Using multi-objective optimisation with ADM1 and measured data to improve the performance of an existing anaerobic digestion system

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Using multi-objective optimisation with ADM1 and measured data to improve the performance of an existing anaerobic digestion system

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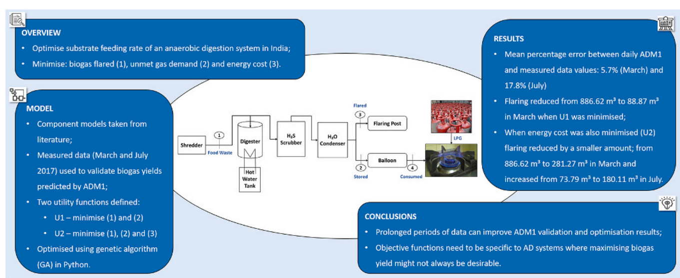
HIGHLIGHTS

- A multi-objective AD system optimisation model is demonstrated for a one tonne per day case study plant in India.
- Mean percentage error between daily ADM1 and plant data values was 5.7% (March 2017) and 17.8% (July 2017).
- GA was used to minimise biogas flaring and unmet gas demand for cooking.
- Flaring reduced from 886.62 m^3 to 88.87 m^3 (March 2017) by controlling the substrate feeding rate.
- Minimising energy cost increased flaring.

GRAPHICAL ABSTRACT



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ABSTRACT

This paper presents a method to model and optimise the substrate feeding rate of an anaerobic digestion (AD) system. The method is demonstrated for a case study plant in Bangalore, India, using onsite kitchen waste to provide biogas for cooking. The AD system is modelled using Anaerobic Digestion Model No. 1 (ADM1) and a genetic algorithm (GA) is applied to control the substrate feeding rate in order to simultaneously minimise the volume of flared biogas, unmet gas demand and energy cost. Our results show that ADM1 can predict biogas yield from a continuously operated digester well with mean percentage errors between daily predicted and measured data values of only 5.7% for March 2017 and 17.8% for July 2017. When biogas flaring and unmet gas demand were minimised, the amount of biogas flared reduced from 886.62 m^3 to 88.87 m^3 in March and from 73.79 m^3 to 68.49 m^3 in July. When the energy cost was also considered within the objective function, the biogas flared reduced from 886.62 m^3 to 281.27 m^3 for March, but increased from 73.79 m^3 to 180.11 m^3 for July. The amount of flaring increased in July as the energy cost function increased biogas yield without considering surplus gas production beyond demand and storage capacity. As AD systems are often operated to maximise biogas production, these results highlight the need for multi-objective optimisation, particularly for off-grid AD systems.

Author contributions statement

R.J. Ashraf: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. J.D. Nixon: Conceptualization, Methodology, Resources, Writing – review & editing, Supervision,

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1. Introduction

Anaerobic digestion (AD) systems are typically controlled to maximise their biogas output (Nixon, 2016). Research, therefore, has had a tendency to focus on optimising the operational decisions that influence yields (e.g. feedstock mixture, temperature, and loading rate) to increase the production of biogas from digesters (Huang et al., 2014a) (Akbaş et al., 2015) (Enitan et al., 2014) (Balaji et al., 2018). However, there are a wide range of downstream applications of the produced biogas (electricity generation, cooking, and injection into gas networks) and this paper investigates how to address the AD system optimisation problem when there are multiple conflicting technical and financial objectives.

To obtain an optimised AD system, all components (pre and post treatment technologies, digester type and operating conditions) need to be simultaneously selected and optimised. However, most researchers tend to focus only on the optimisation of the digester. For example, Huang et al. (2014b), Akbaş et al. (2015), Enitan et al. (2014), Balaji et al. (2018) and García-Diéguez et al. (2011) investigated optimising similar objective functions based on maximising biogas yield and methane content and/or minimising effluent chemical oxygen demand (COD). The optimisation variables in these studies included digester temperature, pH, hydraulic retention time (HRT), substrate feeding rate and carbon/nitrogen (C/N) ratio. These authors did not assess how digester performance affects other components in the system and whether an overall financial improvement in system performance was achieved or not from their digester parameter optimisation.

Research focusing on digester optimisation has typically relied on simple data-driven or first-order kinetic anaerobic digestion models to predict biogas yields. Huang et al. (2014b) used an artificial neural network (ANN) to create a data-driven AD model, Balaji et al. (2018) used lab experimental data to predict yields from a full-scale digester – although Kowalczyk et al. (2011) notes that the ability of lab-scale digesters to accurately predict biogas yields for full-scale digesters depends on the similarity in digester operating conditions, digester geometry, mixing type, substrate properties and feeding frequency – and Enitan et al. (2014) used the first-order Chen and Hashimoto AD model to determine biogas yields from an industrial wastewater treatment plant. The advantage of these relatively simple AD models is that it reduces the computational complexity for an optimisation algorithm, particularly when there are a large number of system variables. The use of a more detailed digester model, such as the well-established Anaerobic Digestion Model No. 1 (ADM1), could offer greater opportunities for AD system control and multi-objective optimisation.

In comparison to optimising the operation of a specific AD component, such as a digester, there has beenlimited research on AD technology combination and selection. Mavrotas et al. (2015) minimised the net present value (NPV) and greenhouse gas (GHG) emissions when finding the optimal combination of AD technologies that can be used to process different types of municipal solid waste (MSW). In addition to anaerobic digestion, other alternate waste processing pathways were investigated, such as composting, landfilling and recycling. Balaman and Selim (2014) looked at maximising the profit of the biomass supply chain, defining system boundaries to include biomass transportation, storage, energy generation and fertilizer disposal. Rather than optimising the AD system and its components, their study mainly focused on financial aspects of transporting and storing biomass at anaerobic digestion sites and the costs associated with supplying electricity to the grid.

There are only a few studies that have investigated optimising an entire AD system considering multiple objectives. Yan et al. (2016) looked at minimising energy consumption and maximising green degree and biomethane production when finding the optimal combination of digestion temperature, methane recovery ratio, feedstock co-digestion ratio and biogas upgrading technology. Li et al. (2018) aimed to find optimal combination of digester operational variables, feedstock mixtures, biogas upgrading technologies and digester heating technologies when minimising the NPV and maximising the green degree. Yan et al. (2016) and Li et al. (2018) both predicted digester biogas yields using simple correlations between the rate of methane production and temperature, as reported in literature for different feedstock co-digestion ratios. Both studies used non-dominated sorting genetic algorithm (NSGA-II) to perform multi-objective optimisation and obtained a set of Pareto optimal solutions. However, this resulted in numerous optimal solutions (i.e. combination of decision variables) and this can make it difficult for decision makers to decide on the best case scenario. This limitation can be overcome by combining multiple objectives in a single utility function.

This paper aims to present a method for enabling multi-objective optimisation of an AD system, where each of the components are modelled in detail, to arrive at a single optimal result. The paper further aims to investigate how ADM1 can be used with plant data to improve system control with an optimisation algorithm to balance 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 substrate feeding rate.

In the next section the methodology used is outlined and demonstrated for a case study system defined in section 3. The models used for each system component and the formulation of the utility functions are given in section 4. The results are discussed in section 5 and the paper concludes by reflecting on how this method can be extended to other existing AD systems in section 6.

2. Methodology

A case study AD system is initially defined which provides gas for cooking and storage, with excess gas being flared. The challenge for the system operators is to balance meeting demand without excessive flaring or use of an expensive non-renewable gas backup tank. The case study system, therefore, represents well a multi-objective AD optimisation problem. Measured data from the case study system is available for the months of March and July 2017, and this data is used to validate the performance of an ADM1 model used to predict the biogas yield from the digester. First order AD models are not used as according to Ashraf et al. (2021), Deepanraj et al. (2017), Donoso-Bravo et al. (2010) and Kafle et al. (2016), they are more suitable for batch operated systems and not continuously fed digesters. The ADM1 model used is this work is based on Nguyen's (2014) implementation of ADM1 in Matlab, which has been translated to Python for the purposes of this research. Since the standard ADM1 model is typically used for modelling the anaerobic digestion of wastewater, Nguyen (2014) altered the stoichiometric, biochemical and physiochemical coefficients of ADM1 to make the model suitable for food waste. An assumption made in this study is that these same coefficients can be used to adequately model the digestion of food waste processed at the case study system.

Once the performance of ADM1 was found to be satisfactory, each component of the case study system was modelled and two multi-objective optimisation problems were formulated: (i) minimise flared biogas and unmet gas demand, and (ii) minimise energy cost along with flaring and unmet gas demand. Utility functions were created for each optimisation scenario by normalising and adding the individual objective functions to give a single objective function value to be minimised. A utility value was considered to be converged when the percentage change in subsequent values was less than 0.01%, for five consecutive iterations. The optimisation problem was set-up in Python and genetic algorithm (GA), with a population size of 20, from Python's multi-objective optimisation library 'pymoo' was used to determine the optimised solution.

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 an onsite kitchen, consisting of preparation waste and cooked food waste. On average, as recorded by the facility operators and mentioned in a confidential plant performance report, the plant produces around 126 m^3 of biogas per tonne of food waste added, which is used for cooking or stored in a balloon. Any excess biogas produced that cannot be stored is flared. A back-up Liquefied Petroleum Gas (LPG) connection exists for any gas demand, which cannot be met from the AD system.

Data recorded from the plant on a daily basis includes the amount of substrate added (kg), biogas going to the balloon (m^3), the amount of biogas flared (m^3) and the biogas consumed (m^3) for cooking. Due to the location of the measuring points (Fig. 1), the total biogas produced (m^3) from the digester in a day is determined by adding the biogas going to the balloon and the amount flared. For the months of March and July 2017, no demand was met by the backup LPG cylinders. The datasets are shown in the supplementary material Tables S1 and S2. Note that for the month of March, data is missing from measuring points (2, 3 and 4) on March 12th and 13th, 2017. These two days are excluded from the measured and predicted mean error percentage calculations. Assumed values for LPG, flaring and demand are shown in Table S1. The only information regarding the characteristics of the food waste available were the total and volatile solids content, which are shown in Table 1.

4. Model formulation

This section details how the components in the case study system were modelled, followed by definitions for the utility functions and the formulation of the optimisation problem. A flowchart is also shown to illustrate how the optimisation problem is solved.

4.1. Component models

Equations from literature were used to model the components in the system. Values of unknown parameters, either taken from literature or the case study report, are outlined in Table 2. It is assumed that the mass of substrate added to the shredder and the digester are the same ($m_{f1} = m_{f2}$) and that biogas volume does not change when it passes through the hydrogen sulphide (H_2S) scrubber and water (H_2O) condenser, as shown in Fig. 1 ($V_{BP1} = V_{BP2} = V_{BP3}$).

4.1.1. Shredder

Bitra et al. (2009) regressed the total specific energy of a shredder as a function of the screen size, mass feed rate and motor speed to obtain second order polynomial equations for switch grass, wheat straw and corn stover. The assumption made was that the second order polynomial equation for corn stover could be used for food waste. The total specific energy consumption of a shredder can be calculated as (Bitra et al., 2009),

$$E_{shredder} = \left(a - bD \times cF + dN - eDF - fFN + gDN + hD^2 + iF^2\right) m_{f1} 10^{-3} \tag{1}$$

where, $E_{shredder}$ is the total specific energy consumption of the shredder (kWh/day), D is the screen size (mm), F is the mass feed rate (kg/min), N is the motor speed (rpm) and a-i are coefficients obtained by Bitra et al. (2009) from multiple regression analysis (shown in Table 2) and m_{f1} is the substrate added to the shredder (kg/day).

Table 1
Properties of the food waste used in the case study system.

Parameter	Unit	Value
Type of food waste	–	Kitchen waste (uncut and leftover vegetables and vegetable peels, rice, curry, bread etc.)
Total Solids (TS)	% of wet weight	15
Volatile Solids (VS)	% of TS	90

4.1.2. Digester

Equation (2) was used to determine the energy needed to heat the substrate going into the digester.

$$E_{heat} = m_{f2}\left(c_w\left(1 - \frac{TS}{100}\right) + c_S\frac{TS}{100}\right)(T_D - T_F) \tag{2}$$

where, E_{heat} is the energy needed to heat the digester (kJ/day), m_{f2} is the substrate added to the digester (kg/day), c_w and c_S are the specific heat capacity of water and substrate, respectively (kJ/kgK). TS is the total solids content in the substrate (%) and T_D and T_F are the digestion and inlet substrate 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 substrate.

$$T_{w2} = \frac{E_{heat}}{2\pi r_c h_c h_{water}} + T_F \tag{3}$$

where, T_{w2} is the temperature of the water in the coil (°C), r_c and h_c are the radius and length of the coil (m), respectively, and h_{water} is the convection heat transfer coefficient of flowing water (W/m^2K).

The mass of water to be heated in the coil is determined by assuming that the coil is cylindrical in shape.

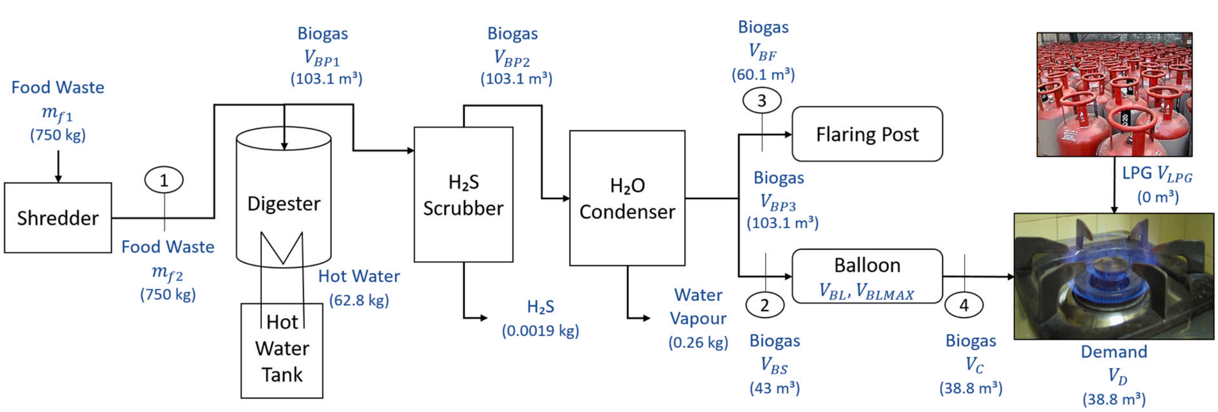

Fig. 1. The case study anaerobic digestion (AD) system showing mass flows into and out of the components and measuring points 1 (food waste added), 2 (biogas going to balloon), 3 (biogas flared) and 4 (biogas consumed from balloon). The mass flows are calculated by the model when 750 kg of substrate was added on the March 1, 2017, as seen from supplementary tables S1 and S2.

Table 2
Model inputs and their associated values and references.

Parameter	Definition	Units	Value	Reference
Shredder:				
D	Screen size	mm	25	Bitra et al. (2009)
N	Motor speed	rpm	1440	Case Study Plant Report
a	Coefficient	–	20.3836	Bitra et al. (2009)
b	Coefficient	–	5.1879×10^{-1}	Bitra et al. (2009)
c	Coefficient	–	8.9192	Bitra et al. (2009)
d	Coefficient	–	1.3455×10^{-1}	Bitra et al. (2009)
e	Coefficient	–	2.4206×10^{-1}	Bitra et al. (2009)
f	Coefficient	–	2.4531×10^{-1}	Bitra et al. (2009)
g	Coefficient	–	3.9630×10^{-4}	Bitra et al. (2009)
h	Coefficient	–	2.2116×10^{-2}	Bitra et al. (2009)
i	Coefficient	–	2.3247	Bitra et al. (2009)
Digester:				
c_w	Specific heat capacity of water	kJ/kgK	4.2	Engineering ToolBox (2004c)
c_S	Specific heat capacity of substrate	kJ/kgK	2.16	Manjunatha et al. (2020)
T_D	Temperature inside the digester	°C	38	Case Study Plant Report
T_F	Temperature of substrate entering the digester	°C	30	Assumed
r_c	Radius of the coil around the digester in which hot water circulates	m	0.02	Case Study Plant Report
h_c	Length of the coil around the digester in which hot water circulates	m	50	Case Study Plant Report
h_{water}	Convention heat transfer coefficient of flowing water	W/m^{2}K	1000	Engineering ToolBox (2003c)
ρ_{H2O_l}	Density of water	kg/m^3	1000	Engineering ToolBox (2003b)
Tw_1	Initial temperature of water in the hot water tank	°C	25	Assumed
r_d	Radius of the digester	m	1.798	Case Study Plant Report
h_{air}	Height of the digester	W/m^{2}K	0.265	Engineering ToolBox (2003a)
T_{amb}	Temperature of ambient air outside the digester	°C	25	Assumed
ρ_s	Density of substrate	kg/m^3	800	TUHH et al. (2018)
V_dig	Total volume of the digester	m^3	20	Case Study Plant Report
V_liq	Volume of the liquid part of the digester	m^3	15	Case Study Plant Report
Storage:				
V_{BLMAX}	Maximum storage capacity of the balloon	m^3	240	Case Study Plant Report
H_2S Scrubber:				
H_2S_{in}	Concentration of H_2S in biogas entering the scrubber	mg/m^3	485	Kuo and Dow (2017)
H_2S_{out}	Concentration of H_2S in biogas leaving the scrubber	mg/m^3	300	Case Study Plant Report
η_{absrb}	Removal efficiency of the scrubber adsorbent	%	0.2	Pagliai and Di Felice (2015)
C_{absrb}	Cost of a kilogram of adsorbent	$/kg	0.87	Abatzoglou and Boivin (2008)
H_2O Condenser:				
B_{H2O}	Water vapour content in biogas	%	0.05	Mamun and Torii (2017)
ρ_{H2O_v}	Density of water vapour	kg/m^3	0.051	Engineering ToolBox (2004a)
P_S	Saturation vapour pressure of biogas	mmHg	37.7	Engineering ToolBox (2004b)
T_{dew}	Dew point temperature of water	°C	33	Engineering ToolBox (2004b)
Energy Cost:				
C_{elec}	Cost of electricity in India	$/kWh	0.111	GlobalPetrolPrices (2021)

$$m_w = \pi r_c^2 h_c \rho_{H2O\_l} \tag{4}$$

where, m_w is the mass of water in the tank heated by electricity (kg/day) and ρ_{H2O_l} is the density of water (kg/m^3).

The electrical energy needed to heat the water to the required temperature for heating the digester was determined using Equation (5).

$$E_{heatwater} = m_w c_w (T_{w2} - T_{w1}) \tag{5}$$

where, $E_{heatwater}$ is the electrical energy needed to heat a fixed mass of water that can travel in the coil (kJ/day) and T_{w1} 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. As only the volume of the digester was known, it was assumed that its height was equal to twice the radius.

$$E_{loss} = \left(2\pi r_d h_d + 2\pi r_d^2\right) h_{air} (T_D - T_{amb}) \tag{6}$$

where, E_{loss} is the energy loss to 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 convection heat transfer coefficient of free air (W/m^{2}K) and T_{amb} is the ambient temperature (°C).

The quantity of biogas produced from the digester was determined using ADM1. A modified ADM1 model by Nguyen (2014), including the ADM1 coefficients and substrate initial conditions for food waste, is used in this work. The assumption was, therefore, made that the food waste substrate modelled by Nguyen would be representative of the food waste processed at the case study plant. For example, the total and volatile solids content of the substrate used in Nguyen's (2014) work were 21.3% and 89.2%, respectively, which were similar to the 15% and 90% provided in Table 1; however, further parameters such as volatile fatty acids content, total organic carbon and nitrogen were not available for the case study plant. Nguyen (2014) determined the ADM1 model coefficients using the Transformer Tool (Zaher et al., 2007). The full substrate parameters, coefficients and ADM1 pathway equations used are available in Nguyen (2014). Methane concentration in biogas is generally considered to be between 50% and 70% (Monlau et al., 2015), and a value of 60% was assumed for this study.

When ADM1 is used to model the anaerobic digestion of a substrate, calibration is required to allow the model to adjust to the system. For example, Ozkan-Yucel and Gökçay (2010) recorded data from a wastewater treatment plant for 375 days and used the initial 150 days to calibrate the model. Other researchers modelled a start-up phase where the initial coefficient values for ADM1 were taken from a digester at steady state, with the same inoculum and substrate additions, as the digester in their system (Fatolahi et al., 2020). Poggio et al. (2016) set up an experimental 2.4 L semi-continuous digester where they gradually increased the organic loading rate (OLR), for the first 80 days to allow the digester to settle, before starting to record biogas yields. The experiment was ran for 142 days in total. When the experiment was modelled in ADM1, a similar approach was followed where the OLR was gradually increased, to calibrate ADM1 for 80 days, before comparing the biogas yields with the experimental values. A similar approach to Poggio et al. (2016) was used in this study where the substrate feeding rate in the ADM1 model was gradually increased for 30 days, for both March and July, until the required substrate feeding rates on the first days of those months was reached. After these initial 30 days of adjusting the model to the flowrates used in the case study plant, the model results were compared with the measured data on the first days of both March and July. The flowrate values used to gradually adjust the model to the substrate additions, for March and July, are shown in the supplementary material Tables S3 and S4. Feedstock flow rate was used as the OLR was not known. The volume of the substrate entering the digester was determined by dividing the substrate feeding rate by the density of shredded food waste (ρ_s) (TUHH et al., 2018). The liquid and total volume of the digester were taken from the case study report to be were 15 m^3 and 20 m^3, respectively (see Table 2).

4.1.3. Balloon storage

Before the system could be optimised, the amount of biogas in the balloon on day 0, for both March and July, is determined. This was done by subtracting the biogas consumed from the balloon V_C from the biogas entering the balloon V_{BS} on day 1, as shown in supplementary materials Tables S1 and S2. This value was used to determine the amount of biogas in the balloon on day 0.

$$V_{BL}(0) = \begin{cases} V_{BLMAX} - (V_{BS} - V_C), & (V_{BS} - V_C) \geq 0 \\ -(V_{BS} - V_C), & otherwise \end{cases} \quad (7)$$

where, V_{BL} is the level of biogas in the balloon (m^3) at time t = 0 and V_{BLMAX} is the maximum balloon capacity (m^3).

4.1.4. Hydrogen sulphide scrubber

The mass of H_2S removed by the scrubber in a day was determined using Equation (8). As shown in Table 2, the concentration of H_2S entering the scrubber was taken from literature as 323 ppm (485 mg/m^3), as that value could not be determined from ADM1. The concentration of H_2S in the biogas when leaving the scrubber was assumed to be 200 ppm (300 mg/m^3). This was the limit set by the local environmental protection agency and assumed to be met by the scrubber.

$$m_{H2S} = (H_2S_{in} - H_2S_{out})V_{BP1}10^{-6} \quad (8)$$

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 scrubber (mg/m^3) and V_{BP1} is the volume of biogas produced by the digester (m^3/day).

The removal efficiency of the adsorbent was used to determine the 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}).

4.1.5. Water condenser

The mass of water to be removed from the biogas is given by,

$$m_{H2O} = V_{BP2}B_{H2O}\rho_{H2O\_v} \quad (10)$$

where, m_{H2O} is the mass of water in the biogas V_{BP2} (kg/day), V_{BP2} is the volume of biogas entering the condenser (m^3/day), B_{H2O} is the water content in biogas (%) and ρ_{H2O_v} is the density of water vapour (kg/m^3) taken from Engineering ToolBox (2004a), assuming that the temperature of biogas is 40 °C.

By assuming that the biogas entering the scrubber is at atmospheric pressure, the saturation vapour pressure (P_S) of biogas is determined by multiplying the atmospheric pressure with the percentage of water in biogas. The exact percentage of water in the biogas, when the biogas was at 38 °C, was not known. Hence, it was assumed that the water content in the biogas was 5%, as reported by Al Mamun and Torii (2017) to be the water content in biogas when it is at 32 °C.

Once the P_S was known, the P_S against temperature table (Engineering ToolBox, 2004b) was used to determine the dew point temperature of water (°C) at that P_S. The energy needed to cool the biogas to that dew point temperature was then determined using Equation (11).

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

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

4.2. Defining the utility functions

For the months of March and July 2017, two optimisation scenarios are considered: (i) minimise flared biogas and unmet gas demand, and (ii) minimise energy cost along with flaring and unmet gas demand. The unmet gas demand is determined by calculating the volume of LPG used. The individual objective functions are normalised before being added together so that a dimensionless utility value can be obtained. As stated by Grodzevich and Romanko (2006), objective functions can be normalised by dividing their optimised values by their absolute values at current design. This approach is followed in this study where the amount of biogas flared, LPG consumed and energy cost are divided by their values at current design and then added together, with equal weightings, to give a single utility function value as shown in Equations (12) and (13).

The amount of biogas flared in the current system is given in the raw plant data, shown in supplementary material Tables S1 and S2 and the energy cost of the system is calculated using the substrate feeding rate values given in those tables. However, since no LPG was consumed for the months of March and July, the LPG objective function was being divided by zero in Equations (12) and (13). To overcome this issue, as suggested by Chang (2015), non-zero values can be assumed for those objective functions at current design.

Equations (12) and (13) show the utility functions U1 and U2.

U1:

$$\min f(m_{f2}) = \sum_{x\in R} \frac{V_{BF}(m_{f2})}{|V_{BF}(raw)|} + \frac{V_{LPG}(m_{f2})}{|V_{LPG}(raw)|} \quad 0 < m_{f2} < 1000, \; x \in R \quad (12)$$

U2:

$$\min f(m_{f2}) = \sum_{x\in R} \frac{V_{BF}(m_{f2})}{|V_{BF}(raw)|} + \frac{V_{LPG}(m_{f2})}{|V_{LPG}(raw)|} + \frac{C_{EC}(m_{f2})}{|C_{EC}(raw)|} \quad 0 < m_{f2} < 1000, \; x \in R \quad (13)$$

where, V_{BF} is the volume of biogas flared (m^3/day), V_{LPG} is the volume of LPG required (m^3/day) and C_{EC} is the energy cost of the system ($/$m^3$biogas). V_{BF}(raw), V_{LPG}(raw) and C_{EC}(raw) are the biogas flared (m^3/day), volume of LPG required (m^3/day) and energy cost ($/$m^3$ biogas), respectively, of the current system.

4.2.1. System storage, flaring and gas consumption logic

The balloon level V_{BL}, volume of biogas flared V_{BF} and the volume of LPG required to meet the unmet gas demand V_{LPG} during the optimisation study were determined using Equations (14)–(16), respectively.

$$V_{BL}(t) = \begin{cases} 0, & V_D \geq V_{BP3} + V_{BL}(t-1) \\ V_{BLMAX}, & V_D = 0 \ \ and \ \ (V_{BP3} + V_{BL}(t-1)) \geq V_{BLMAX} \\ (V_{BP3} + V_{BL}(t-1)) - V_D, & otherwise \end{cases} \quad , t = 1, 2 \ldots n \tag{14}$$

$$V_{BF}(t) = \begin{cases} V_{BP3}, & V_D = 0 \ and \ V_{BL}(t-1) = V_{BLMAX} \\ (V_{BP3} + V_{BL}(t-1)) - V_{BLMAX}, & V_D = 0 \ and \ (V_{BP3} + V_{BL}(t-1)) > V_{BLMAX} \\ ((V_{BP3} + V_{BL}(t-1)) - V_D - V_{BLMAX}, & V_D < (V_{BP3} + V_{BL}(t-1)) \ - \ V_{BLMAX} \\ 0, & otherwise \end{cases} \quad , t = 1, 2 \ldots n \tag{15}$$

$$V_{LPG}(t) = \begin{cases} V_D - \ ((V_{BP3} + V_{BL}(t-1)), & V_D > ((V_{BP3} + V_{BL}(t-1)) \\ 0, & otherwise \end{cases} \quad , t = 1, 2 \ldots n \tag{16}$$

where, V_D is the gas demand (m^3/day) and V_{BP3} is the volume of biogas leaving the condenser (m^3/day).

4.2.2. Energy cost

Equation (17) was used to determine the energy cost of the system.

$$C_{EC} = \left(\left(E_{shredder} + \frac{E_{heatwater} + E_{loss} + E_{condenser}}{3600} \right) C_{elec} + C_{H2S} \right) \Big/ V_{BP1} \tag{17}$$

where, C_{elec} is the cost of electricity in India ($/kWh). .

4.3. Setting up the optimisation problem

Fig. 2 shows how the optimisation problem was formulated and solved. For all optimisation scenarios, a run time of around 45 min, running on Intel Broadwell nodes (Intel ® Xeon ® CPU E5-2683 v4 @ 2.10 GHz) was recorded.

5. Results and discussion

This section presents and discusses the results obtained when the performance of ADM1 was compared with measured data. Optimal substrate feeding rate values obtained, for March and July 2017, when the biogas flared and unmet gas demand are minimised (U1) and energy cost is also minimised (U2) are shown. Optimised objective function values and the optimal substrate feeding rates are compared with the current performance of the system to assess the performance of the optimiser.

5.1. Comparison of predicted biogas yield with measured data

The graphs in Fig. 3a and b compare the predicted biogas yield with the measured data for the months of March and July 2017.

The results show that the predicted biogas yield agrees well with measured data for both July and March. In March, ADM1 slightly under predicts the biogas yield and in July there is an over prediction. This is most likely due to variations in feedstock composition, as a single TS and VS value were used in the ADM1 model, and therefore more detailed and frequent feedstock characterisation would be needed to improve the accuracy of ADM1. Neglecting any outliers using the interquartile range method, the mean percentage error between the daily predicted and measured data values is 5.7% for March (mean absolute error of 6.7 m^3) and 17.8% for July (mean absolute error of 9.8 m^3). Further discrepancy between the results can be due to a number of other assumptions made in the model, e.g., determining the substrate feeding rate without knowing the OLR, uncertainty regarding the digester operational variables, percentage methane content in the biogas and the substrate feeding rate values used to calibrate ADM1 for 30 days before the start of the month.

To ensure that the predicted model matches the plant data well, the model performance should be compared for the entire year and not specific months and real-time recordings of digester operational variables such as temperature and pressure are needed to model the behaviour of the digester more accurately. If measured data for other parameters such as the volumetric production of carbon dioxide (CO_2), hyrdogen (H_2), total volatile fatty acids (VFAs), valeric, propionic, butyric and acetic acid were also available, they can be used to assess the performance of the individual digestion stages and to determine the stages that are being modelled well and the ones that are not. This can help to identify the ADM1 coefficients that need to be more accurately determined.

5.2. Substrate feeding rate optimisation

This section shows the optimised results obtained, for both March and July 2017, when the utility functions were minimised and compares the results to the present-day performance of the system for those months.

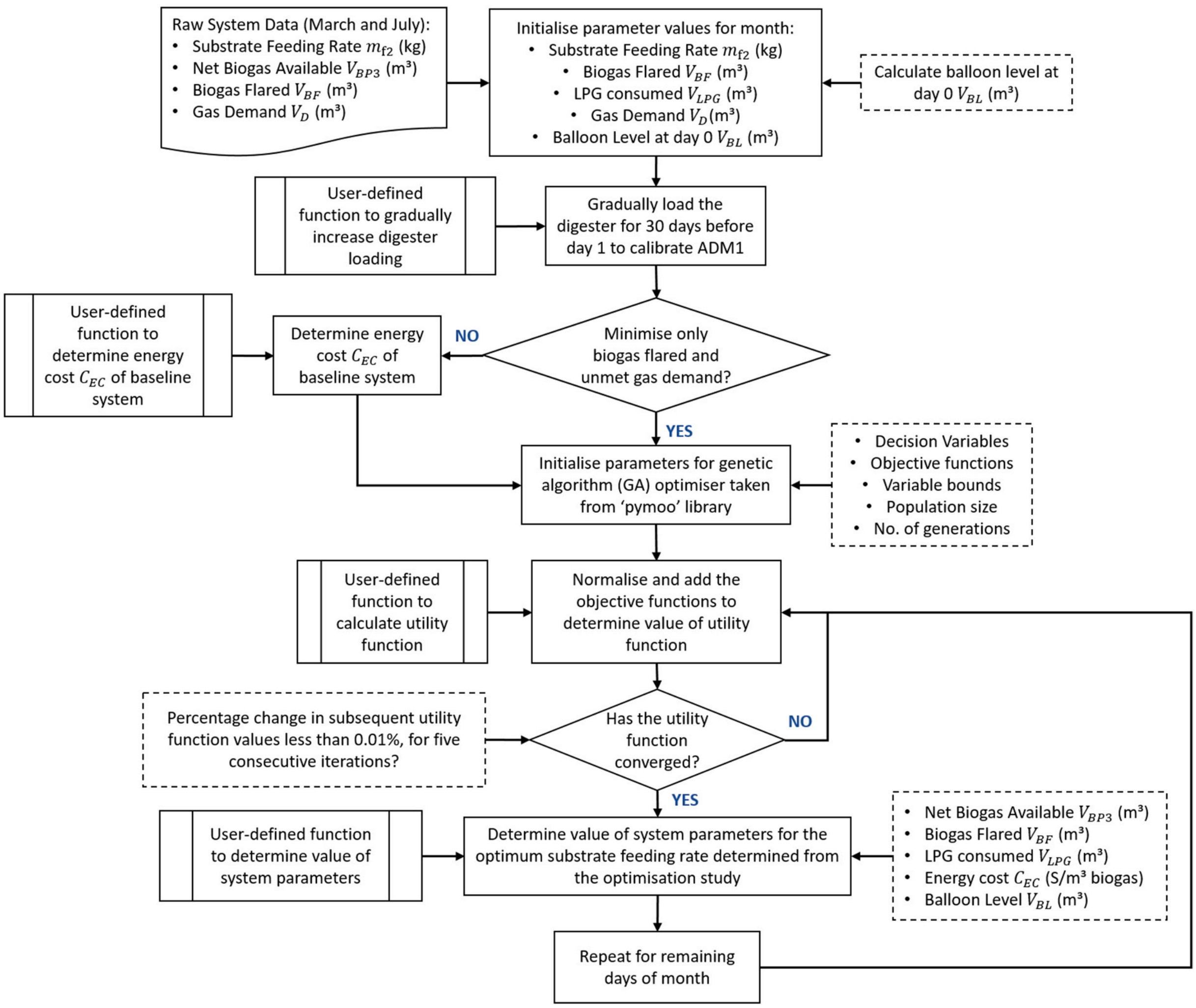

Fig. 2. Flowchart to show how the optimisation scenarios were solved to determine the optimum substrate feeding rate for each month.

5.2.1. Optimised result for March 2017

Fig. 4a–e shows the result for March 2017 when the substrate feeding rate was optimised for U1 and U2 and compares the optimised system performance with the current performance.

According to the measured data, daily biogas production from the system is between 100 m^3 and 120 m^3; however, since the gas demand is low, a large quantity of the biogas is flared (see Fig. 4a) (approximately 60 m^3 of biogas is flared on both the 7th and 8th of March). The anaerobic digestion process is commonly considered to be carbon neutral (Larsen et al., 2018); however, combustion of biogas can lead to net GHG emissions to the atmosphere (US EPA, 2017). According to Oil and Gas Authority (2020), 1 m^3 of natural gas flared equates to 30 g of CO_2-eq

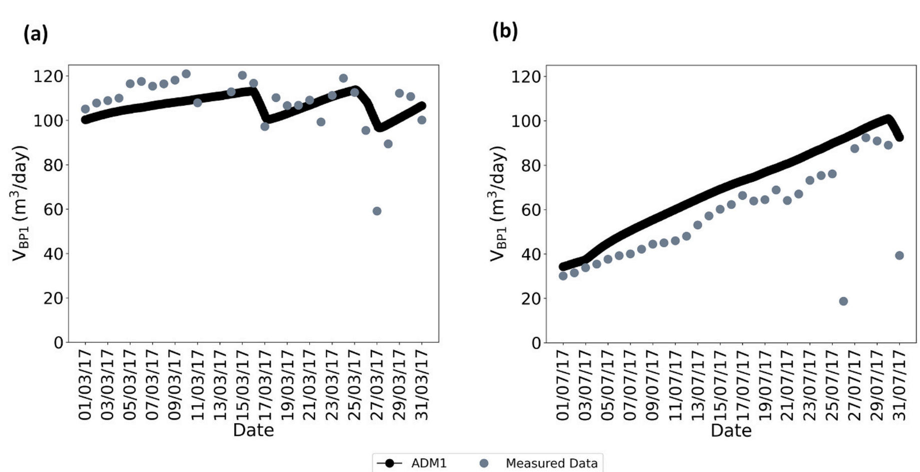

Fig. 3. Comparison of the predicted biogas yield with measured data for March (a) and July (b) 2017.

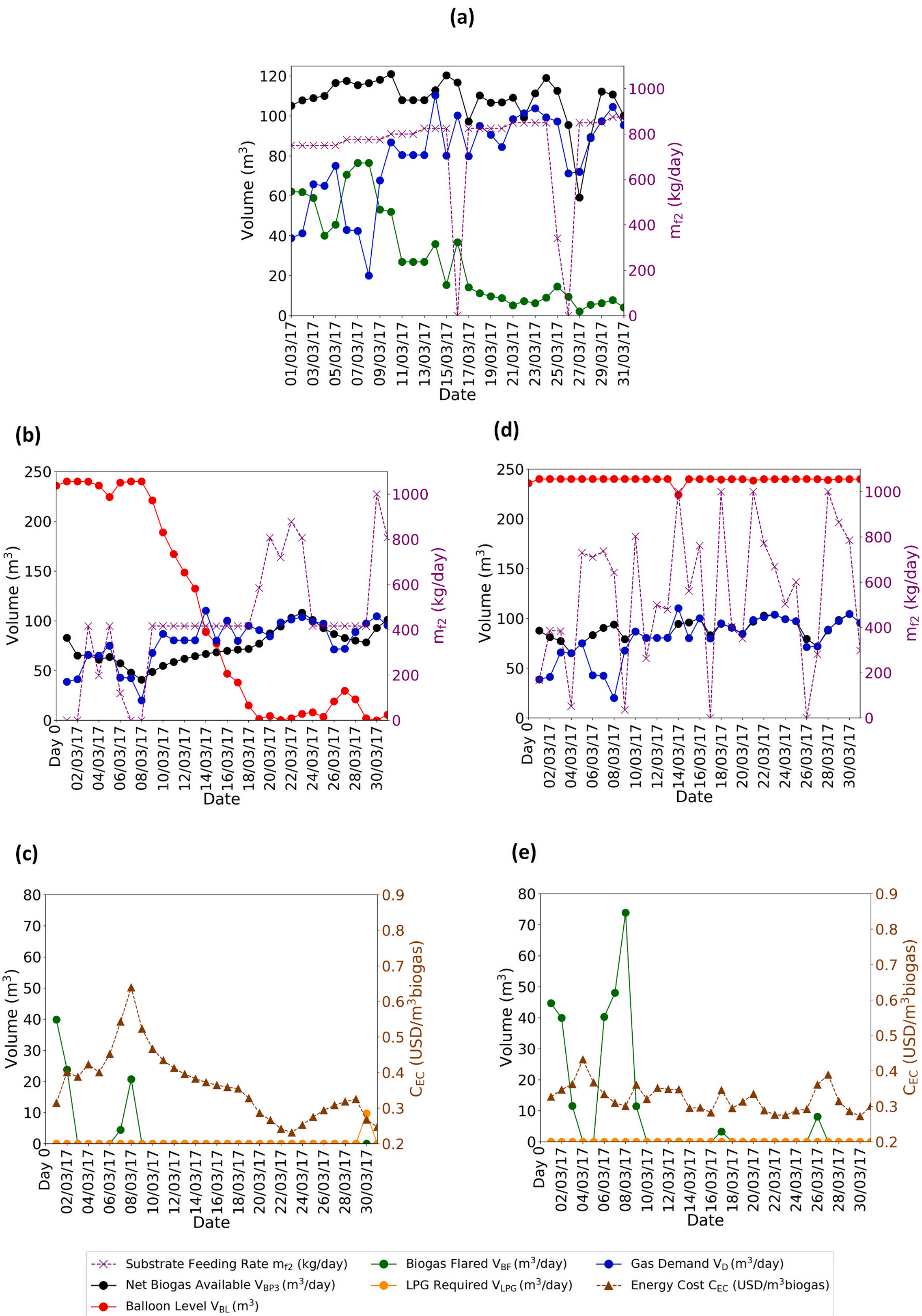

Fig. 4. Comparison of the current system performance (a) for March 2017 with the optimised results; U1 – minimisation of biogas flaring and unmet gas demand (b and c) and U2 – minimisation of the energy cost along with flaring and unmet gas demand (d and e).

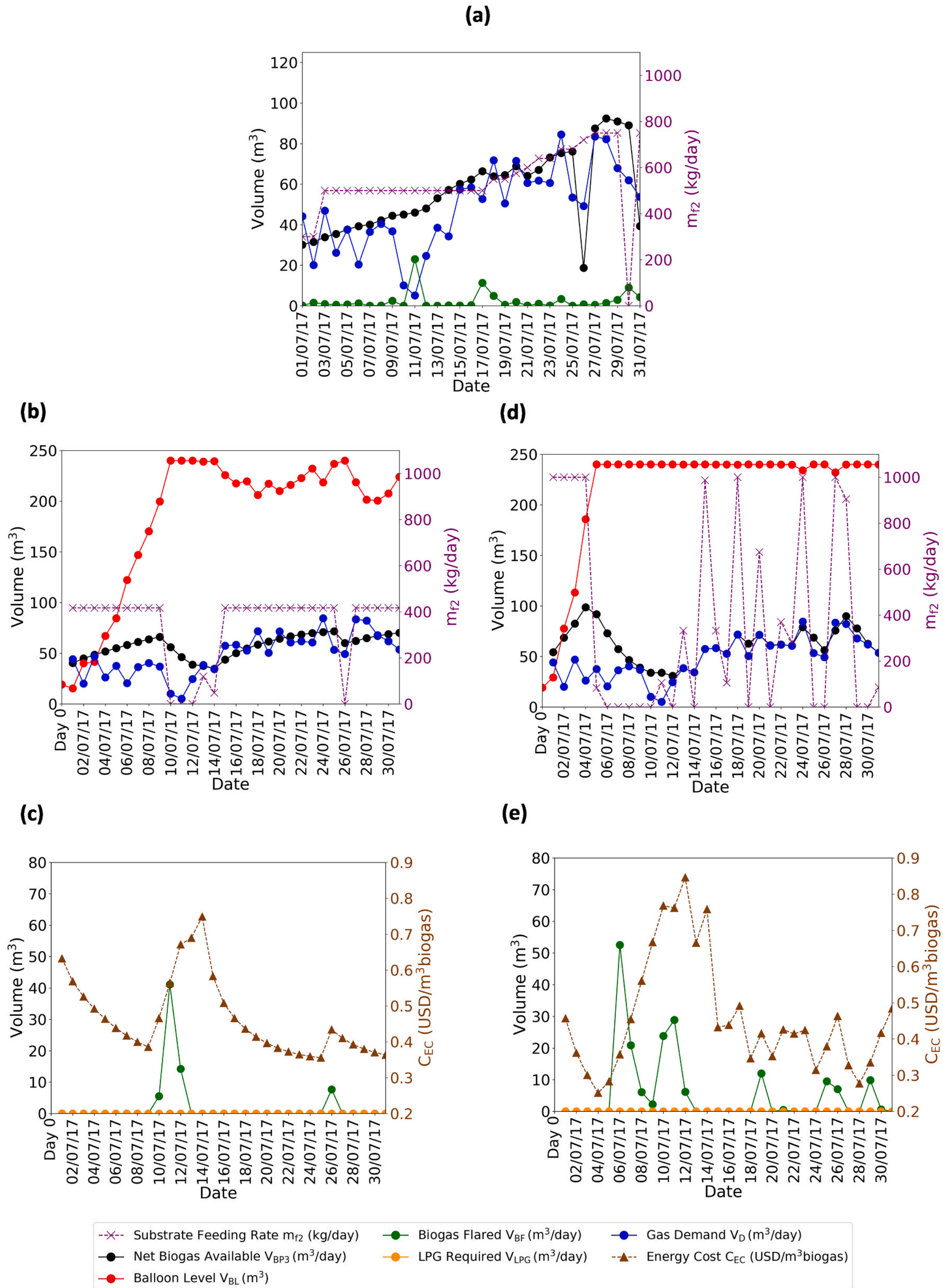

Fig. 5. Comparison of the current system performance (a) for July 2017 with the optimised results; U1 – minimisation of biogas flaring and unmet gas demand (b and c) and U2 – minimisation of the energy cost along with flaring and unmet gas demand (d and e).

Table 3
Comparison between the current system performance and the optimised system performance.

Month	Scenarios	Substrate Added m_{f2} (kg)	Biogas Flared V_{BF} (m^3)	LPG Needed V_{LPG} (m^3)	Avg. Energy Cost C_{EC} (USD/m^3 biogas)
March	Present-day	23,065	886.62	0	–
	U1	12620.78 (↓10444.22)	88.87 (↓797.75)	9.71 (↑9.71)	0.344
	U2	16439.53 (↓6625.47)	281.27 (↓605.35)	0 (no change)	0.304
July	Present-day	16,735	73.79	0	–
	U1	10175.34 (↓6559.66)	68.49 (↓5.3)	0 (no change)	0.440
	U2	11177.70 (↓5557.3)	180.11 (↑106.32)	0 (no change)	0.430

emissions. Since, biogas is taken to be 60% methane, flaring around 60 m^3 of biogas in a day equates to 1080 g of CO_2-eq emissions. India is the third highest CO_2 emitter in the world (Statista, 2021a) however, apart from different state governments imposing their own taxes to capture the cost of negative externalities, India does not have a uniform carbon taxation system across the country (Raghunathan, 2021). Hence, most plant owners find it economical to flare excess biogas. If this plant was located in Sweden instead, a country which imposes the highest carbon tax in the world (137 \$/tonne CO_2-eq emissions (Statista, 2021b)), 1080 g of CO_2-eq emissions would cost the plant owners \$0.15 everyday.

As seen from Fig. 4b, when the biogas flared and unmet gas demand were minimised, the optimiser ensures that the demand is met by the balloon and the substrate is only added when the balloon is empty. However, when the energy cost is also minimised, the system produces more biogas than needed to reduce the energy cost. This causes an increase in flaring, but only results in a small reduction in energy cost. This result signifies that the definition of the energy cost function needs to be considered carefully and could include an environmental penalty linked with flaring.

5.2.2. Optimised result for July 2017

Fig. 5a–e shows the result for July 2017 when the substrate feeding rate was optimised for U1 and U2 and compares the optimised system performance with the current system performance.

When the first utility function is minimised (Fig. 5b and c), the amount of biogas flared is similar to the current system. This is because less flaring is recorded in July in the first instance as seen in Fig. 5a and supplementary materials tables S1 and S2 due to empty storage at the start of the month. Similar to March, when the energy cost is added as an objective function, flaring increases in comparison to the first optimisation scenario, due to an increase in the amount of biogas produced.

5.2.3. Comparison between current and optimised system

The overall performance of the optimisation algorithm is evaluated by comparing the substrate feeding rate, biogas flared, LPG consumption and energy cost in the current and optimised systems (Table 3). When the substrate feeding rate is optimised, the quantity of substrate used in March is almost half of what is currently used and for July it is almost a third less. Significant reductions in biogas flaring have been achieved for March; from the present-day flaring of 886.62 m^3 it was reduced to 88.87 m^3 for U1 and to 281.27 m^3 for U2. In July, the present day flaring of 73.79 m^3 was reduced to 68.49 m^3 for U1 and increased to 180.11 m^3 for U2. Flaring is higher in U2, for both March and July, as extra biogas is produced to reduce the energy cost. An increase in flaring, from the present-day performance of the system, is seen in U2 for July and similarly even though the unmet gas demand was zero for both March and July in the current system, an increase of 9.71 m^3 is seen in U1 for March. These results show that even though significant improvement in system performance i.e. reduction in the amount of feedstock used and biogas flared were achieved, there were instances where flaring and unmet gas demand slightly increased.

As energy cost values for the current system were not available, a direct comparison cannot be made between the current energy cost of the system and the optimised results. Between U1 and U2, the energy cost reduces from 0.344 USD/m^3 biogas to 0.304 USD/m^3 biogas for March and from 0.440 USD/m^3 biogas to 0.430 USD/m^3 biogas for July. This suggests that the optimisation scenario U2 is not achieving a large improvement in system performance in comparison to U1. This can be improved by either redefining the energy cost objective function or by assigning different weightings to each of the objective functions in U2. An alternate method could be to explore the economic value of other products from the system such as composting the excess feedstock. According to Raviprasad (2015), compost produced from municipal solid waste (MSW) can act as a soil enriching agent and can be sold to private parties and government agencies at a rate of INR 3500 per tonne and between INR 2100 and 2700 per tonne, respectively. If food waste from this system is assumed to be the same as MSW, for March, this can equate to a profit of INR 36,555 for U1 and INR 27,287 for U2.

6. Conclusions and further work

To conclude, this study investigated modelling and optimising a case study AD system for producing gas for cooking. By optimising the substrate feeding rate, the volume of biogas flared, unmet gas demand and energy cost were minimised. When the predicted biogas yield was compared with measured data, it was found that ADM1 was able to model the digester performance well and the difference in the results was due to assumptions made regarding the digester. Results from the optimisation study show that when the amount of biogas flared and the unmet gas demand are minimised, significant reductions in gas flaring can be achieved. However, the energy cost objective function, which was based on maximising biogas yield, needs further evaluation as this can result in increasing surplus gas production and thus flaring. This study demonstrates how objective functions should be specific to an anaerobic digestion system, based on its setup and design, and that maximising the biogas yield might not always be desirable.

Further work is needed to improve the performance of ADM1 and the optimisation results. Feedstock used in the case study system should be better characterised so that accurate ADM1 coefficients can be determined. Prolonged periods of plant data will also help to better assess the predictive capabilities of ADM1 and allow for the optimiser to run for longer times so that its performance can be evaluated in different scenarios. Formulation of the utility functions can be improved by assigning weightings to individual objective functions and minimising the objective functions individually first and then normalising them by the differences in their optimal values over the Pareto front. The energy cost objective functions need to be better defined, such as adding a cost penalty to flaring or assigning a cost to unmet gas demand.

To extend this work further, the performance of the system when alternate optimisation approaches are assessed, such as increasing the size of the balloon to store the excess biogas, converting all of the biogas to electricity or liquefying and selling the biogas instead, can be considered. Further pre and post treatment technologies could be included so that the effect of alternate technologies and/or adding or removing components from the system on the objective functions can be analysed. The model presented can be further expanded to include multiple decision variables, objective functions and to improve the performance of other case study systems.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chemosphere.2022.134523.

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