Optimal feed scheduling and co-digestion for anaerobic digestion sites with dynamic demands

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Abstract

Sustainable feed supply to anaerobic digestion (AD) plants is a significant challenge, particularly considering uncertainties in the energy demand market. This study proposes a new approach to feed scheduling and optimisation to address this challenge. A practical framework is proposed to determine the optimal co-digestion strategy for efficiently managing time-varying demands. Additionally, the research explores the impact of storage capacity and demonstrates the adaptability of the proposed model in contributing to emission reduction policies. Two case studies illustrate the model's flexibility and the impact of storage on increased productivity. The storage increase, results in a 23% reduction in gas grid reliance for the case study. Also, incorporating global warming potential in the objective function results in negligible changes to production metrics.

**Keywords**: Feed Scheduling, Optimisation, Anaerobic Digestion, Co-digestion

# Introduction

During the last decade, there has been a rise in interest in anaerobic digestion (AD) as a renewable technology for energy recovery from biogas generation to overcome the intermittency challenges of other renewable sources. In line with the UK Biomass Strategy, AD can use sustainable biomass and contribute to the UK's net-zero target, while providing benefits like food waste recycling and reducing natural gas imports (GOV.UK, 2023). However, when considering the availability of feedstock for scheduling and demand-oriented models based on AD plant capacities, research on the technology for large-scale operations has been limited. This study aims to optimise AD processes by integrating demand profiles, feedstock scheduling, co-digestion, and global warming potential (GWP) minimisation in an optimisation framework. Since there is currently no tool available to operators, this kind of integration is crucial for optimising AD. The approach helps operators make strategic decisions about feedstock selection, scheduling, and striking a balance between biogas potential and reducing emissions. Current modelling approaches, such as modifications to Batstone et al.’s (2002) Anaerobic Digestion Model Number 1 (ADM1), which takes co-digestion and demand-oriented models into consideration, present challenges for real-time optimisation due to its non-linearity and data availability.

Demand-oriented models, which solely consider demand profiles and storage capacities, assume continuous feedstock availability, simplifying the AD process. This simplicity lowers the precision with which models can estimate whether demand can be met. Feedstock supply and scheduling needs to be considered simultaneously to generate reliable estimates. Liu et al., (2021) employed a hybrid model with simplified system boundaries and a one-day modelling timeframe to optimise co-digestion in a demand-oriented biogas supply chain. More accurate simulations of co-digestion and biogas output are provided by a recent digital twin of AD proposed by Moretta et al. (2022), however feedstock acquisition, timing, and co-digestion is not considered. According to Lv et al. (2014), feeding schedule changes increased the unpredictability of biogas output and hence impacts operators’ decision-making. Supply chain logistics, the growth of energy crops, and possible feedstock storage degradation are some of the factors that affect feedstock selection and whether it can meet demand. Current modeling approaches predominantly cover short time periods of a few months. However, AD processes at a large scale necessitate an annual timeframe that provides a more accurate representation of biogas demand throughout the year, to help decision-making early on for future predictions. Hence, it is important to devise a methodology that considers all these factors to help operators with key decision-making by optimising the best outcome in meeting demand while considering emission reduction.

# Methodology

To formulate the optimal feeding plan for an AD reactor, several considerations must be addressed. This involves optimising the acquisition of feeds through an optimal blending pattern to exploit synergies, minimising feeding rates while maximising biomethane yield. Simultaneously, the feeding rate needs regulation to align closely with the fluctuating and uncertain market demand or price profile. Additionally, environmental concerns, specifically GWP factors, should be factored into the decision-making process.

The model comprises two distinct optimisation stages implemented in Pyomo, a Python-based package for optimisation. The initial stage computes the optimal blending pattern using a simplified approach proposed by Moretta et al. (2022). The goal is to optimise the feeding ratio of components ($x\_{j}$) that results in the highest ultimate biomethane yield in the co-digestion process (i.e., the objective is to maximise $B\_{CoD})$.

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| $$B\_{CoD}= \sum\_{j=1}^{3}x\_{j}B\_{j}+ \left[\sum\_{j,k \in feed pairs }^{}x\_{j}x\_{k}+\prod\_{j=1}^{3}x\_{j}\right]B\_{mix}$$ | (1) |
| $B\_{mix}= β\_{0}+β\_{1}\sum\_{j=1}^{3}x\_{j} (\frac{c}{N})\_{j}+β\_{2}BD\_{mix}+ β\_{3}(\sum\_{j=1}^{3}x\_{j} (\frac{c}{N})\_{j})^{2}+β\_{4}BD^{2}\_{mix}$  | (2) |
| $BD\_{mix}= \sum\_{j=1}^{3}x\_{j}\frac{B\_{j}}{TB\_{j}} $  | (3) |
| $TB\_{j}=\frac{\left(\frac{n}{2}+\frac{a}{8}-\frac{b}{4}-\frac{3c}{8}-\frac{d}{4}\right)\_{j} 22415}{(12n+a+16b+14c+32d)\_{j}}$  | (4) |

The model is limited to three substrates *j*, in our illustrative example, and the $B\_{CoD}$ is calculated based on feed data parameters such as the experimental biomethane yield for each substrate $(B\_{j}$) and their mixture ($B\_{mix}$), carbon to nitrogen ratio (*C/N*) and the theoretical biomethane yield ($TB\_{j}$) of each of the substrates. The parameters such as a, b, c, d and n in Eq. (3) are the number of atoms in each mole of substrate based on the chemical formula of $C\_{n}H\_{a}O\_{b}N\_{c}S\_{d}.$ The regression parameters $(β\_{0}, β\_{1}, β\_{2}, β\_{3}, β\_{4}$) used in Eq. (2) are 21.7, 1.26, 445.7, -0.02 and -7.82 respectively according to Moretta et al. (2022).

It is important to highlight that the co-digestion correlations mentioned above do not consider complex phenomena such as the inoculum effect. The first stage’s output is contingent upon the number of feed substrates *j*, resulting in collections of either two- or three-component sets *I*. These sets subsequently serve as potential feedstocks for the second optimisation step.

The second optimisation step utilises the output from the first and the demand profile (biogas demand as a function of time/day) as inputs. It then generates the optimal feeding schedule that aligns plant production with the demand profile.

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| $$Objective: min \sum\_{dϵDays}^{}(P\_{d}-D\_{d})^{2}+ γ\_{grd}S^{-}\_{d}+ γ\_{stg}S^{+}\_{d}+γ\_{gwp}GWP\_{t}$$ | (5) |
| $$S^{+}\_{d}=P\_{d}+S^{+}\_{d-1}+ S^{-}\_{d}-D\_{d}$$ | (6) |
| $P\_{d}= \sum\_{iϵI}^{}\left(\frac{B\_{i}}{t\_{duration}\_{i}}\right)w\_{i} y\_{p}\_{i,d} $ $∀ d\in Days, ∀ i\in I$ | (7) |
| $t\_{start\_{i}}-M(1-y\_{p}\_{i,d}) \leq d$ $\leq t\_{finish\_{i}}+M(1-y\_{p}\_{i,d})$ ∀ 𝑑 ∈ D𝑎𝑦𝑠, ∀ i ∈ I | (8) |
| $\sum\_{d \in Days}^{}S^{+}\_{d} \leq S\_{max}$  | (9) |

In this model the gas production ($P\_{d}$), demand ($D\_{d}$), storage (or surplus of gas $S^{+}\_{d}$) and deficit (or gas production shortage supplied from the grid, $S^{-}\_{d}$) are indexed on a “daily” basis. The feed set *I* consists of mix-feeds *i,* which includes 2 or 3-components of j (depending on the first optimisation step output). The penalty factor for daily supply of gas from the grid (deficit of gas compared to the daily demand), unnecessary storage and GWP are specified as $γ\_{grd}$, $γ\_{stg}$ and $γ\_{gwp}$ respectively. The time required to process the whole feed blend *i* ($t\_{duration}\_{i})$ is calculated according to the substrates’ weights and plant feeding capacity. The binary variable $y\_{p}\_{i,d}$ determines the selection of a feed mixture *i* to be fed into the digester for $t\_{duration}\_{i}$ days. The plant maximum cumulative storage capacity of surplus production is indicated as $S\_{max}$.

The total global warming potential $GWP\_{t}$ is the sum of cultivation, transportation, plant’s external energy consumption and leakage GWPs:

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| --- | --- |
| $GWP\_{t}= GWP\_{C}+ GWP\_{T}+GWP\_{E}+GWP\_{L}+ GWP\_{CHP}$  | (10) |

Which can be expressed using the detailed formula as:

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| --- | --- |
| $GWP\_{t}=(1.1 \sum\_{j\in I}^{}w\_{j} Ts\_{j} α\_{C}\_{j}\hat{ y\_{j}})+(\sum\_{j \in J}^{}w\_{j} α\_{T}\_{j} L\_{j} + \sum\_{j \in I}^{}w^{'}\_{j} α^{'}\_{T}\_{j} L^{'}\_{j})+\left(α\_{E} E\_{elect}+ α\_{H} E\_{heat}\right)+\left(18.09 B\_{j} α\_{L} f\_{CH\_{4}}\right)+(α\_{\acute{E}} E\_{elect}+ α\_{\acute{H}} E\_{heat})$  | (11) |

Eq. (11) details the individual GWPs defined in Eq. (10). The AD system carbon footprint is calculated by creating formulas using some existing processes provided by various datasets, literatures, and government reports. The methodology of the framework incorporates environmental burdens associated with the principal products and processes analysed in this study. The GWP factors $α\_{C}$, $α\_{T}$, $α\_{E/H}$, $α\_{L}$ and $α\_{\acute{E}/\dot{H}}$ represent cultivation, transportation, imported electricity/heat, leakage, and CHP produced electricity and heat. These parameters are obtained from other LCA studies such as the work of Slorach et al., (2019). Substrates’ weight and total solids are defined as $w\_{j}$ and $Ts\_{j}$ respectively. $\hat{ y\_{j}}$ is the user-defined binary parameter indicating the cultivation of specific substrate *j*. $L\_{j}$ is the distance of *j* from its origin ($L^{'}\_{j}$) relates to the digestate disposal distance. In the leakage term, $f\_{CH\_{4}}$ is the fraction of methane in the biogas.

# Case study

A consumption profile representing 3000 households is generated based on random distribution, using the annual average natural gas consumption of a medium-sized household in the UK as the demand profile. Consumption values are reported on a weekly basis for computational efficiency. Three substrates, namely "Maize," "Straw," and "Sheep manure," are chosen as example feed candidates, with specified characteristics from the work of Moretta et al. (2022). The plant feeding rate is constrained to a maximum 100 tonnes per day and the storage capacity is assumed to be 5000 m3.

To investigate the impact of storage capacity and GWP factors, two distinct case studies were conducted. In the first case study, GWP effects were excluded, and optimisation was performed for storage capacities of 5000 m3 and 10,000 m3. In the second case, GWP was considered for a fixed storage capacity of 5000 m3, with the simplifying assumption of neglecting GWP effects related to leakage and heat-electricity supply. The penalty factors for grid supply and storage are considered as 108 and for GWP it is set to 103. This is to ensure that gas supply has low reliance on the national grid while minimising unnecessary storage providing GWP with a sufficient impact on the objective function. The feeding system was assumed to be able to mix two component types (resulting in three 2-substrate feeding scenarios). Decision-making was limited to selecting among these three feeding scenarios to address three major intervals of the year: low, medium, and high consumption periods. The model is formulated as a Mixed-Integer Nonlinear Programming (MINLP) problem in Pyomo and is solved using BARON with the statistics provided in Table 1.

Table 1: Model statistics

|  |  |  |  |
| --- | --- | --- | --- |
| No. of Continuous variables | No. of Binary & Integer variables | No. of Constraints | Solution time |
| 173 | 179 | 506 | 53 s |

# Results and discussions

As per the initial optimisation step, Table 2 presents the optimal blending pattern for the three available substrates along with their predicted biomethane yields. This optimal blending is subsequently employed by the second optimisation step as the set of available feeding scenarios for scheduling purposes.

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| Table 2: The result of the first optimisation step which optimises co-digestion patterns |
| **Feed No.** | **Two-component Co-digestion** | **Composition %** | **Methane yield (m3/tfeed)** |
| 1 | Comp. 1: Sheep manureComp. 2: Straw | Comp. 1: 33%Comp. 2: 67% | 163 |
| 2 | Comp. 1: Sheep manureComp. 2: Maize | Comp. 1: 67%Comp. 2: 33% | 189 |
| 3 | Comp. 1: StrawComp. 2: Maize | Comp. 1: 57%Comp. 2: 43% | 219 |
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| Table 3: The result of the second optimisation function, demand-oriented supply, with and without considering GWP |
| **Case study** | **Total gas product (m3)** | **Total gas deficit****(m3)** | **Total feed weight (tonnes)** | **Total GWP** **(t CO2)** |
| 1  | 5000 m3 storage | 3,567,115 | 259,520 | 18,470 | 2,761 |
| 10,000 m3 storage | 3,625,202 | 200,695 | 17,913 |
| 2 | 5000 m3 storage, No GWP | 3,567,115 | 259,520 | 18,470 | 2,761 |
| 5000 m3 storage, with GWP | 3,567,115 | 259,520 | 18,590 | 2,127 |

The first case study results are plotted in Figure 1, where the effect of increasing the storage on the reduction of gas deficit and the increase in production are presented. As seen in Table 3, doubling the storage capacity from its base case value has led to an approximately 58,000 m3 increase in production, thereby reducing grid supply by 23% and with a modest 3% saving on feedstock procurement. Furthermore, considering the implementation of the GWP in the optimisation results, Table 3 clearly indicates the model's adaptability in incorporating GWP without a significant impact on feed consumption. Figure 2 illustrates how the optimiser has adjusted the feeding schedule in response to the inclusion of the GWP factor.

(a)

Figure 1: The presentation of optimisation results for matching the average production rate with the gas demand of a prototype district with 3000 households by an AD plant with (a) 5000 m3 and (b) 10,000 m3 storage capacity. GWP is not considered.

(b)

Figure 2: (a). AD plant feed scheduling for the base case scenario (b) Feed scheduling for the scenario considering GWP.

(b)

(a)

A comparison between Figure 2(a) with (b) reveals a shift in the choice of candidate feeds between ("Straw", "Maize") and ("Sheep manure", "Maize") for the initial production period, which is the shortest duration. Given that the GWP related to cultivation outweighs that of transportation, it is evident that the Straw and Maize should be allocated to the shortest period of operation (i.e., the smallest number of feedstocks).

# Conclusions

The proposed methodology introduces an intuitive and streamlined approach for optimal scheduling of diverse feedstocks in response to dynamic demand profiles. The model underscores the pivotal role of storage capacity in augmenting the flexibility of AD plants, navigating the challenges of fluctuating gas demand, and enhancing production rates within the confines of plant infrastructure. The case study illustrates 23% reduction in grid supply reliance by doubling the initial 5000 m3 storage capacity. Furthermore, by delineating the optimal blending pattern for substrates, the model adeptly addresses concerns associated with GWP with negligible changes to the production rate, presenting potential advantages to the plant in anticipation of the growing prevalence of carbon credit and trading mechanisms.

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