Optimising feedstock flowrate to improve the performance of an existing anaerobic digestion system

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Abstract

This paper presents an approach to model and optimise the feedstock flowrate of an anaerobic digestion (AD) cooking system by simultaneously minimising the volume of flared biogas, the unmet cooking demand and the energy cost. As research has typically focused on optimising the digester and its associated parameters to maximise the biogas yield; this research examines how different objectives can influence how one might want to control the system. The system is initially modelled and validated with measured data and an optimisation algorithm is then applied to control the feedstock flow rate. The results show that the performance of first order AD models, in predicting the biogas yield, only differs from measured data by 9% and that by controlling the feeding rate, the amount of flared biogas and unmet cooking demand can be reduced by 100% and approximately 87%, respectively when they are the only objective functions considered. If the energy cost is also added an objective function, then more precise control of feeding rate is needed to ensure that all three conflicting objectives are equally minimised. This result highlights the importance of using the correct feeding rate in the system and considering the overall system during optimisation as producing more biogas might not result in the most cost-effective system.

Keywords: feedstock flowrate, case study, measured data, multi-objective optimisation

1. Introduction

Research on mathematical optimisation of anaerobic digestion (AD) systems has typically been focused on the design and optimisation of the digester tank to maximise the methane yield. Furthermore, authors have either created predictive models using measured data, used experimental results or the mechanistic anaerobic digestion model 1 (ADM1) to determine biogas yield from the digester. Huang et al. [1], Akbaş et al. [2], Enitan et al. [3], Balaji et al. [4] and García-Diéguez et al. [5] all looked at similar objective functions of maximising the biogas yield and/or the methane content in biogas and minimising the effluent chemical oxygen demand (COD). They found optimal values for digester temperature, pH, hydraulic retention time (HRT), feedstock flowrate and carbon/nitrogen (C/N) ratio. García-Gen et al. [6] used linear programming to optimise the substrate blend going into the digester with the aim of maximising the methane yield. To determine the biogas yield, some of these authors used predictive models, some experimental results and some ADM1 however, the limitation of these methods are that predictive models rely on having measured data, experimental results are not accurate to predict real-world digester performance and ADM1 is complex to use as it requires values for many unknown coefficients. Furthermore, the authors did not consider any other components in the system, apart from the digester, i.e. pre and post treatment technologies, digester type, feedstock(s) and operational conditions and optimised only the technical performance of the digester. To obtain an optimised AD system, all its components need to be simultaneously selected and optimised. Nixon [7] states the importance of optimising an AD system both technically and economically to ensure that an overall efficient system is achieved.

To control AD systems and consider both the technical and economic performance, authors defined system boundaries to include pre and post treatment technologies, feedstock blends and digester operational variables. They defined net present value (NPV), bio-methane production and green degree as objective functions. Some authors also conducted broader scoped studies where they did not model the technologies in detail. Yan et al. [8] and Li et al. [9] aimed to find the optimal co-digestion ratio of the feedstocks used (chicken manure (CM) with rice straw (RS), wheat straw (WS) and corn stalk (CS)) and biogas to bio-methane upgrading technology when performing multi-objective optimisation of an existing AD system. With respect to the digester, Yan et al. [8] optimised the temperature and Li et al. [9] optimised the heat supply technologies. To determine the amount of biogas produced, the authors used correlations, found in literature, between the rate of methane production and temperature for the different feedstock co-digestion ratios used. The limitation of this method to determine the biogas yield is that, the performance of the digester is dependent not only on the temperature but also other operational variables, such as the hydraulic retention time (HRT), pressure, pH, mixing and organic loading rate (OLR) [10]. Furthermore, for existing AD systems the cost involved in making modifications to the system need to be considered as that can influence the optimised solution. Mavrotas et al., [11] found optimal combination of technologies that can be used to process the types of waste (i.e. glass, plastic, and metals) found in municipal solid waste (MSW). Similarly, Balaman and Selim [12] looked at maximised the profit of the biomass supply chain, defining system boundaries to include biomass transportation, storage, energy generation and fertilizer disposal. However, these broader scope studies did not consider each of the individual components in detail and their effect on the optimised result. Hence, the use of simple, first order AD models with optimisation of AD systems, for a number of conflicting objectives needs to be investigated.

This paper presents an approach to optimise the feedstock flowrate into an existing AD system with the aim of investigating how first order AD models can be used with plant data to improve system control by balancing conflicting objectives. The results will provide insightful details for designers, engineers, and operators of these systems on how they can use multi-objective optimisation to enhance system performance by controlling the feedstock input.

2. Methodology

Two optimisation scenarios are considered; 1) only flared biogas and unmet demand are minimised 2) the energy cost of the system is also minimised along with flaring and unmet demand.

The biogas yield from the digester is determined using the modified Gompertz model as it has been found to perform better than other kinetic AD models. This is due to it being an 'S' shaped curve and hence, being able to model the lag phase of microbial growth in digesters well [13]. Coefficients for the model are taken from Nguyen et al. [14] study as the properties of their feedstock were similar to the feedstock used in the case study system. The predicted biogas yields were then compared with measured data from the plant for the month of July and December 2017 to determine the accuracy of the model. All the other components in the case study system such as the shredder, H_2S scrubber and H_2O condenser were also modelled so that their energy costs, in relation to the amount of feedstock added, could be determined.

The optimisation problem was set-up in Python and non-dominated sorting genetic algorithm (NSGA-II), from Python's multi-objective optimisation library 'pymoo', was used. The population size and number of generations were both set to 100.

3. Case Study System

Plant performance data is taken from a one tonne per day anaerobic digestion facility in Bangalore, India. The facility handles food waste from the onsite kitchen, consisting of preparation waste (uncut vegetables etc.) and cooked food waste (rice, vegetable peels, chapatti, curries etc.). It was estimated that approximately 162 m^3 of biogas is estimated to be produced from the digester for every tonne of waste added.

The key parameters of the digestion process in the case study plant are shown in Table 1.

Table 1 Key operating parameters of the case study anaerobic digestion (AD) facility.

Parameter	Description/Value
Feedstock type	Kitchen waste (uncut and leftover vegetables, curry, bread etc.)
Feedstock Volatile Solids Content (VS)	14.25%
Hydraulic retention time (HRT)	28 days
Temperature (mesophilic)	38 °C

Data recorded from the plant on a daily basis includes the amount of feedstock added (kg), the biogas stored in the twin-balloon system (m^3), the amount of biogas flared (m^3) and the biogas consumption (m^3) for cooking. Due to the location of the measuring points (Figure 1), the total biogas produced (m^3) from the plant in a day was determined by adding the biogas stored in the balloons and the amount flared. Data was available for the months of March, July and December 2017. It is assumed that a back-up Liquefied Petroleum Gas (LPG) connection exists for any unmet demand.

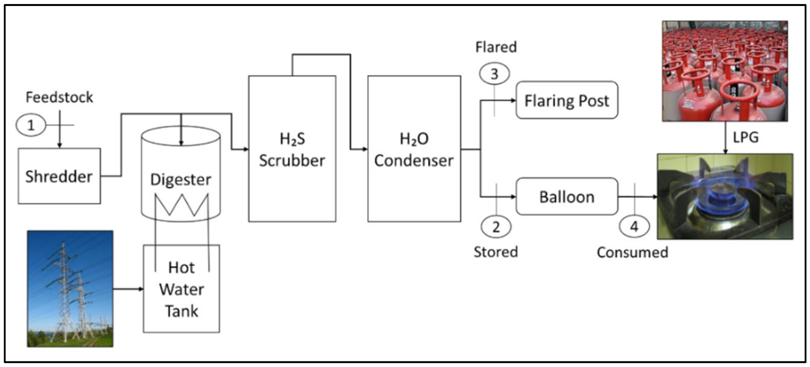

Fig. 1 Set-up of the case study anaerobic digestion (AD) system showing the components and measuring points.

4. Model Formulation

4.1. Component Models

4.1.1. Shredder

Equation 1 was used to determine the total specific energy consumption of the shredder, as a function of screen size, flow rate and motor speed [15].

$$\begin{aligned} E_{shredder} = {} & 20.3836 - (5.1879 \times 10^{-1} \times D) \times (8.9192 \times F) + (1.3455 \times 10^{-1} \times N) \\ & - (2.4206 \times 10^{-1} \times D \times F) - (2.4531 \times 10^{-1} \times F \times N) \\ & + (3.9630 \times 10^{-4} \times D \times N) + (2.2116 \times 10^{-2} \times D^2) + (2.3247 \times F^2) \end{aligned} \quad (1)$$

where, $E_{shredder}$ is the total specific energy consumption of the shredder (kWh/tonne), D is the screen size (mm), F is the feedstock flowrate (kg/min) and N is the motor speed (rpm).

The total energy consumption of the shredder (E_{shred}) in a day was determined by multiplying the feedstock flowrate into the system with the total specific energy consumption.

4.1.2. Digester

The equation used to determine the energy needed to heat the feedstock going into the digester is shown below.

$$E_{heat} = m_f \times \left(c_w(1 - TS) + c_S(TS)\right) \times (T_D - T_F) \quad (2)$$

where, E_{heat} is the energy needed to heat the digester (kJ/day), c_w and c_S are the specific heat capacity of water and substrate, respectively (kJ/kgK), m_f is the mass flow rate of feedstock going in the digester (kg/day), TS is the total solids content in the feedstock (%) and T_D and T_F are the digestion and inlet feedstock temperatures (°C), respectively.

Equation 3 is used to determine the temperature of the water required in the coil so that it can provide the thermal energy needed to heat the feedstock.

$$Tw_2 = \frac{E_{heat}}{2\pi r_c h_c \times h_{water}} + T_F \quad (3)$$

where, Tw_2 is the temperature of the water in the coil (°C), r_c and h_c are the radius and length of the coil (m) and h_{water} is the convention heat transfer coefficient of flowing water (W/m^{2}K)

The electrical energy needed to heat the water to the required temperature for heating the digester was determined using Equation 4.

$$E_{heatwater} = m_w \times c_w \times (Tw_2 - Tw_1) \quad (4)$$

where, $E_{heatwater}$ is the electrical energy needed to heat a fixed mass of water that can in the coil (kJ/day), m_w is the mass of water in the tank heated by electricity (kg/day) and Tw_1 is the initial temperature of water (°C).

The heat loss from the digester was determined by assuming that the digester was cylindrical in shape and that heat loss occurred from the top, bottom and sides of the digester to free flowing air, as the digester stood on legs. As only the volume of the digester was known, it was assumed that its height was equal to twice the radius.

$$E_{loss} = (2\pi r_d h_d + 2\pi r_d^2) \times h_{air} \times (T_D - T_{amb}) \quad (5)$$

where, E_{loss} is the energy needed loss the ambient air from the digester (kJ/day), r_d and h_d are the radius and height of the digester (m), respectively, h_{air} is the convention heat transfer coefficient of free air (W/m^{2}K) and T_{amb} is ambient temperature of air (°C).

The amount of biogas produced from the digester was determined using the modified Gompertz model.

$$G(t) = G_o \times \exp\left\{-\exp\left[\frac{R_{max \times e}}{G_0}\right](\lambda - t) + 1\right\} \quad (6)$$

where, $G(t)$ is the biogas yield at hydraulic retention time t (m^3/kgVS), G_0 is the maximum biogas yield (m^3/kgVS), R_{max} is the maximum biogas production rate (m^3/kgVS day), λ is the duration of lag phase (day) and t is the hydraulic retention time (days).

Equation 7 was then used to determine the daily predicted biogas yield.

$$V_{B\_P} = m_f \times VS \times G(t) \quad (7)$$

where, V_{B_P} is the biogas produced (m^3/day), VS is the volatile solids content of the feedstock and $G(t)$ is the biogas yield (m^3/kgVS) at HRT of 28 days.

The predicted biogas yield for July and December 2017 was compared with measured data and the performance of the model was accessed.

4.1.3. Hydrogen Sulphide Scrubber

The mass of hydrogen sulphide (H_2S) that has to be removed by the scrubber in a day was determined using Equation 8.

$$m_{H2S} = \frac{(H_2S_{in} - H_2S_{out}) \times V_{B\_P}}{1000} \quad (8)$$

where, m_{H2S} is the mass of the H_2S that needs to be removed (kg/day), H_2S_{in} and H_2S_{out} are concentrations of H_2S in the biogas entering and leaving the digester (ppm).

The removal efficiency of the adsorbent was used to determine mass of adsorbent required in a day to remove the H_2S.

$$m_{adsrb} = \frac{m_{H2S}}{\eta_{absrb}} \quad (9)$$

where, m_{adsrb} is the mass of adsorbent required (kg/day) and η_{absrb} is the removal efficiency of the adsorbent (%).

The cost associated with scrubbing off the required H_2S (C_{H2S}) was determined by multiplying the mass of adsorbent required with the cost of a kilogram of adsorbent (C_{absrb}).

4.1.4. Water Condenser

Equation 10 was used to determine the mass of water that needs to be removed from the biogas.

$$m_{H2O} = V_{B\_P} \times B_{H2O} \times \rho_{H2O} \quad (10)$$

where, m_{H2O} is the mass of water in the biogas V_{B_P} (kg/day), B_{H2O} is the water content in biogas (%) and ρ_{H2O} is the density of water (kg/m^3).

By assuming that the biogas entering the scrubber is at atmospheric pressure, the saturation vapour pressure of the biogas is determined by multiplying its pressure with the water content in the biogas (%). The saturation vapour pressure (P_S) against temperature table is used to determine the dew point temperature of water (°C) at that pressure.

The energy needed to cool the biogas to water's dew point temperature is then determined.

$$E_{condenser} = m_{H2O} \times c_w \times (T_D - T_{dew}) \quad (11)$$

where, $E_{condenser}$ is the cooling energy needed to condense the water out of biogas (kg/day) and T_{dew} is the dew point temperature of water (°C).

4.2. Defining the Optimisation Problem

Equations 12 and 13 show the formulation of the two optimisation problems where 1) only the flared biogas and unmet demand are minimised and 2) energy cost is added as a third objective function. The feeding rate was optimised for each day of the month based on that day's cooking demand. The volume of LPG required equals the amount of unmet cooking demand.

$$\begin{aligned} &\text{Min. } V_{B\_F}(x) \\ &\text{Min. } V_{LPG}(x) \\ &\text{s.t.} \\ &0 < x < 1000,\ x \in R \end{aligned} \quad (12)$$

$$\begin{aligned} &\text{Min. } V_{B\_F}(x) \\ &\text{Min. } V_{LPG}(x) \\ &\text{Min. } C_{EC}(x) \\ &\text{s.t.} \\ &0 < x < 1000,\ x \in R \end{aligned} \quad (13)$$

where, x is the feedstock flowrate (kg/day), V_{B_F} is the volume of biogas flared (m^3), V_{LPG} is the volume of LPG required (m^3) and C_{EC} is the energy cost of the system ($/kgVS).

4.2.1. System Storage, Flaring and Gas Consumption Logic

The Flowchart in Figure 2 shows the method used to determine the volume of biogas flared and the volume of LPG required to meet any excess biogas required for cooking.

4.2.2. Energy Cost

Equation 14 was used to determine the energy cost of the system.

$$C_{EC} = \left(\left(\left(E_{shred} + \frac{(E_{heatwater} + E_{loss} + E_{condenser})}{(1000 \times 3.6)}\right) \times C_{elec}\right) + C_{H2S}\right) \Big/ (m_f \times VS) \quad (14)$$

where, C_{EC} is the energy cost of the system ($/kgVS), E_{shred} is the energy consumption of the shredder (kWh), $E_{heatwater}$ is the energy needed to heat the water in the digester coil (kJ), E_{loss} is the heat loss through the digester walls (kJ), $E_{condenser}$ is the energy needed to condense the water out of the biogas (kJ), C_{elec} is the cost of electricity in India ($/kWh), C_{H2S} is the cost of removing H_2S from biogas ($), m_f is the flowrate of the feedstock (kg/day) and VS is the volatile solids content of the feedstock (%).

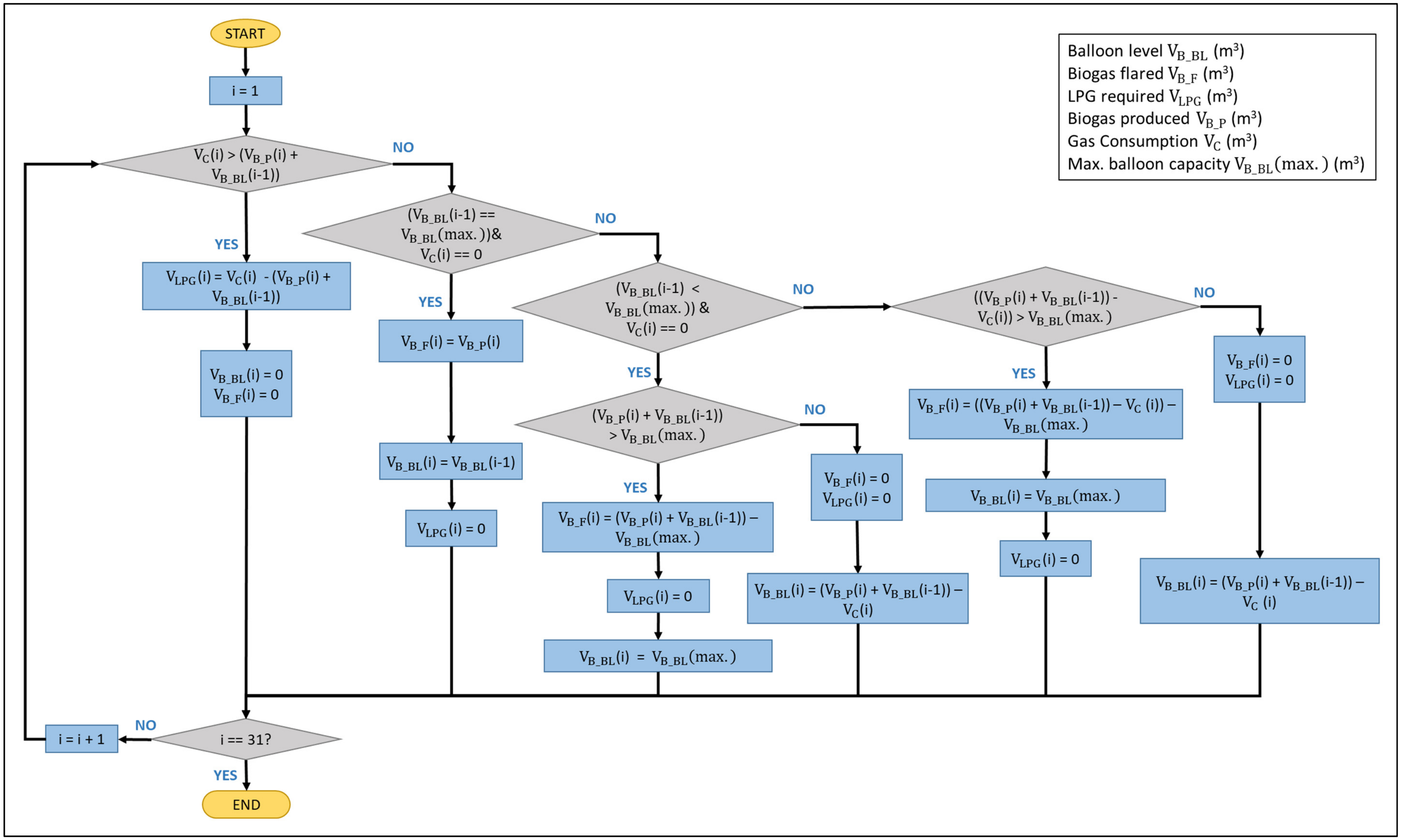

Fig. 2 Flowchart to determine the balloon level V_{B_BL} (m^3), the volume of biogas flared V_{B_F} (m^3) and the volume of LPG required V_{LPG} (m^3) based on the biogas produced V_{B_P} (m^3) the gas consumption V_C (m^3) and the maximum balloon capacity $V_{B\_BL}(max.)$ (m^3).

Table 2 shows the different inputs used in the model and their associated references.

Table 2 Model inputs and their associated values and references.

Parameter	Units	Value	Reference
Shredder:			
D	mm	25	[15]
N	rpm	1440	Case Study Plant Report
Digester:			
c_w	kJ/kgK	4.2	[16]
c_S	kJ/kgK	2.16	[17]
TS	%	23	[14]
VS	%	21	[14]
T_D	°C	38	Case Study Plant Report
T_F	°C	30	Assumed
r_c	m	0.02	Case Study Plant Report
h_c	m	50	Case Study Plant Report
h_{water}	W/m^2K	1000	[18]
Tw_1	°C	25	Assumed
r_d	m	1.798	Case Study Plant Report
h_{air}	W/m^2K	0.265	[19]
T_{amb}	°C	25	Assumed
$G(t)$	m^3/kgVS	0.46	[14]
G_0	m^3/kgVS	1.25	[14]
R_{max}	m^3/kgVS day	0.023	[14]
λ	days	8.84	[14]
t	days	28	Case Study Plant Report
H_2S Scrubber:			
H_2S_{in}	ppm	323	[20]
H_2S_{out}	ppm	200	Case Study Plant Report
η_{absrb}	%	0.2	[21]
C_{absrb}	\$/kg	0.87	[22]
H_2O Condenser:			
B_{H2O}	%	0.05	[23]
ρ_{H2O}	kg/m^3	1000	[24]
P_S	mmHg	37.7	[25]
T_{dew}	°C	33	[25]
Energy Cost:			
C_{elec}	\$/kWh	0.111	[26]
Balloon and Flaring System:			
$V_{B_{BL}}(\text{max.})$	m^3	84	Case Study Plant Report
$V_{B_{BL}}(\text{day } 0)$	m^3	84	Case Study Plant Report

5. Results and Discussion

5.1. Comparison of Predicted Biogas Yield with Measured

The graph in Figures 3 (a) and (b) compare the predicted biogas yield with the measured data for July and December 2017.

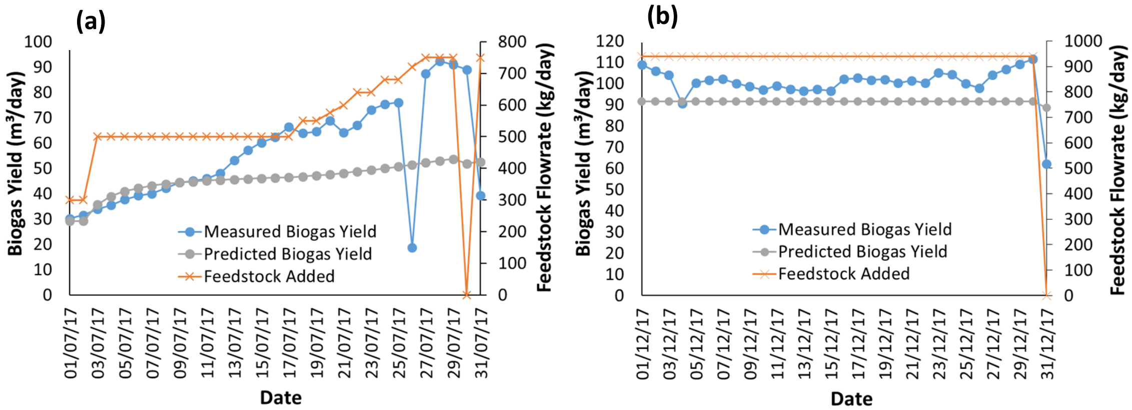

Fig. 3 Comparison of the measured biogas yield with the predicted for July (a) and December 2017 (b).

It can be seen from the graphs that the model agrees well with the measured data for December 2017 and for the first 10 days of July 2017. However, in July, as the feedstock flowrate is increased the difference between the predicted and measured biogas yields increases. This observation highlights that the modified Gompertz model is able to predict the biogas yield accurately when the digester loading rate is constant however, as the loading rate changes the prediction accuracy decreases.

Biogas yield from food waste is reported to be around 0.43 m^3/kgVS for batch systems handling food waste [27] and between 0.415 m^3/kgVS and 0.495 m^3/kgVS for substrates consisting mainly of carbohydrates and protein by [28]. These values give us confidence in the performance of the model. In addition, authors have usually used the modified Gompertz model in predicting biogas yields from digesters operating in batch mode [29] [30] [31] and not in continuous mode, hence, making it less suitable for use in this case study system. Comparing the model performance with measured data for the entire year and not just the two months and getting real-time recordings of digester operational variables such as temperature, pressure can help determine what causes the difference between the predicted and measured results. Furthermore, suitable yet simple digester models, for continuously operated AD systems, need to be researched. At present, since the performance of the model was satisfactory for December 2017, it was decided to use this month's data for further analysis.

5.2. Model of Current Case Study System

Graphs in Figure 4 (a) and (b) show the difference between the performance of the AD system with both the predicted and measured biogas yields.

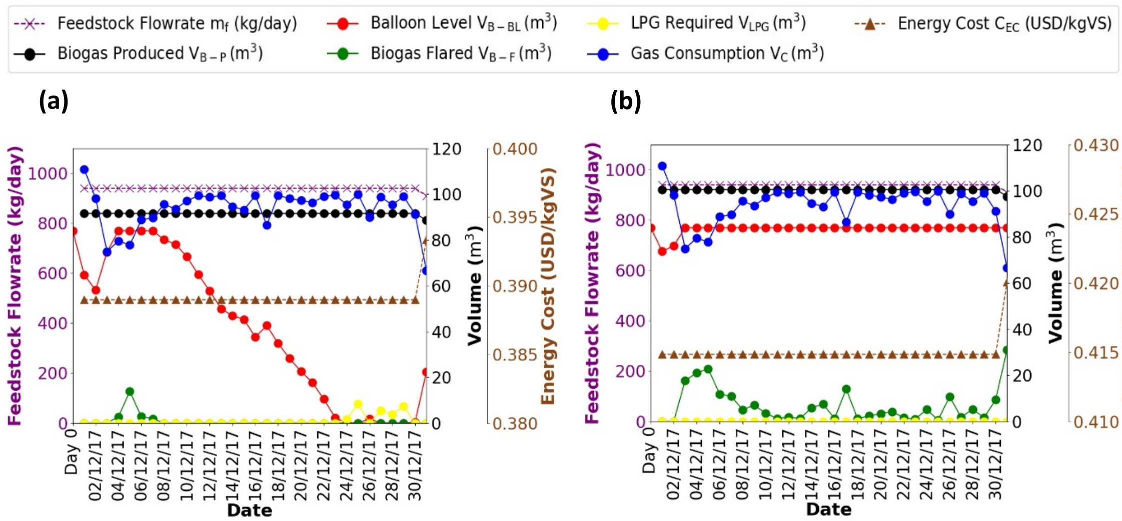

Fig. 4 Comparison of the difference in plant performance if predicted biogas yield is used (a) or if measured biogas yield is used (b).

When the predicted biogas yield is used (Figure 4 (a)), the demand is predominantly being met by the biogas stored in the balloon and flaring occurs only a few days in the month when the balloon is at its maximum capacity. On days when the consumption cannot be met by the system, the back-up LPG supply is used to meet any unmet demand. When the model simulates the performance of the system with the measured biogas yield values (Figure 4 (b)), for most days of the month, the system is producing more biogas than that is needed and since the storage is already at its maximum capacity, the excess biogas is flared. The energy cost of the system is also higher this time since more biogas needs to be cleaned before usage.

The results highlight the importance of optimising the feedstock input into the system so that the amount of biogas produced matches the consumption requirements of the system. This would ensure any flaring is avoided and also that minimum fossil fuel backup is required to meet the unmet demand. Higher biogas yields also mean higher energy consumption of the system (Figure 4 (b)) as more energy is needed to scrub the H_2S and remove water vapour from the biogas. If energy consumption of the system increases due to increase in biogas production than the extra biogas produced should be used or stored so that it does have to be flared. Flaring makes the system extremely inefficient and has a negative impact on the environment [32].

5.3. Optimisation of Case Study System

Figure 5 (a) and (b) show the results of optimisation problems 1 and 2, defined in Equations 12 and 13 respectively.

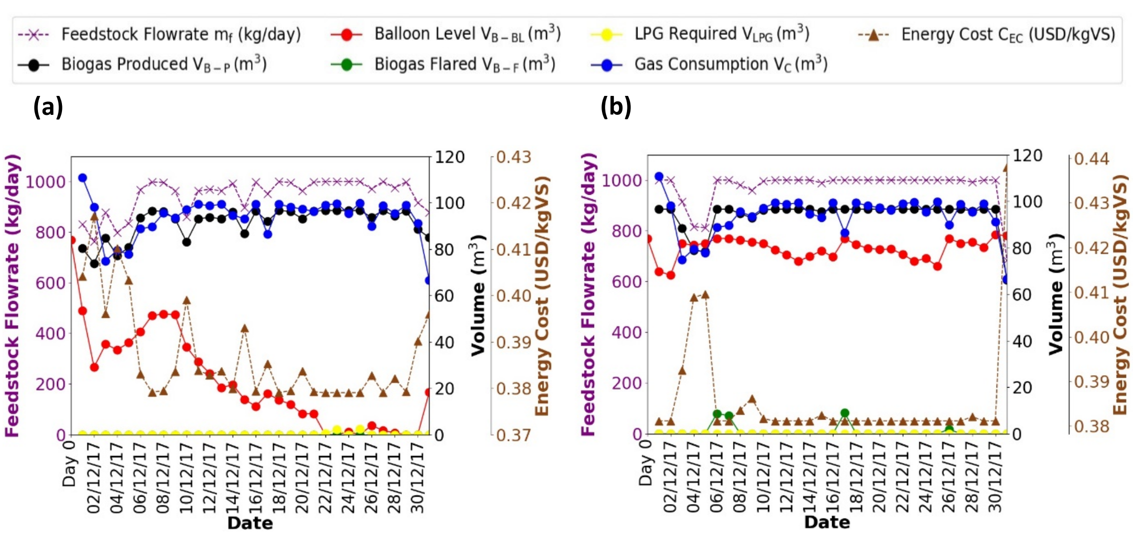

Fig. 5 Comparison of the system performance when two objective functions; biogas flared and volume of LPG required are minimised (a) and when an additional objective function of minimising the energy cost is also added (b).

When the objective functions are to simultaneously minimise the amount of biogas flared and the unmet demand, the optimiser suggests adding only enough feedstock so that the amount of biogas produced is almost equal to the consumption. In Figure 5 (a) that there is almost no flaring on any day of the month and there is only some unmet demand towards the end of the month. This is because the balloon was already empty and the cooking demand was higher than the amount of biogas being produced. Since the energy cost was not an objective function to be minimised in the first optimisation problem, its value fluctuates up and down with the fluctuating feedstock input. When the energy cost is added as an objective function to be minimised (Figure 5 (b)), the feedstock input does not reduce as much as that would increase the energy cost of the system. Unlike the first optimisation problem, the optimiser only alters the feedstock input if the demand is affected for a number of days of the month instead of a single day. Due to this, some biogas does get flared in this system.

The results of the optimisation study highlight the importance of choosing the right objectives functions when optimising different parameters in the AD system since, the optimal values of the feeding rate, suggested by the optimiser, in optimisation scenario one and two are quite different. In reality, the energy cost of the system needs to be included as an objective function as it takes into account the economic performance of the system [8]. Furthermore, to evaluate the performance of the optimised system with the current system, the results should be assessed over the entire month instead of comparing individual days.

6. Conclusions and Future Work

This study looked at modelling and validating a case study AD system and optimising its feedstock flowrate, when the objectives of minimising the volume of biogas flared, the unmet demand and energy cost of the system were set.

When the predicted biogas yield was compared with measured data, it was found that the model was under predicting biogas production and was not able to accurately model it when the feedstock flowrate changed abruptly. Hence, even though typical biogas yields from food waste were found to agree with the constants used in the modified Gompertz model, a better AD model is needed to determine the biogas yields from continuously operated digesters. Furthermore, if available, measured plant data for an entire year will be taken and the model performance will be compared against it. If operating parameters such as temperature, pressure are monitored then they can provide insight into what happens to the model performance with the feeding rate changes.

The results from the optimisation scenarios, showed that when the amount of biogas flared and the unmet demand are minimised, without taking the energy cost of the system into account, the optimiser reduces the feedstock input so that the amount of biogas produced is almost equal to the consumption. When the third objective of minimising the energy cost of the system is considered, the model keeps the feedstock flowrate more consistent than the previous case as reducing the feeding rate increases the energy cost. The performance of the optimiser will be analysed further by assigning weightings to the objective functions and adding an environmental penalty to flaring biogas, so a trade-off between meeting demand and reducing energy costs can be achieved.

This study looked at optimising a single aspect of the case AD system however, it be now be expanded to determine the effect of alternate technologies and/or sizing the components differently on the objective functions. The model will be expanded to include multiple decision variables and objective functions. The effect of modifying different aspects of the case study system such as the method used to heat the digester, the size of the storage balloon and the possibility of producing electricity from the system instead of using it for cooking. The feasibility of composting the excess feedstock instead of creating excess biogas will also be investigated and whether certain technologies i.e. H_2S scrubber and H_2O condenser are in fact needed for this system or not will be assessed.

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