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Designing and optimising anaerobic digestion systems: a multi-objective non-linear goal programming approach

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Abstract

This paper presents a method for optimising the design parameters of an anaerobic digestion (AD) system by using first-order kinetics and multi-objective non-linear goal programming. A model is outlined that determines the ideal operating tank temperature and hydraulic retention time, based on objectives for minimising levelised cost of electricity, and maximising energy potential and feedstock mass reduction. The model is demonstrated for a continuously stirred tank reactor processing food waste in two case study locations. These locations are used to investigate the influence of different environmental and economic climates on optimal conditions. A sensitivity analysis is performed to further examine the variation in optimal results for different financial assumptions and objective weightings. The results identify the conditions for the preferred tank temperature to be in the psychrophilic, mesophilic or thermophilic range. For a tank temperature of 35 °C, ideal hydraulic retention times, in terms of achieving a minimum levelised electricity cost, were found to range from 29.9 to 33 days. Whilst there is a need for more detailed information on rate constants for use in first-order models, multi-objective optimisation modelling is considered to be a promising option for AD design.

Keywords: Kinetics; Nonlinear programming (NLP); Levelised cost of electricity (LCOE); Levelised energy cost (LEC); Bioenergy; Multi-objective optimization.

Nomenclature

CAPEX	Capital cost ($)
Cc	Initial setup cost ($)
Cf	Cost of handling feedstock ($/kg)
Ch	Cost of auxiliary heating ($/kWh)
Cheat	Total cost of auxiliary heating ($)
Cm	AD capacity dependent cost variable ($/kW)
C_{ps}	Specific heat capacity of organic solids (kJ/kg°C)
C_{pw}	Specific heat capacity of water (kJ/kg°C)
d	Discount rate (%)
E_m	Energy density of methane (MJ/m^3)
FCR	Fixed charge rate (%)
h	Height of reactor tank (m)
HRT	Hydraulic retention time (days)
I	Annual insurance and maintenance costs (%)
k	Rate constant ($days^{-1}$)
$k_{c,air}$	Heat loss coefficient from digester to air (W/m^2.°C)
$k_{c,grd}$	Heat loss coefficient from digester to ground (W/m^2.°C)
LCOE	Levelised cost of electricity ($/kWh)
n	Period of loan (year)
OLR	Organic loading rate (kgVS/m^3.day)
OPEX	Total fixed annual operating cost ($/a)
PY	Proportion of methane yield (%)
Qi	Energy requirement to heat feedstock (kWh/year)
Qloss	Digester tank heat losses (kWh/year)
Qn	Annual electricity produced (kWh/year),
r	Radius of digester tank (m)
Ta	Average annual ambient temperature (°C)
Tf	Initial feedstock temperature (°C)
Tg	Average annual ground temperature (°C)
Tr	Temperature of digester tank (°C)
TS	Percentage of total solids (%)
Vr	Volume of digester tank (m^3)
VS	Percentage of volatile solids (%)

Y	Yield of methane (m^3/kgVS)
Ym	Ultimate methane yield (m^3/kgVS)
η_g	Gas engine efficiency (%)
ρ_f	Density of feedstock (kg/m^3)

Sub- super- scripts

a	Achieved objective
$d-$	Negative deviation from goal
$d+$	Positive deviation from goal
g	Target goal for objective
t	Variable tank temperature (denotes a tank temperature dependent variable for the non-linear goal programming model)
w	Weighting for deviations from target goal

1. Introduction

Anaerobic digestion (AD) involves the degradation of organic matter by microorganisms in an oxygen free environment. The valuable outputs from this process are a biogas containing methane and a nutrient rich digestate. Biogas is typically used in gas engines for producing electricity, but it can be used directly as a fuel for heating or upgraded for injection into natural gas grids. Digestate can be used as a soil conditioner to mitigate the use of conventional chemical fertilisers. As AD is a relatively clean and scalable system, it is becoming an increasingly attractive option for producing affordable renewable energy.

There are a variety of AD technology types, and systems range in capacity from a few kilowatts to several megawatts. In developed countries, large AD systems are being increasingly utilised for treating and recovering energy from the organic fraction of municipal solid waste (OFMSW). In developing hot countries, such as India—where hundreds of millions of people still live in remote areas without access to grid electricity—small decentralised AD systems use ambient temperatures to process food waste to generate gas for cooking [1] and electricity for street lighting [2]. There are also a few large-scale power generation systems in India (*ibid.*). As there are many options regarding feedstock types and operational practices, there is a need for both the technical and financial optimisation of AD systems.

Research on AD optimisation has had a tendency to purely evaluate alternative technologies and operating conditions. Ward et al. [3] review optimisation techniques that have been discussed in the literature and these include mixing, immobilisation of microbial biomass, temperature, pH, feedstock selection, control systems and wet and dry systems. Where optimisation studies have been performed, there has been a focus on maximising biogas yields. However, it does not necessarily always make sense to optimise AD plants for this parameter, as it may not result in the most cost-effective design. For some AD systems, a more suitable design objective might be to minimise the cost of producing electricity or maximise the substrate mass reduction.

There are many mathematical models that have been developed for simulating AD process dynamics and these models provide opportunities for improving and optimising entire AD systems [4,5]. Anaerobic digestion model No.1 (ADM1), developed by the International Water Association (IWA), is a popular method for modelling and optimising AD systems [6,7]. Another area of research is on first-order kinetic models to predict degradation rates and microbial dynamics, and several authors have shown these models to have a good correlation with experimental results [8,9]. However, first-order models are difficult to use for optimisation due to the complexity of microbial dynamics. Furthermore, to optimise an AD system, numerous decision variables need to be considered and suitable objectives have to be considered.

Multi-criteria algorithm-based optimisation methods, such as neural networks and linear programming, have been widely used in optimisation studies, and applications range from spacecraft trajectory optimisation [10] to hospital room allocation [11]. There are also numerous applications of linear programming for energy planning [12]; however, its use for AD system optimisation is limited. Aceves et al. [13] use linear programming to estimate kinetic parameters and yield coefficients for AD, but they do not pursue the use of this information for optimising the design parameters of AD systems. Álvarez et al. [14] used linear programming to determine optimal feedstock mixtures to maximise methane production rates. The specific operational parameters of AD systems were not included. Non-linear programming has also been used to evaluate co-digestion of wastewaters [15]. Optimising the supply chain for AD systems has been tackled using linear programming [16] and similar studies have been done for other biomass technologies [17]. However, there is no methodological approach for optimising AD systems for potentially different objectives or multiple conflicting objectives. Furthermore, there is a need for research to show how the ideal design parameters for an AD system, determined for specific objectives, may vary for different installation sites.

This study aims to develop and outline a model—that integrates multi-objective non-linear programming with a first-order kinetic model—for specifying an AD system's optimal design parameters. To investigate the variability of the optimal results, different site locations, financial assumptions and objectives are to be analysed.

In the following section, the methodological approach is outlined and rationale for the chosen objectives, decision variables and case studies is provided. In section 3, the model is defined in detail, and, in section 4, it is applied to two different case study locations. The results are provided and a sensitivity analysis is carried out in section 5. The paper concludes by discussing the study’s key findings and providing recommendations for further work.

2. Methodology

The model developed in this study is based on non-linear goal programming and determines optimal design parameters for different objectives. The model can be used to minimise levelised cost of electricity (LCOE), maximise energy potential, or maximise waste reduction. The model can also be used for determine a trade-off among these objectives by assigning weightings. The LCOE has been used as it provides an objective that encompasses both technical and economic performance. LCOE is a widely accepted indicator for energy technology evaluations and it is based on discounted cash flows and energy production [18]. Specifically, it is the average price a plant must receive for a unit of produced electricity to break-even over its lifetime, and it has been used as the criterion for many energy optimisation and comparative studies [19-21]. However, the LCOE does not typically consider subsidies and other incentives, and it also relies on process and debt interest stability. The objective for maximising energy potential is based on the total methane production. The methane yield per kilogram is used as an indicator for mass reduction.

The decision variable to be optimised is the hydraulic retention time (HRT). The model considers every possible HRT value for a range of different tank temperatures. The retention time and tank temperature have been chosen as decision variables as they are two design parameters, which are commonly used to investigate AD performance [3]. To determine methane yields, a first-order kinetic model for a continuously stirred tank reactor (CSTR) system has been used. A first-order model has been used as it provides a simple method for predicting stable AD performance in practical conditions [8], and thus minimises the number of variables for the non-linear programme. First-order models have also been shown to have a good agreement with experimental results if retention times are more than a few days [22]. Reaction rate constants for different psychrophilic, mesophilic and thermophilic temperature conditions have been gathered by reviewing the literature. Limitations on the use of these rate constants are considered, as they are not only temperature dependent. Waste composition, experimental methods and other operational parameter conditions influence growth rates, microbial diversity and inhibitory factors [23]. Based on a range of reported values for food waste, rate constants have been assumed for a specific feedstock being processed at several different tank temperatures.

The model is demonstrated for systems operating in two case study locations: the UK, and India. These sites have been chosen as they represent significant differences in economic and environmental climates. For each location, site specific environmental and financial data have been gathered. The objective initially considered for these case study locations is minimising LCOE. To examine how the optimised LCOE and HRT would change for different financial assumptions and design objectives, a sensitivity analysis is performed.

The model is solved for each case study using LINGO®, which is an established software package for expressing and performing non-linear optimisation calculations. A global solver has been run initially to determine a feasible solution. However, due to the nature of non-linear non-convex models, the global solver cannot always claim that a global optimum has been found. On these occasions, a local solver has also been used. To avoid the solver stopping at locally optimal points, and thus potentially missing a global optimum, a multi-start solver type–using ten starting points–has been used. Throughout the study, both solver types return the same optimised solution.

3. The non-linear programming model

The objective function and decision variables for the non-linear goal programming model are initially defined. The model also consists of a number of constraints which are used to define an AD system's technical and economic performance. All temperature dependent variables are given the subscript, *t*, and the model performs a series of iterative calculations for all possible temperature variants ($t = 1, 2, \dots n$). All assumptions and simplifications made for outlining the model are explicitly stated.

3.1 Multi-objective function

The multi-objective function is defined by considering positive, $^{+d}$, and negative deviations, $^{-d}$, from target goals for the levelised cost of electricity, LCOE ($/kWh), energy potential, Q (kWh/year), and methane yield, Y (m^3/kgVS). Weightings, $_w$, differentiate the importance of deviations from an objective and they enable a trade-off among the objectives to be made. For the weightings to be comparable, the percentage deviation from a target objective has to be considered. Negative LCOE deviations and positive Q and Y deviations are considered to be desirable. The value achieved for an objective, $_a$, is determined from a summation of the objective's target goal and any positive or negative deviations.

$$
\begin{aligned}
Minimise \sum_{i=1}^{n} LCOE_w^{+d} . \left(\frac{LCOE^{+d}{}_t}{LCOE.0.01}\right) - LCOE_w^{-d} . \left(\frac{LCOE^{-d}{}_t}{LCOE.0.01}\right) \\
- Q_w^{+d} . \left(\frac{Q^{+d}{}_t}{Q.0.01}\right) + Q_w^{-d} . \left(\frac{Q^{-d}{}_t}{Q.0.01}\right) \\
- Y_w^{+d} . \left(\frac{Y^{+d}{}_t}{Y.0.01}\right) + Y_w^{-d} . \left(\frac{Y^{-d}{}_t}{Y.0.01}\right), \qquad t = 1, 2, \dots n
\end{aligned} \tag{1}
$$

3.2 Decision variable

The objective function is minimised by optimising the hydraulic retention time, HRT (day^{-1}). As the hydraulic retention time has to be greater than zero days, the following limit is applied:

$$0 < HRT_t, \qquad t = 1, 2, \dots n \tag{2}$$

A further limit can be placed on the volume of the digester, Vr (m^3) or the parameters used to size the system.

$$0 < V_r \leq 2500, \qquad t = 1, 2, \dots n \tag{3}$$

3.3 System constraints

In this study, a simplified expression for the levelised cost of electricity is used based on a capital cost, CAPEX, fixed charge rate, FCR, fixed annual operating cost, OPEX, and fixed annual production of electricity, Qn (kWh/year). For systems with variable annual costs and electricity production, a different LCOE calculation can be performed, as outlined in ref. [24].

$$LCOE_{a,t} = LCOE_g + LCOE^{+d}{}_t - LCOE^{-d}{}_t = \frac{(CAPEX_t.FCR) + OPEX_t}{Qn_t}, \quad t = 1, 2, \dots n \tag{4}$$

The capital cost of the system is determined from an initial investment cost, *Cc*, and a capacity dependent cost variable, *Cm*.

$$\mathrm{CAPEX}_t = C_m . \frac{Qn_t}{8760} + Cc, \qquad t = 1, 2, \dots n \tag{5}$$

A fixed charge rate, FCR, is calculated from a real debt interest or discount rate, *d*, and an *n* number of years when loan repayments are required [24].

$$FCR = \frac{d(1+d)^n}{(1+d)^n - 1} \tag{6}$$

The operational costs are calculated from the total feedstock cost and cost of heating, *Cheat*. Annual maintenance, insurance and repair costs, *I*, are included and assumed to be a percentage fraction of the capital cost.

$$OPEX_t = \left(Cf.\rho_f.Vr.\frac{365}{HRT_t}\right) + Cheat_t + I.CAPEX_t, \qquad t = 1, 2, \dots n \tag{7}$$

The total cost of handling the feedstock, *Cf*, in $/kg, is based on the density of the feedstock, ρ_f, volume of the digester, and the retention time. The annual amount of feedstock processed is assumed to be based on 365 days divided by the hydraulic retention time, HRT.

The operating costs for heating the digester tank are calculated from the energy required to heat the feedstock, *Qi*, and maintain the tank temperature due to heat losses, *Qloss*. The cost of the auxiliary heat, *Ch*, will depend on the form of heating used, which could be from electrical heaters, gas heating or heat recovered from a gas engine.

$$Cheat_t = (Qi_t + Qloss_t).Ch, \qquad t = 1, 2, \dots n \tag{8}$$

The energy requirement to initially heat the feedstock is calculated from the tank volume, feedstock density, loading rate, percentage of total solids, *TS*, specific heat capacity of solids, C_{ps}, and water, C_{pw}, and difference in tank temperature, *Tr*, and initial feedstock temperature, *Tf*. The specific heat capacity of water is taken as 4.2 kJ/kg°C. The specific heat capacity for the total solids is taken as 1.3 kJ/kg°C [25].

$$Q_{i_t} = \rho_f Vr \frac{0.1}{HRT_t}\left[C_{pw}.(1-TS) + C_{ps}.TS\right](Tr_t - Tf), \qquad t = 1, 2, \dots n \tag{9}$$

The heat loss is calculated by assuming that the digester tank is cylindrical with a radius, *r* and a height, *h*,.

$$Qloss_t = 17.52\pi rh.k_{c,air}(Tr_t - Ta) + 8.76\pi r^2\left[k_{c,air}(Tr_t - Ta) + k_{c,grd}(Tr_t - Tg)\right], \qquad t = 1, 2, \dots n \tag{10}$$

The heat transfer coefficients from the tank walls to the air, $k_{c,air}$, and from the tank to the ground, $k_{c,grd}$, are taken respectively as 0.265 W/m^2.°C and 0.235 W/m^2.°C [26]. The average annual ambient temperature, *Ta*, and ground temperature, *Tg*, depend on the site location. Any heat generated by the substrate during decomposition is neglected.

The energy potential of the system is characterised by the yield of methane, *Y*, organic loading rate, *OLR*, methane energy content, *Em*, and the volume of the reactor. Note that *Eq.*(9–11) have conversion factors applied to arrive at units of kWh/year. The subsequent electricity generation potential, *Qn*, is based on the efficiency of a gas engine connected to a generator, η_g.

$$Q_{a,t} = Q_g + Q^{+d}{}_t - Q^{-d}{}_t = (Y_g + Y^{+d}{}_t - Y^{-d}{}_t).Vr.OLR_t.E_m.101.39, \qquad t = 1, 2, \dots n \tag{11}$$

$$Qn_t = (Q_g + Q^{+d}{}_t - Q^{-d}{}_t).\eta_g, \qquad t = 1, 2, \dots n \tag{12}$$

The yield of methane gas at a given retention time, *Y*, can be estimated using kinetic models. Several kinetic models have been developed for determining degradation rates and biogas yields from AD systems [4,27], and they include first-order models and more advanced pseudo-parallel first-order degradation models [28,29]. The approximation of the methane yield from a CSTR system based on a first-order kinetic model is expressed as [30],

$$Y_{a,t} = Y_g + Y^{+d}{}_t - Y^{-d}{}_t = \frac{HRT_t.k_t.Ym}{HRT_t.k_t + 1}, \qquad t = 1, 2, \dots n \tag{13}$$

where *Ym* is the ultimate methane yield achievable and *k* is the reaction rate constant.

The organic loading rate (OLR) in kgVS/m^3.day can be determined from the initial percentage concentration of volatile solids, *VS* [30].

$$OLR_t = \frac{k_t.VS.\rho_f}{Y_t/(Ym - (Y_g + Y^{+d}{}_t - Y^{-d}{}_t))}, \qquad t = 1, 2, \dots n \tag{14}$$

3.4 First-order rate constants

Reaction rate constants have been determined experimentally by many authors for different feedstocks, temperatures and tank conditions. Whilst rate constants are sometimes given for overall systems, the majority of rate constants in the literature are stated for the hydrolysis step of AD, as it is considered to be the rate limiting stage for solid wastes [31]. However, this has been contested for the thermophilic temperature range [32]. Table 1 shows a range of reported rate constants for various feedstocks at 20, 30, 35, 40 and 55 °C. The differences in values and the range stated for some rate constants is due to the testing of different mixtures, tank conditions and feedstock compositions. Based on these reported values, a series of rate constants to use in this study are assumed (see Table 1). Using these values in *Eq.*13, Figure 1 shows the cumulative methane yield from OFMSW at temperatures ranging from 20–55 °C. Rate constants for different feedstocks outside of this temperature range have not been widely reported.

Table 1: First-order rate constants for various feedstocks at different temperatures (k, day^{-1}).

Feedstock	20 °C	30 °C	35 °C	40 °C	55 °C	Ref.
OFMSW	-	-	0.19	-	-	[22]
OFMSW	-	-	-	-	0.581	[33]
OFMSW	0.11	-	-	-	-	[34]
OFMSW	-	-	-	-	-	[35]
OFMSW	-	-	0.256	-	0.41	[36]
OFMSW	-	-	0.147-0.256	-	-	[37]
OFMSW	-	0.14	0.35	0.38	0.42	[38]
Vegetable wastes	-	-	0.053-0.125	-	-	[39]
Market food waste	-	-	0.25	-	-	[40]
Cabbage waste	-	-	0.031-0.041	-	0.031-0.075	[41]
Potato processing waste	-	-	-	-	0.089	[30]
Food waste and dewatered sludge	-	-	0.5	-	-	[42]
Food waste with sewage sludge	-	-	0.15-0.22	-	0.21-0.35	[43]
Orange peels	0.145	0.264	-	0.474	-	[44]
Grass	0.035	0.09	-	0.266	-	[44]
Straw	0.024	0.087	-	0.14	-	[44]
Pond silt	-	0.013	-	-	-	[45]
Forest soils	0.035 - 0.09	0.54	-	-	-	[45]
Cattle manure	-	-	-	-	0.13	[46]
Sludge (waste water)	0.11-0.15	-	-	-	-	[47]

Maize silage	-	-	0.032	-	-	[48]
Beet silage	-	-	0.316	-	-	[48]
Rye silage	-	-	0.041	-	-	[48]
Cattle slurry	-	-	0.047	-	-	[48]
Model assumptions for OFMSW (present study)	0.1	0.14	0.26	0.28	0.42	

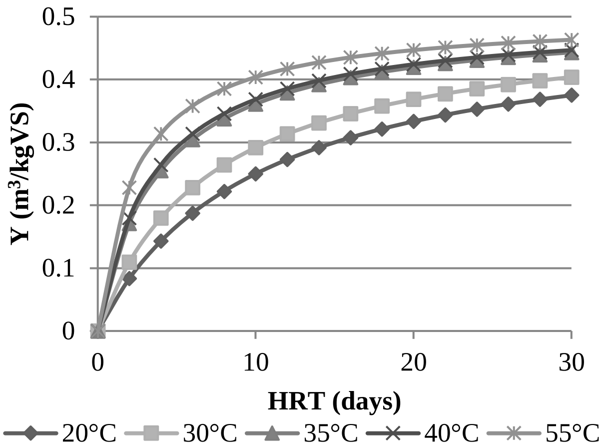

Figure 1: Cumulative methane yield from anaerobic digestion of OFMSW at different temperatures.

Rate constants depend on a number of factors in addition to temperature which can impact microbial growth rates and dynamics (e.g. temperature, Ph, loading rates and nitrogen content). High OLRs can lead to inhibition from the accumulation of volatile fatty acids and the impact on total methane production in a CSTR system can be found in ref. [49]. However, a balance needs to be found with OLRs as the retention time needs to be long enough to degrade a substance. As the model determines an optimum retention time for each temperature condition, and the OLR is a variable in this study, a correction factor is included into *Eq.*11 based on refs. [50,51]. The empirical relationship between the proportion of methane yield, PY, and OLR for food waste in a CSTR is expressed as,

$$PY_f = -0.0064.OLR_f^{\ 2} + 0.0414.OLR_f + 0.8905 \tag{15}$$

4. Case studies

To demonstrate and test the model, it is now applied to two case study locations: the UK and India. In each case study, a range of system temperatures are evaluated and the local financial and environmental conditions are considered. The model is initially tested for minimising

LCOE only; therefore, the LCOE weightings are set at 1 and the weightings for *Y* and *Q* are set a zero. Target goals for LCOE, *Q* and *Y* are set respectively at 0.1 \$/kWh, 10 GWh/year and 0.4 m^3/kgVS.

4.1 Feedstock data

The feedstock characteristics required by the model include density, percentage of total solids, percentage of volatile solids and ultimate yield of methane, *Ym*. The reported values for these parameters vary in different literary sources [22,52-54]; however, the values assumed for this study are shown in Table 2. The energy content of methane is taken to be 35 MJ/m^3 [55]. Maximum limits for the tank radius and height are set at 10 metres and 8 metres, respectively, which allows a maximum tank volume of approximately 2500 m^3.

Table 2: Feedstock data including density, fraction of volatile solids and ultimate methane yield.

Feedstock	Density ρ_f (kg/m^3)	Total solids *TS* (%)	Volatile solids *VS* (%)	Ultimate yield of methane *Ym* (m^3/kgVS)	Energy content of methane *Em* (MJ/m^3)
OFMSW	600	0.2	0.18	0.5	35

4.2 Environmental and financial assumptions

The setup costs of AD plants are variable in different countries because of labour, material and manufacturing costs, and issues regarding permitting and regulations. The capital cost of AD systems in the UK has been reported to cost in the range of 5800–11,700 \$/kW_{el} for capacities ranging from 50–500 kW_{el} [56]. Costs in India are significantly lower and AD technology is normally used for small off-grid applications; for capacities of 50–500 kW_{el}, the costs are expected to range from 800–3500 \$/kW [57,58]. The real discount rate for AD is taken as 10% [59], and the operational period is taken as 25 years. The fixed operational cost (insurance, maintenance) is taken as 2% of the capital. Assuming that the plant is not using a CHP system, the cost of gas heating is initially taken as 0.04 \$/kWh for the UK [60] and 0.2 \$/kWh in India [61]. The cost associated with handling and processing OFMSW is dependent on feedstock quality, AD technology type, plant capacity and downstream applications. It will also vary in different localities due to labour costs and supply. For the UK, a value of 0.015 \$/kg is assumed [62]. As there are more manual processing operations and labour costs are lower for AD plants in India, a value of 0.1 $/kg is used. For the purposes of this study, incentives, such as gate fees and feed-in-tariffs, which are available in the UK, have been neglected.

Average annual ambient temperatures vary significantly in different site locations. In the inner parts of India, annual average temperatures are typically in the range of 26 °C. In the UK, average temperatures are lower, ranging from 8.5–11 °C. Ground temperatures and feedstock temperatures will tend to be slightly above ambient temperatures. A summary of the environmental and financial assumptions made for each case study location are given in Table 3.

Table 3: Financial and average annual temperature assumptions for each case study location.

Model constraints	Units	UK	India
Temperature of feedstock (*Tf*)	°C	13	30
Ambient temperature (*Ta*)	°C	10	26
Ground temperature (*Tg*)	°C	11	27
Cost of feedstock (Cf)	$/tonne	0.015	0.01
Cost of heating (*Ch*)	$/kWh	0.04	0.02
Capacity dependent cost (*Cm*)	$/kW	5,191	500
Setup cost (*Cc*)	$	324,444	150,000

5. Results

The optimised results for the two case study locations are shown in Tables 4–5. The optimised HRT and OLR values for a digester operating from 20–55 °C in the UK were found to range respectively from 27.1 to 39.5 days and 2.73 to 3.99 kgVS/m^{3}day. The preferred tank temperatures were determined to be 35 °C and 55 °C, as they produced a minimum LCOE of 0.139 $/kWh. In India, the optimised retention times were higher, ranging from 29.4 to 45.5 days. In terms of minimum LCOE, mesophilic and thermophilic conditions were found to be equally preferred with a value of 0.045 $/kWh. The LCOE increased to 0.049 $/kWh for a digester tank temperature of 20 °C. Based on the optimal decisions made by the model, results for capital cost, heat demand, methane yield and energy potential are also provided in Tables 4-5.

Table 4: Optimised results for the UK case study.

Model outputs			Tank temperature				
			20°C	30°C	35°C	40°C	55°C
Capital cost	*CAPEX*	$	2569052	2853763	3562345	3638967	4019098
Operations cost	*OPEX*	$/y	265218	298540	366421	377379	424042
Plant capacity	*Pc*	kW	432	487	624	639	712
Organic loading rate	*OLR*	kgVS.$(m^3d)^{-1}$	2.73	3.00	3.62	3.68	3.99
Retention time	*HRT*	days	39.5	36.0	29.9	29.3	27.1
Volume of digester	*Vr*	m^3	2512	2512	2512	2512	2512
Heat demand	*Qi*	kWh/y	98040	260996	407573	509000	858142
Heat loss to air and ground	*Qloss*	kWh/y	24770	50185	62893	75601	113725
Methane yield	Y_a	m^3/kgVS	0.41	0.42	0.44	0.45	0.46
Energy potential	Q_a	MWh/y	9469	10671	13660	13983	15587
Levelised cost of electricity	$LCOE_a$	$/kWh	0.1447	0.1436	0.1389	0.1391	0.1390

Table 5: Optimised results for the India case study.

Model outputs			Tank temperature				
			20°C	30°C	35°C	40°C	55°C
Capital cost	*CAPEX*	$	341773	368612	435544	443171	480643
Operations cost	*OPEX*	$/y	127726	142144	177518	183212	207586
Plant capacity	*Pc*	kW	384	437	571	586	661
Organic loading rate	*OLR*	kgVS.$(m^3d)^{-1}$	2.37	2.64	3.27	3.34	3.67
Retention time	*HRT*	days	45.5	40.9	33.0	32.3	29.4
Volume of digester	*Vr*	m^3	2512	2512	2512	2512	2512
Heat demand	*Qi*	kWh/y	0	0	83806	171172	470361
Heat loss to air and ground	*Qloss*	kWh/y	0	9520	22228	34936	73060
Methane yield	Y_a	m^3/kg VS	0.42	0.43	0.45	0.45	0.46
Energy potential	Q_a	MWh/y	8400	9575	12507	12841	14482
Levelised cost of electricity	$LCOE_a$	$/kWh	0.0492	0.0477	0.0451	0.0452	0.0450

5.1 Sensitivity analysis

As the model results are highly dependent on the objective weightings and the financial and environmental assumptions, a sensitivity analysis is carried out for the UK case study. The study is performed by varying the assumptions for the heating cost, plant setup cost and methane yield objective weighting.

As heating for an AD plant can be met in different ways, the cost of heating is varied from 0 to 0.15 $/kWh. Figure 2 shows that the minimum LCOE is achieved by thermophilic conditions when the cost associated with heating falls below 0.04 $/kWh. For costs in the range of 0.04–0.15 $/kWh, a tank temperature of 35 °C gives the lowest LCOE. Above 0.15 $/kWh, a tank temperature of 20 °C would provide a lower LCOE. The HRT is relatively insensitive to different costs associated with heating. The optimum HRT is more sensitive to changes when plant setup costs are low (see Figure 3). To investigate how the optimised variables change with capital cost, the plant setup cost has been increased from 0 to 500,000 US Dollars. This reveals that a tank temperature of 35 °C is preferred until set-up costs become as high as $350,000, at which point thermophilic conditions provide the lowest LCOE.

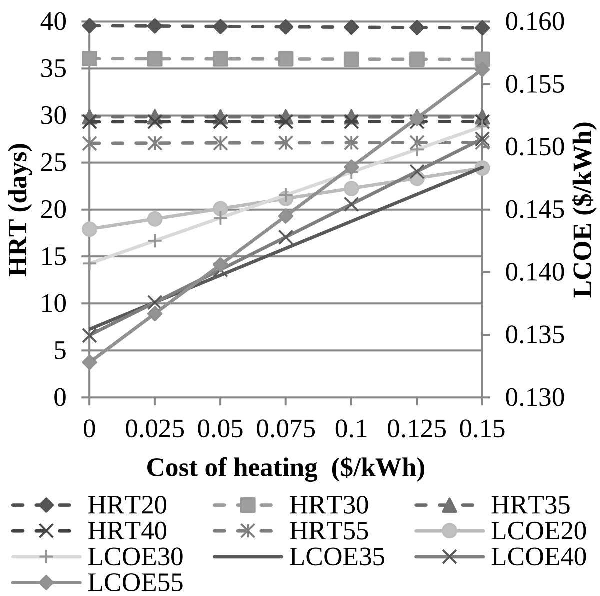

Figure 2: Effect of increasing heating costs on optimal HRT and LCOE for AD systems operating at temperatures of 20, 30, 35, 40 and 55 °C, in the UK.

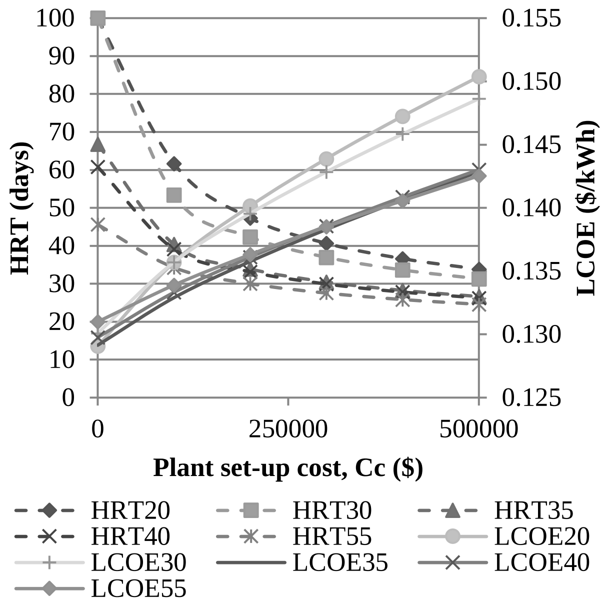

Figure 3: Effect of increasing plant setup costs on optimal HRT and LCOE for AD systems operating at temperatures of 20, 30, 35, 40 and 55 °C, in the UK.

Figure 4 shows how the optimal values form HRT and LCOE change when the importance of maximising methane yield is increased. As expected, increasing the gas yield weighting encourages longer retention times to maximise the waste mass reduction. When increasing methane yield is equally as important as reducing LCOE (i.e. a methane yield weighting of 1), 55 °C is the preferred operating tank temperature. For methane yield weightings below 0.3, mesophilic conditions are preferred.

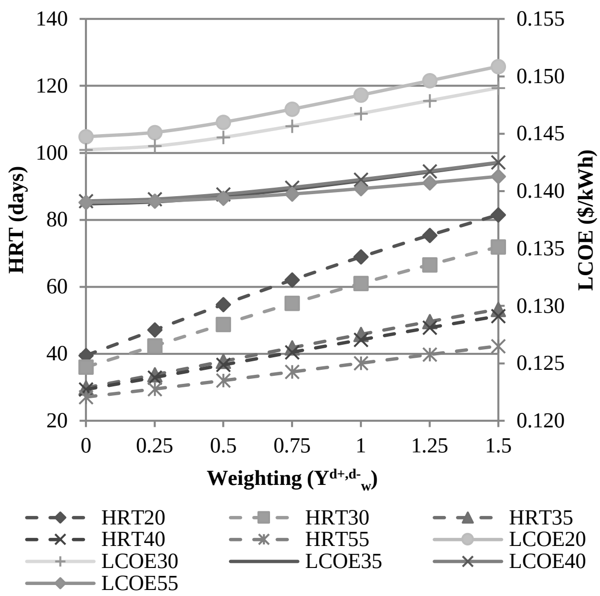

Figure 4: Effect of increasing the weighting for methane yield deviations on optimal HRT and LCOE for AD systems operating at temperatures of 20, 30, 35, 40 and 55°C, in the UK.

6. Discussion

The model outlined in this study has highlighted the differences in optimal AD design parameters for alternative objectives, site locations and economic costs. Retention times and organic loading rates varied significantly for different tank temperatures. For a tank temperature of 35 °C, the ideal HRT to minimise the LCOE was 29.9 days for the UK and 33 days for India. The optimised HRT increased to 45.5 days for a digester operating under psychrophilic conditions in India. For thermophilic conditions (55 °C), the HRT was reduced to 27.1 and 29.4 days in the UK and India, respectively. Optimal HRT values reported for AD are often conflicting, but the HRT values determined in this study for mesophilic conditions are comparable with values reported elsewhere [3]. The HRT results for thermophilic conditions are relatively high. This is largely attributed to the 0.42 rate constant and other model assumptions, such as the volatile solids content. Rate constants are more widely reported for mesophilic conditions and it would therefore be worth evaluating and considering more rate constants for thermophilic conditions. The volatile solids content has a significant impact on the optimal HRT. For example, by increasing the rate constant to 0.58 (see Table 1) and reducing the volatile solid content to 0.1 [63], the ideal HRT for a digester in the UK operating at 55 °C would reduce from 27.1 days to 18.5 days. Furthermore, the LCOE would increase significantly from 0.1376 to 0.1844 $/kWh. With minimised LCOE values for the UK and India case studies ranging respectively from 0.139–0.145 $/kWh and 0.045–0.049 $/kWh, it is interesting that there was not a significant variation in minimised LCOE for AD systems operating at different tank temperatures.

The LCOE values determined for the UK are comparable to those reported elsewhere. The international renewable energy agency (IRENA) suggest that for digesters with investments costs of 2574-6104 $/kW, the LCOE ranges from 0.06-0.15 $/kWh [64]. The Department of Energy and Climate Change outlines that for AD plants with capacities greater than 500 kW and starting operations in 2012, the real LCOE would be 0.154 $/kWh, assuming a discount rate of 10% [65]. The levelised costs in India are significantly lower, but this is not unexpected given the low cost assumptions. IRENA further suggest that LCOE values for biomass power in India are in the range of 0.04 $/kWh, and the low value is at a sacrifice of lower environmental standards [66]. As grid-connected large-scale AD systems in India emerge, there will be a need to assess LCOE values in more detail. As a result of the lower capital cost, AD plants in India were found to favour longer retention times. Conversely, a reduction in the costs associated with feedstock preparation and handling, resulted in shorter retention times being preferred.

Increasing biogas yields by utilising higher tank temperatures does have to be balanced with increases in energy demand. The sensitivity analysis highlighted that the cost associated with heating an AD system in the UK will influence whether psychrophilic, mesophilic or thermophilic conditions are preferred in terms of the minimum LCOE. For large-scale AD systems producing electricity, there will be a surplus of heat available for recovery from a gas engine. However, smaller AD plants may not use a combined heat and power system due to high investment costs. Many small scale AD plants generating electricity for street lighting in India are not using additional heating (i.e. they rely solely on ambient conditions), and the results suggest that they could still use electrical or gas heaters to increase biogas yields at a similar levelised cost of electricity. However, there are control and stability issues associated with thermophilic digestion, which could increase operational costs and reduce performance.

There are a number of factors that have not been considered in this study which would improve the economic feasibility of the modelled case study plants. There are numerous incentives for AD plants and gate fees or tipping fees are available for waste feedstocks in many countries. Larger continuous multi-stage systems would further improve plant economics. Whilst digestate from AD is another potential source of revenue, the market is still relatively immature. For example, some AD plants in the UK currently give away their digestate to local farmers. The recently introduced renewable heat incentive in the UK, which enables AD plants to receive money for capturing and using heat from a biogas engine, is another incentive that could be considered in AD plant design and optimisation.

It is important to note that first-order rate constants are restricted in their application for optimisation studies. The results are highly dependent on the first-order kinetic model used in this study and rate constants are not purely temperature dependent; they will vary based on feedstock composition, AD operating parameters and system type. For complex structures, such as food waste, first-order models are also less accurate. To address this, more advanced models such as pseudo-parallel first-order degradation models offer improvements as the readily degradable and less readily degradable material fraction of a feedstock can be considered. Other advanced methods have also been developed to take into account a lag phase and the formation of inhibitory products and substrates [67]. However, there is a need for more research to characterise a range of rate constants for well described systems, feedstocks and conditions, and this will improve their use as a means to model AD systems. There are also advanced dynamic models, and it would be interesting to investigate integrating multi-objective goal programming with a model such as ADM1.

Food waste, with a certain composition, was the only feedstock considered in this study. In future studies—and with more detailed information on rate constants—different feedstocks, compositions and mixtures could be compared. A wider range of temperatures could also be analysed (e.g. hyperthermophilic conditions). There are several other extensions to the model that could be considered in further work. Continuous multi-stage or small batch systems could be modelled. The variation in biogas methane content for different operational parameters could be included. Additional objectives and decision variables could also be incorporated into the model. For example, different installation sites could be compared and analysed.

7. Conclusion

This study has outlined an approach to optimising AD systems using multi-objective non-linear goal programming. Rather than optimising a specific system, the model was demonstrated for two case study locations (the UK and India) to show the potential variation in results for different environmental and economic assumptions. The optimised levelised cost of electricity and hydraulic retention time for the two case study locations ranged respectively from 0.042–0.145 $/kWh and 27.1–45.5 days. Comparable LCOE values were obtained for mesophilic and thermophilic digestion; however, greater variations in optimal parameters emerged for different model objectives and financial costs. The method presented overcomes some of the difficulties associated with using reaction rate constants for AD optimisation, and several suggestions have been made for model extensions and further work.

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Figures and Tables

Figure 1: Cumulative methane yield from anaerobic digestion of OFMSW at different temperatures.

Figure 2: Effect of increasing heating costs on optimal HRT and LCOE for AD systems operating at temperatures of 20, 30, 35, 40 and 55 °C, in the UK.

Figure 3: Effect of increasing plant setup costs on optimal HRT and LCOE for AD systems operating at temperatures of 20, 30, 35, 40 and 55 °C, in the UK.

Figure 4: Effect of increasing the weighting for methane yield deviations on optimal HRT and LCOE for AD systems operating at temperatures of 20, 30, 35, 40 and 55°C, in the UK.

Table 1: First-order rate constants for various feedstocks at different temperatures (k, day^{-1}).

Table 2: Feedstock data including density, fraction of volatile solids and ultimate methane yield.

Table 3: Financial and average annual temperature assumptions for each case study location.

Table 4: Optimised results for the UK case study.

Table 5: Optimised results for the India case study.