai et al. (2018) formulated and simulated an input–output linearizing control strategy in a upflow anaerobic sludge blanket (UASB) reactor with recirculation. They used an observer to estimate non-measurable variables and a compensator that interpreted the behavior of the system through energy recovery. Robles et al. (2018) simulated and validated a fuzzy-logic controller on a pilot-scale fixed-bed reactor, fed with industrial winery wastewater to optimize CH4 production. The strategy used the concentration of volatile fatty acids (VFA) in the effluent as the control variable, which was maintained at 750 mg chemical oxygen demand (COD)/L, reaching a yield of 0.29 L CH4/g COD with a COD removal efficiency of up to 85%. Ahmed & Rodríguez (2020) proposed a model predictive control system based on the AD Model No. 1 for the start-up of an anaerobic digester. The acetate equivalent COD in the effluent, the biomass, and the CH4 production rate were the control variables, while the volumetric feeding rate and the dilution rate were the manipulated variables. The strategy achieved a stable CH4 production in 39 d, instead of the 70 d required by the system under conventional operation. Lara-Cisneros et al. (2015) proposed an extremum-seeking control to optimize the process dynamics by adjusting the VFA concentration to improve the CH4 production. In this study the biomass and substrate concentrations were estimated using a state observer (used to estimate the values of unmeasured variables of a dynamic system given its mathematical model and using the online measurements) and the results were only tested using numerical simulations. Vargas & Moreno (2015) proposed a simple output-feedback controller combined with a state machine using the AD Model 2 model to maximize the biogas production rate in a continuous reactor where the dilution rate is the controlled input and the biogas production rate is the measured output. Later, Vargas et al. (2019) modified its application for maximizing the CH4 production in a UASB reactor from the degradation of agave bagasse hydrolysates by alternating between two dilution rates, using only online measurements of the biogas flow rate.

The use of FCS for AD processes for a variety of homogenous liquids substrates has been proposed, but in most cases, the validation of the control strategy has been only with numerical simulations (Jimenez et al. 2015). On the other hand, the development and applications of FCS on FW treatment are very limited (Lu et al. 2020). Furthermore, due to the FW characteristics, the range of disturbances, and the lack of suitable mathematical models for the process, most AD processes using FW have been proposed as discontinuous. It is therefore necessary to develop a robust FCS, that increases the biogas production, independent of the initial FW characteristics (Nsair et al. 2019). The aim of this study was to evaluate the biogas and energy production in an anaerobic sequencing batch reactor (ASBR) through a feedback control strategy, which takes decisions with the support of historical process data and uses only the online biogas production measurements to define the reaction phase duration (Tf) of each operation cycle, i.e. stopping the reaction phase when it infers that the soluble substrate has been almost depleted. This strategy is here called Depletion-Time Control (DTC). Similar strategies have been proposed particularly for nitrification–denitrification aerobic SBRs, where the properties of easily measured signals such as pH, oxidation reduction potential, or dissolved oxygen concentration are analyzed automatically to determine the duration of the aerobic, anoxic and/or anaerobic phases (Puig et al. 2005; Villez et al. 2010; Dutta & Sarkar 2015).

**METHODS**

**Feedstock**

A single sample of FW (350 kg) was obtained from a municipal market of the city of Querétaro, Mexico. The sampling and preparation of this FW sample was performed according to Santiago et al. (2019). The feedstock was homogenized and refrigerated at 4 °C for preservation. The FW contained the following fractions: 64.7% green vegetables (lettuce, cabbage, chard, coriander, prickly pear, radish leaves); 5.2% cauliflower; 6.3% potato; 1.6% broccoli; 1.3% sweet potato; 3.1% watermelon; 7.1% tomato; 1.9% melon and papaya; 1.4% onion; 5.4% carrot; and 2.0% meat. It is important to point out that more than 60% of the used FW sample had residues with high lignocellulose content. Table 1 presents the characterization of three samples from the homogenized FW. The FW was reduced to a particle size of less than 2 mm using a semi-industrial blender prior to feeding the anaerobic digester.

The physicochemical parameters: moisture, pH, total solids (TS), volatile solids (VS), fixed solids (FS) were determined according to standard methods (2540, APHA 2005). The COD was determined by HACH Reactor Digestion Method. The
soluble carbohydrates and COD were measured after filtering the samples (0.45 μm). Density was obtained by dividing the weight of the blended feedstock by the volume of the residue. The concentration of carbohydrates and lipids were analyzed using the phenol–sulfuric acid method and sulfo-phospho-vanillin colorimetric method described by Dubois et al. (1956) and Bligh & Dyer (1959), respectively. Protein quantification was performed using the technique proposed by Lowry et al. (1951). N–NH₃ was measured by the nitrogen-ammonia Nessler method (HACH method 8038).

### Experimental start-up and reactor operation

Granular sludge from an anaerobic digester for wastewater treatment was used as an inoculum, adding 70 mg/L volatile suspended solids for the reactor start-up. The experimental system operation was divided into two stages: (i) conventional operation and (ii) operation using the DTC proposed. Figure 1 shows the process flow diagram of the experimental AD system. A reactor of 3.2 L with a 20% headspace was used (INFORS HT model Labfors 5). The reactor had a heat exchanger, a paddle stirrer, a pH sensor, and a PT-100 thermocouple. The digestate was discharged with a peristaltic pump (Masterflex, 77601-10) to a storage tank with a capacity of 2 L. The feedstock was maintained at 4 °C in an agitated storage tank (4 L). The substrate was fed to the digester with another peristaltic pump (Masterflex, 07552-02). Biogas production was measured with a flow meter (BPC μFlow) that transmitted a 4–20 mA signal that was acquired with a data acquisition device (NI USB-6008). Liquid fluids were transported through 12.7 mm PVC tubing to minimize possible plugging, and biogas through 8 mm diameter tubing. Dynamic equipment and instruments were connected to a personal computer that controlled the process and operated based on the control algorithm presented in Figures 2 and 3. The ASBR used a 20% exchange volume, agitation of 120 rpm, pH 7.6, and temperature 37 °C. The duration of settling, filling, and draw phases were 1 h, 0.05 h, and 0.01 h, respectively. The reaction time was fixed at 2.08 d during the conventional operation of the reactor and variable when the control strategy was applied. This controller was implemented using the LabVIEW 7.0 software in a personal computer, which served as a human–machine interface where the operator could monitor variables and set the operating values of temperature, pH, and agitator speed.

The biogas composition (CH₄ and CO₂) was determined by a gas chromatograph (SRI 6890 N model, Agilent Technologies) equipped with a thermal conductivity detector and two packed columns (6’ × 1/8’’ silica gel packed column and 6’ × 1/8’’ molecular sieve 13X packed column) according to Buitrón & Hernández-Mendoza (2014). Hydrogen sulfide (H₂S) concentration was determined in a gas chromatograph (SRI 8610-C, SRI Instruments, USA) equipped with a flame ionization detector and a Restek MXT-1 column (60 m × 0.53 mm × 5 μm), since this technique has shown to be effective and reliable (Quijano et al. 2018).

### Feedback control strategy proposed

Figure 2 shows the three general elements that comprise a control strategy as established by Gaida et al. (2017) and Nguyen et al. (2015): sensor, controller, and actuator. The sensor was the flowmeter (BPC μFlow) which quantified the biogas

| Parameter          | Value               |
|--------------------|---------------------|
| Total carbohydrates| 13.22 ± 0.84 g/L    |
| Soluble carbohydrates| 6.73 ± 1.02 g/L |
| Lipids             | 2.5 ± 0.4 g/L       |
| Total proteins     | 19.32 ± 0.80 g/L    |
| pH                 | 4.3 ± 0.15          |
| N–NH₃              | 1.3 ± 0.5 g/L       |
| COD total          | 200.0 ± 6.7 g/kg    |
| COD soluble        | 160.2 ± 2.2 g/kg    |
| Moisture           | 92.4 ± 1.8%         |
| TS                 | 87.9 ± 1.3 g/kg     |
| VS                 | 60.7 ± 1.2 g/kg     |
| FS                 | 13.1 ± 1.2 g/kg     |
| Density            | 1.08 ± 0.01 kg/L    |

Table 1 | Characterization of FW
Figure 1 | Process flow diagram of the experimental AD system.

Figure 2 | Main elements of a control strategy.

Figure 3 | Conventional anaerobic digester operation.
production, and its value was transmitted to a computer via a data acquisition device. A computer and the LabVIEW 7.0 software comprised the controller, which received the information collected by the flowmeter and took a decision. The actuator in this case was the signal that ended the reaction phase by stopping the stirrer and starting the discharge pump. Since the system is an ASBR, a timed automation process established the duration of the phases of the cycle by sending appropriate electrical signals that turned into physical actions: turning the stirrer and the feed and discharge pumps on and off, and opening and closing solenoid valves. The proposed controller operated only during the reaction phase by setting its duration using feedback information from the sensor.

**DTC algorithm**

The proposed DTC algorithm does not require a predictive mathematical model. It uses the biogas production rate as a control variable to define the reaction phase duration ($T_r$) of each operation cycle taking into account a direct relationship between the available soluble substrate and the methane production rate. The controller uses the shape of the curve of accumulated biogas volume of each operation cycle to find the maximum methane production rate (MMPR) and later define the $T_r$ of that cycle. It is assumed that the consumption of COD$_{soluble}$ produces biogas faster (associated with an exponential phase), while the consumption of COD$_{particulate}$ implies a slower biogas production (associated with the stationary phase); therefore, the MMPR is achieved before the COD$_{soluble}$ has been consumed.

From the collected data in conventional operation, it was found that the accumulated volume of biogas fitted well a modified Gompertz model (Equation (1)) (Santiago et al. 2019), which is an empirical function of time that represents the accumulation of biogas volume from two types of substrates: COD$_{soluble}$ and COD$_{particulate}$:

$$H(t) = H_{max} \exp\left[-\exp\left(\frac{R_{max}}{H_{max}}(\lambda - t) + 1\right)\right] + mt$$

where $t =$ time, $H =$ accumulated biogas volume, $H_{max} =$ maximum biogas volume, $R_{max} =$ maximum biogas production rate from COD$_{soluble}$, $\lambda =$ latency time, $m =$ biogas production rate from COD$_{particulate}$.

The first part of this model represents 80% production of biogas from COD$_{soluble}$, including a latency time, while 20% comes from COD$_{particulate}$ with a fixed small rate ($m$). A control strategy that has already been explored, but for biohydrogen production, consists of fitting the online gathered data to the modified Gompertz model and using the estimates of the model parameters to decide when to stop the reaction phase (Jiménez-Ocampo et al. 2021). Although this strategy could also work for a methanogenic ASBR, here a simpler strategy that does not require fitting a model online was proposed. This eliminates the need for complex online calculations (e.g. solving a nonlinear programming problem) but retains the basic idea behind the original strategy: to end the reaction phase when the biogas flowrate has already peaked and maintains a constant low value, indicating that the soluble substrate has been depleted.

The DTC was based on measuring the slopes of the biogas volume curve periodically and comparing them to the maximum registered slope to determine when to stop the reaction phase and thus set the value of $T_r$ for that cycle.

The flowrate sensor measures directly the slope of the biogas volume curve, but the measurement is noisy and constantly fluctuating. Therefore, the procedure consisted first of integrating the digitally filtered flowrate measurements to find the accumulated biogas volume. Acquisition of the data was made every $T_s$ seconds. Every $T_m$ minutes, a window of collected data was adjusted using linear regression to find $q_b$, the mean slope of the biogas curve for each window of data, with a 95% confidence interval. The slope $q_b$ obtained for each window was compared with the slope of the previous window ($q_{b-1}$) and if it was significantly greater, the new maximum slope $q_{max}$ was redefined. Initially, it is expected that new maxima will be found, but after reaching the MMPR, new calculated slopes will be smaller than $q_{max}$. Eventually, the calculated slope will be a small percentage of $q_{max}$ but also the next slopes will be sustained and not significantly different, indicating that the biogas production is only due to degradation of COD$_{particulate}$. The algorithm detects this by ending the reaction phase when the current $q_b$ is less than $p \cdot q_{max}$ with $0 < p < 1$, but also the slopes $q_{b}, q_{b-1}, \ldots, q_{b-N}$ are not statistically different for a certain number $N$ of windows of previous data.

Let $t_r$ represent the reaction time, which is reset to zero at the beginning of each reaction phase. In addition to $T_s, T_m, p,$ and $N$, the algorithm uses another two operating parameters: $T_{r, min}$, is the minimum reaction time, such that the calculation of slopes does not begin until $t_r > T_{r, min}$; and $T_{r, max}$ is the maximum reaction time, such that the reaction is forced to end when $t_r > T_{r, max}$. The algorithm has the following steps:
1 Set \( q_{\text{max}} = 0 \) and \( t = 0 \); start the reaction phase and until \( t_r > T_{r,\text{min}} \); then collect the data for the first window to find \( q_0 \), i.e., the slope for \( k = 0 \). Set \( k = 1 \) and reset a counter: \( c = 0 \).

2 Collect data of the window and calculate the slope \( q_k \pm \Delta_k \) with a 95% confidence interval using linear regression.

3 Set new maximum: if \( q_k > q_{\text{max}} \) then set \( q_{\text{max}} = q_k \); otherwise, do not change \( q_{\text{max}} \).

4 Check significant decrease of slope and compare to previous slope to define counter:
   - If \( q_k + \Delta_k < p \cdot q_{\text{max}} \), then check:
     - If \( q_k + \Delta_k > q_{k-1} - \Delta_{k-1} \) or \( q_k - \Delta_k < q_{k-1} + \Delta_{k-1} \), increase the counter: \( c = c + 1 \);
     - Otherwise, set \( c = 0 \).
   - Otherwise (i.e., \( q_k + \Delta_k > p \cdot q_{\text{max}} \)), reset \( c = 0 \).

5 Check conditions for establishing \( T_i \):
   - If \( c = N \) or if \( t_r > T_{r,\text{max}} \), go to step 6;
   - Otherwise \((c < N)\), increase \( k = k + 1 \) and return to step 2.

6 End the reaction phase and continue with sedimentation, discharge and filling for the next cycle, returning to step 1 when the reaction begins.

### Microbial community characterization

An analysis of the microbial community was carried out in different operating cycles. The samples collected from the anaerobic digester were stored at \(-70^\circ\)C in a Revco freezer and were subsequently analyzed using molecular techniques. DNA extraction was done according to manufacturer recommendations, using the DNeasy PowerSoil kit (QIAGEN). DNA integrity and quality were assessed on an agarose gel stained with 1% SYBR Green and quantified using a Nanodrop (Thermo Scientific). DNA was stored at 20°C until its analysis. DNA was sent to the Research and Testing Laboratory (RTL, Texas, USA) for its sequencing using the MiSeq Illumina platform. The 16S rDNA genes were amplified with the primer sets 517F (GCYTAAAGSRNCCGTAGC) and 909R (TTTCAGYCTTGCGRCCGTAC) for archaea, and 28F (GAGTTT-

### RESULTS AND DISCUSSION

#### Conventional system operation

During the conventional operation (without DTC), a previous acclimation period of 16 days was applied to obtain stable CH₄ production. After that, the anaerobic digester was operated for 33 cycles at constant \( T_r \) of 2.08 d, HRT of 10.41 d, and OLR of 10 gVS/L/d (Figure 3). The total cycle duration was 2.13 d. Figure 3 shows the behavior of the anaerobic digester without using the DTC. An average accumulated methane volume \((V_{\text{CH₄}})\) of 5.72 L CH₄/cycle was observed with a CH₄ percentage in the biogas of 67%. The average energy production of the conventional system without DTC was 30.7 kJ/d with a maximum yield of 275.2 mL CH₄/g COD, which is 18% lower than the value reported by Yeshanew et al. (2016). The pH value was 7.1 ± 0.1 during the reactor operation. H₂S concentration in the biogas was 1,519 ppm in cycle 1; then the H₂S filter was implemented in cycle 2, reducing the H₂S to less than 88 ppm for the next cycles.

#### DTC experimental validation

Figure 4 illustrates the operation of the DTC in one representative cycle of conventional SBR operation. The values of the operating parameters were established based on experience and were set as follows: \( T_{r,\text{min}} = 0.17 \) d, \( T_{r,\text{max}} = 12 \) d, \( T_s = 30 \) s, \( T_m = 10 \) min (20 points of data in the slope calculation window), \( p = 0.1 \), and \( N = 5 \). This last value is a compromise to ensure that the slope satisfies the condition despite noise in the signal. The exchange volume was 0.5 L/cycle.

The top figure shows the data of biogas flow rate \( q(t) \) during the first 20 h and the calculated cumulative biogas volume, obtained by numerically integrating the flow rate data. The bottom figure illustrates the DTC: every 0.5 h, the mean biogas flow rate \( q_k \) (for \( k = 1, 2, \ldots \)) is calculated from the collected data in the window, together with a 95% confidence interval; shown as bar graphs with error bars. The maximum \( q_{\text{max}} \) is also established every 0.5 h, and a counter is reset or incremented.
by comparing $q_k + \Delta_k$ with $p \cdot q_{max}$, using $p = 0.1$. When the counter reaches the pre-established value of $N = 5$, the reaction would have ended as indicated by the arrow at a reaction time of 17 h.

The experimental system was operated using the proposed DTC for 40 d (10 operation cycles) (Table 2). The feed was constant at 25 gVS/cycle, and the OLR was $10.4 \pm 4.7$ gVS/L/d (varying due to the changes in the $T_r$ derived from the control). The $T_r$ varied from 1.2 to 6 d. In 70% of the cycles evaluated, the $T_r$ was less than three days (the average value for $T_r$ was $2.9 \pm 1.3$ d), modifying the HRT with an average value of $14.7 \pm 6.7$ d since the HRT depends on the feed flow, and that in turn is directly associated with the time $T_r$ defined by the DTC. A maximum yield of 87 L CH$_4$/kgVS with an OLR of 3.3 gVS/L/d was obtained, agreeing with Zhang et al. (2019b) (89 L CH$_4$/kgVS), who applied a strategy to optimize CH$_4$ production based on intermittent agitation, and with the 80.9 L CH$_4$/kgVS obtained by Nguyen et al. (2019), who used a control strategy to assess the VFA accumulation through micro-aeration, when treating organic waste with high lignocellulose content. The implementation of the DTC was successful and reached a maximum methane production rate of 1.22 L CH$_4$/d, showing an average of $0.73 \pm 0.3$ L CH$_4$/d. Productivity was $273 \pm 112$ mL CH$_4$/L$_{reactor}$/d, with two maximum points of 486 and 408 L CH$_4$/L$_{reactor}$/d (at cycles 1 and 7). The productivity is the amount the biogas produced considering the volumetric capacity of the digester. There was no significant relationship between HRT and yield since the DTC does not need a specific HRT to achieve a constant biogas production rate.

Table 3 shows the substrate and digestate characterization at cycle 5. The COD removal of 81% was three-fold higher than conventional operation and similar to that obtained by Robles et al. (2018) who used a fuzzy-logic controller for CH$_4$ optimization in a fixed-bed reactor. The COD, lipids, and protein percentage removal agree with the result of Li et al. (2017) for different composition of organic solid waste by the anaerobic process.

The experimental validation of the DTC was based on mass and energy balances. The mass balance was carried out in terms of COD in steady state, using the same $T_r$ of 2.08 d as the conventional system, reaching a theoretical productivity.
value of 238 mL CH$_4$/L$_{reactor}$/d and energy production of 48.56 kJ/cycle. The evaluation of the energy production of the experimental system that uses the DTC was made with an energy balance in steady state according to Ruggery et al. (2015), considering the following equation, which contemplates the energy produced by CH$_4$ minus the energy used for heating, mixing, and pumping, as well as that lost to the environment (Equation (2)):

$$E_{\text{net}} = E_{\text{CH}_4\text{produced}} - (E_{\text{heating}} + E_{\text{loss}} + E_{\text{mixing}} + E_{\text{pumping}})$$  (2)

It was assumed that the energy per pumping was negligible compared to the energy used for stirring the reactor (the pumping time was of the order of $10^{-3}$ h compared to the duration of the mixing time of 50 h). Considering an efficient thermal insulation (energy losses negligible), the system presents a positive net energy of 37.2 kJ/cycle, resulting in 76.5% energy in surplus, obtaining an energetically viable CH$_4$ production system from FW.

Figure 5 shows the behavior of energy production in each operating cycle, based on the $T_r$ defined by the control strategy, highlighting that all cycles presented an energy surplus greater than 10.4 kJ/cycle. In 80% of the cycles evaluated, the energy produced by the system is higher than for conventional operation, equivalent to 48.56 kJ/cycle (dotted line). If the energy production per day is compared, the increase of energy achieved by the DTC strategy (26.3 ± 11.9 kJ/d) is higher than the reactor operation under the conventional operation (17.8 kJ/d). Regardless of the characteristics of the organic solid waste fed to the process, the maximum biogas production was obtained in each of the operating cycles, using the soluble organic matter available in the reactor as a direct substrate for biogas production. This explains why the resulting $T_r$ varied for each cycle; the controller establishes the optimal reaction phase duration so that only the available soluble substrate is consumed, which is the one that produces CH$_4$ more rapidly. This adaptability avoids the need to previously establish a relationship between $T_r$ and energy production. Nevertheless, the energy production tends to stabilize at an average value (64 ± 18 kJ/cycle) that is higher than the one for conventional AD. Compared with conventional strategies that consider a fixed and usually large $T_r$, the use of this DTC strategy shows that by optimizing the retention time, more batches may be processed per unit time.

| Cycle | pH | $T_r$ (d) | HRT (d) | Accumulated biogas (L) | % v/v CH$_4$ | Yield (L CH$_4$/kgVS) | Productivity (mL/L/d) | Methane production rate (L/d) |
|-------|----|----------|--------|------------------------|-------------|----------------------|------------------------|-------------------------------|
| 1     | 7.2| 1.7      | 8.6    | 6.4                    | 32.9        | 83.6                 | 487                    | 1.22                          |
| 2     | 6.7| 6        | 30.2   | 4.3                    | 38.5        | 66.5                 | 110                    | 0.27                          |
| 3     | 7  | 4        | 20.1   | 5.3                    | 25.6        | 54.6                 | 136                    | 0.34                          |
| 4     | 7.2| 3        | 15     | 5.8                    | 37.6        | 87                   | 290                    | 0.72                          |
| 5     | 6.9| 2.9      | 14.9   | 4.5                    | 43.5        | 78.4                 | 263                    | 0.66                          |
| 6     | 7  | 3.8      | 19     | 2.4                    | 34.9        | 34.2                 | 90                     | 0.23                          |
| 7     | 7.2| 1.8      | 9      | 5.6                    | 32.8        | 73.3                 | 408                    | 1.02                          |
| 8     | 7.4| 1.2      | 6.1    | 1.7                    | 41.8        | 28.1                 | 229                    | 0.57                          |
| 9     | 7.2| 2.8      | 13.9   | 3.9                    | 42.5        | 67.5                 | 243                    | 0.61                          |
| 10    | 7.3| 2        | 10.2   | 3.9                    | 38.1        | 60.7                 | 299                    | 0.75                          |

| Parameter         | Substrate | Digestate | % Removal |
|-------------------|-----------|-----------|-----------|
| Total carbohydrates| 11.4 g/L  | 2.8 g/L   | 75        |
| Soluble carbohydrates| 3.7 g/L  | 1.3 g/L   | 65        |
| Total lipids      | 2.7 g/L   | 0.7 g/L   | 75        |
| Soluble lipids    | 2.6 g/L   | 0.6 g/L   | 75        |
| Total proteins    | 19.9 g/L  | 4.4 g/L   | 78        |
| COD$_{total}$     | 200 g/kg  | 38 g/kg   | 81        |
Microbial community characterization

Figure 6 shows the microbial characterization during cycles 1 and 10 when the anaerobic digester was operated using the DTC. The percentage of the different operational taxonomic units (OTU) and their classification are shown in the figure. The phylum Firmicutes was the most abundant. Kim et al. (2018) and Tonanzi et al. (2018), who operated stirred reactors under mesophilic conditions for the CH4 production from FW similar to the sample used in this work, mention that the highest proportion of microorganisms in the bacterial domain accounted for 60–80% Firmicutes and 70–80% Bacteroides of the total identified. The use of the DTC strategy leads the community to develop a community with two dominant bacteria: Bacteroides sp. (14% of the OTUs) and Aminobacterium thunnarium (11%). The dominance of Bacteroides sp. in methanogenic reactors and digestates agrees with results obtained by others (Wang et al. 2018; Bernat et al. 2019). The abundance of Bacteroides could indicate the accumulation of VFAs (Hatamoto et al. 2014). A. thumnarium has been identified as an amino acid fermenting bacterium (Hamdi et al. 2015), which could be related to the high removal of protein in the system studied (77.7%).

Three genera represent more than 98% of the archaea present in the community (Figure 6). Under conventional operation without the DTC strategy, the genus Methanosaeta was most abundant (56%), but this relative abundance was reduced to 30% after the use of DTC during 10 operational cycles, where its presence was due to the CH4 production through acetoclastic methanogenesis associated with the acetic acid reduction and responsible for up to 70% of CH4 production in the system (Sposob et al. 2020; Zou et al. 2020). Methanoseta and Methanobacterium were the two genera that represented more than 60% of the archaea in the system, independent of the T, defined by the DTC. According to Kim et al. (2018), constantly they are the most abundant, together with genera Methanoculleus and Methanomassiliicoccus. The genus Methanolinea was displaced as the reactor was operated using the DTC associated with the dominance of the other methanogens. The increase of hydrogenotrophic methanogens such as Methanoculleus sp. (from 2% in cycle 1 to 40% in cycle 10), allows the production of CH4 from H2 produced by fermentative bacteria, associated with the improvement of biogas production (Zhang et al. 2019b), but they also may be responsible for the increase of VFA in anaerobic systems (Kim et al. 2018). The combined activity of Methanoseta and Methanoculleus (acetoclastic and hydrogenotrophic, respectively) in anaerobic systems has been reported at high organic loading rates (Suarez et al. 2018). The decrease of the reaction time, driven by the DTC strategy, is reflected in the increase of both genera, producing high levels of methane from acetic acid, H2, and CO2. The more balanced community distribution between hydrogenotrophic and acetoclastic methanogens is beneficial to a better microbial interaction, which further enhanced the thorough utilization of the organic matter for methane production with better microbial interaction (Feng et al. 2019).

CONCLUSIONS

The proposed DTC was validated and implemented in an ASBR, demonstrating its practical operation. The proposed control strategy is functional, showing promising results, increasing CH4 production and consequently increasing the energy production of the system. The strategy is based on dynamically establishing the reaction phase duration, which is directly related to the availability of soluble substrate within the reactor, regardless of the characteristics of the solid waste fed to
The main advantage of the DTC is that it does not need to perform complex computations for its implementation and operation. With its application in the operation of an anaerobic digester, a maximum value of 87 L CH₄/kgVS and 487 mL CH₄/L-reactor/d were reached. It increased the energy production between 10.4 and 43.8% compared to the conventional AD system operation. The long-term operation of the process will be necessary to support its application to larger-scale systems with different characteristics. Compared to a conventional operating strategy with a fixed retention time, the experimental validation of this DTC has shown that it increases energy production, it improves the global efficiency of the AD from FW, and it may reduce the high investment costs that sophisticated control systems usually require.

Figure 6 | Population dynamics evaluation of the experimental system.
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CONFLICTS OF INTEREST

The authors declare that they have no competing interests.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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