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Changing old habits: The case of feeding patterns in anaerobic digesters

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ABSTRACT

A non-linear programming model was developed to maximize the economic profit from an anaerobic co-digester. The model consists of a combination of technical and economic equations, linked through the biogas production variable. Five scenarios were simulated. These differed with regard to substrate inlet mass flow rate, organic loading rate and hydraulic retention time. The impact on biogas production was investigated and an economic analysis was undertaken based on the concepts of profitability and Net Present Value. The model results indicate that varying the substrate inlet mass flow rate and organic loading rate could have a positive impact on the profitability of co-digesters in Flanders. This can be achieved either by increasing the interval time between feedstock input, or by feeding individual streams of feedstock separately into the system, while at the same time reducing the hydraulic retention time.

1. Introduction

1.1. Objectives of the work

The objective of this research paper is to look for strategies and solutions that operators of anaerobic digesters can apply to improve their economic performance and profitability. More specifically, in this paper, we focus on maximizing profit by optimizing biogas production through optimizing substrate inlet mass flow rate, organic loading rate (OLR) and hydraulic retention time (HRT).

Most research conducted so far has focused either on improving system stability and biogas yield by investigating the microbiological parameters of anaerobic digestion (AD), such as pH, changes in volatile fatty acid (VFA) and ammonia concentration at a laboratory scale, or on economic parameters such as investment costs and subsidies for full-scale anaerobic digesters. Our research is innovative in seeking to bridge the gap between the technical and economic AD models by looking at operational system parameters on the unit-process level, namely substrate inlet mass flow rate, OLR and HRT for a real-life co-digester in Flanders, and linking these to economic parameters.

1.2. Challenges of anaerobic digestion in Flanders

With an estimated average investment cost of €4800 and an operational cost of €520 per kWe installed capacity [1], the Flemish biogas sector represents almost half a billion euros in investment over the past 5 years and an annual turnover of around €50 million. Nevertheless, the sector is faced with loss-making businesses, bankruptcy and deferred investments [2]. It is therefore important to technically and economically optimize the processes involved in biogas production.

Construction and operation of a biogas plant is a combination of economic and technical considerations. Obtaining the maximum biogas yield, through complete digestion of the substrate, requires a long HRT, and subsequently a larger digester size. In practice, the choice of system design, or of applicable HRT, is always based on a compromise between attaining the highest possible biogas yield, on the one hand, and ensuring that the plant is economically justifiable on the other [3]. The industrial viability of AD requires a suitable combination of physical and chemical process parameters and low-cost substrates, hence the need for process optimization [4]. Unfortunately, commercial AD processes often operate well below their optimal performance due to a variety of factors, such as a too low OLR, basic design considerations that try to determine the right balance between the construction practicalities of both mixing and heat loss, and the mixing regime [5,6]. Additionally, AD of single substrates presents some drawbacks linked to substrate

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characteristics. Anaerobic co-digestion overcomes these drawbacks and improves the plant's economic viability [7]. In what follows, referrals to the term AD can be applied to mono- as well as co-digestion.

1.3. AD modeling

In addition to the numerous experiments conducted in the laboratory or in field studies to optimize the AD process, several models have been developed to help understand, simulate and predict the AD process. Modeling is always a goal-driven exercise, and many alternative models have been proposed in the literature, depending on the aim, e.g. process understanding, dynamic simulation, optimization, or control [8]. These models can be divided into two types of models, i.e. biochemical models and economic-financial models.

AD is characterized by high complexity and non-linearity and the difficulties in collecting large amounts of informative experimental data for modeling purposes [8]. The fact is that AD is itself a complicated, multi-stage, dynamic process that requires the concerted efforts of several bacterial groups. The composition of such groups varies in an unknown manner with changes in HRT, feedstock, temperature, reactor type, and other operating conditions [9]. An important variability exists in values reported for the kinetic parameters, even when the same operational and environmental conditions have been evaluated. One of the consequences thereof is a variety of approaches to modeling and parameter identification [8]. While complex models like ADM1 [10] are well suited for process simulation, they are substantially limited when applied to process control and optimization [11]. Because these models demand a substantial quantity of specialized data, they are not accessible to farmers and other stakeholders with limited scientific knowledge on the issue of anaerobic digestion. Therefore, a number of simple calculators were developed to estimate the applicability of the AD process to a specific farm and provide information to a farmer or decision maker [12].

As demand for renewable, clean, local energy increases, so will the need for more accurate and detailed economic information on the financial feasibility of anaerobic digesters [13]. Economic-financial AD models have been developed and described by Anderson et al. [13], Gebrezgabher et al. [14] and Walla and Schneeberger [15], amongst others. They looked at developing tools for assessing the financial feasibility of farm-based anaerobic digesters, disposal of digestate in an economically and environmentally sustainable manner, and optimal size for biogas plants. These and other previous studies have generally found ADs to be a poor investment for private firms, without assistance [14,16–20]. It is therefore in the interests of the sector to increase the profitability of commercial AD applications.

The goal of our research was to link together biochemical and economic-financial models, by maximizing profit at the commercial AD level through optimizing biogas production. Biogas operators are not typically involved in AD experiments at the microbiological level, as they are processing large amounts of feedstock every day for their livelihoods. To maximize their profit, we have looked at strategies to increase biogas yield, and hence economic profit, by proposing small adjustments in their daily operational management. We propose a new type of black-box optimization model, based on algebraic equations, which takes into account the operational parameters of AD, as opposed to reaction mechanisms and experimental measurements for a multitude of parameters, to monitor the operating conditions and performance of an AD treatment process at a small-scale commercial facility.

2. Materials and methods

The aim of our research is to optimize (maximize) economic profit based on the biogas yield of a mesophilic anaerobic farm-scale digester co-digesting three types of feedstock. Our case is a theoretical, hypothetical one but is based on a case study of similar digesters in Flanders [21]. Due to the complexity of the AD process, each type of model has been developed for a different purpose [12]. Since our purpose is to improve the profitability of commercial anaerobic digesters by providing operators with hands-on practical ways to achieve this, we do not focus on the biological or physico–chemical parameters of the process, or on the kinetics of bacterial growth. Rather, the core modeling efforts focus on the operational parameters, such as substrate inlet mass flow rate, OLR and HRT, to calculate substrate degradation and biogas formation.

The model is based on the observation that different types of biomass have different speeds of degradation and different biomethanisation potentials (BMP). In commercial biogas reactors, AD is a continuous process, meaning that there is a daily in- and outflow of biomass. The difference in degradation and BMP for the different input streams for co-digestion implies that some of the biomass will have spent a relatively short time in the reactor and therefore might not have achieved its full potential in gas production before it is pumped out of the reactor. Currently, biogas operators can deal with this challenge, either by installing a secondary, post-digestion reactor which will allow for additional gas production of 5–15%, or by separating the digested biomass and recycling the fiber fraction to extend the HRT for slowly decomposing materials [22]. However, these adaptations imply a trade-off between additional cost and extra gas yield. Our model simulates the in- and outflow of the biomass in a co-digester and identifies the optimal quantity and ratio for each type of feedstock to be inserted at a certain time, as well as the optimal HRT for each 'batch' of feedstock inserted at a certain time, with the aim of increasing biogas yield without additional costs. We assume that co-digestion takes place under optimal mixing conditions. Mixing in an anaerobic digester keeps the solids in suspension and homogenizes the incoming feed with the active microbial community within the digester content. Experimental investigations have shown that the mixing mode and mixing intensity have direct effects on the biogas yield, even though there are conflicting views on mixing design [23]. In this study, however, we do not take into account the possible effects of different mixing modalities on the biogas yield.

2.1. Model description

To achieve our goal, we have developed a simplified AD single objective optimization non-linear programming (NLP) model in GAMS (General Algebraic Modeling System). The model is designed for a one-stage continuously fed mesophilic AD system, in a continuous-flow stirred-tank reactor (CSTR), and aims to maximize the profit from biogas production over a time period of 365 days.

The development of the model is centered around a first-order kinetic cumulative biogas yield function [24] which estimates the cumulative yield $B_{i,t}$ (*l* $CH_4 \cdot kg^{-1}$ *VS added*) of each type of biomass i as a function of the ultimate methane yield $B_{i,max}$ (*l* $CH_4 \cdot kg^{-1}$ *VS added*), μ_i (*day*$^{-1}$) the first-order rate constant and residence time t (*day*). These values are typically determined using BMP assays. To be able to use this function in our model, we needed to adapt the unit of $B_{i,max}$ from 'l $CH_4 \cdot kg^{-1}$ VS added' to 'm^3 $CH_4 \cdot ton^{-1}$ substrate added'. This was done in two steps. Firstly, for each substrate, we calculated the quantity of volatile solids (VS) present in 1 ton of that particular substrate, using total solids (TS) content to make the link between both. This calculation provided us with the unit of 'l

$CH_4 \cdot ton^{-1}$ substrate added'. The data required for this conversion can be found in Table 1 ([25–29]). Secondly, to convert 'l $CH_4 \cdot ton^{-1}$ substrate added' to 'm^3 $CH_4 \cdot ton^{-1}$ substrate added', we divided the values by 1000 (assuming standard reference conditions of 15 °C and 101.325 kPa). Equation (1) was used to calculate μ where values were not provided.

$$B_{i,t} = B_{i,max}{}^* \left[1 - e^{-\mu_i{}^* t}\right] \tag{1}$$

Fig. 1 provides a graphical representation of the main assumptions of the model. The graphs are adapted from Refs. [25,26]. The graph on the left shows the cumulative yield function for organic biological waste (OBW), manure and maize, as these are the three feedstocks that will be used to illustrate the model. The graph shows that the shapes of the cumulative yield curves differ between feedstock types, due to different degradation rates μ, and, hence, that different feedstocks have different 'optimal' HRT, when considering the economics of commercial anaerobic digesters. This implies that, during co-digestion, choices have to be made regarding biogas yield versus retention time. Our model tries to identify this optimal choice based on the price of feedstock and electricity. The graph on the right shows the cumulative methane yield function for manure. As gas production rate changes over the course of the digestion, it is difficult to predict the specific methane yield (SMY) at a given point in time without conducting numerous experiments. Therefore, using the cumulative methane yield function, it is possible to estimate the SMY on a given day by subtracting the cumulative yield for the previous days from the cumulative yield on the current day. In the graph, an example is given for the SMY on day 3 of the manure digestion. This reasoning is translated in the model through Equation (6), given below in the text.

The remainder of this section describes the actual model, in which the technical Equations (6–14) are linked with the economic ones (2–5, 15, 16) through the calculation of biogas production. The model parameters and variables are represented by Greek and Latin symbols respectively. The units are given within brackets and in italics.

The objective function (2) maximizes the total profit P (€) for a period of one year, i.e. the time span for the model,

$$\text{Max. } P \tag{2}$$

and calculates this by subtracting the operational costs OC (€) from the income I (€) (3). Equations (4) and (5) provide the calculations for I and OC and are taken from the aforementioned case-study of Flemish agricultural digesters [21]. The income I (€) (Equation (4)) is calculated based on the total biogas yield $\sum_{i,t'} Y_{i,t'}$ (m^3) and the income from electricity and heat generated by the methane produced. To convert m^3 CH_4 to MWh electric power we multiply the biogas yield with a conversion factor ε, which is set at 0.01 $MWh.m^{-3}$ [30]. The income from biogas consists of four different elements. The first element is the income from the sale of generated electricity π_{elec} ($€.MWhe^{-1}$). The second element is the income from the sale of heat π_{heat} ($€.MWhth^{-1}$). Thirdly, we take into account the subsidies generated by green power. These consist of green electricity certificates σ_{GEC} ($€.MWhe^{-1}$) and green heat certificates σ_{GHC} ($€.MWhth^{-1}$). The final element to be added is the expenses avoided $\pi_{elec,avoid}$ and $\pi_{heat,avoid}$ due to own consumption of generated power ($€.MWhe^{-1}$) and heat ($€.MWhth^{-1}$), respectively. The factors φ_{elec} and φ_{heat} refer to the relative amount of own electricity and heat consumption, respectively. Furthermore, when methane is converted into electricity and heat through a Combined Heat and Power (CHP), we assume this happens with a 35% efficiency for electricity, and a 50% efficiency for heat [30]. The OC calculation (Equation (5)) comprises two parts. The first part (i.e. 115,846.03 $€.year^{-1}$) relates to maintenance and human resource costs, which are constant and independent of the quantity of feedstock. The second part of the calculation (i.e. $110.37 * \sum_{i,t'} Q_{i,t'} - 691,794$ $€.year^{-1}$) relates to the disposal cost of the digestate and is, therefore, linearly dependent on the total amount of feedstock $\sum_{i,t'} q_{i,t'}$ (*ton*) processed. This disposal cost includes the separation through centrifuge of the digestate into a thin fraction, which is applied to the land, and a thick fraction, which is processed by an external processor. The linear correlation was obtained through a linear regression based on calculated digestate disposal costs as a function of ingoing feedstock quantity. In this specific case, digestate disposal costs account for almost half of the total OC.

$$P = I - OC \tag{3}$$

$$\begin{aligned} I = {} & \left(\sum_{i,t'} Y_{i,t'}{}^* \, \varepsilon\right){}^* \Big[0.35{}^* \big\langle (1 - \varphi_{elec}){}^* \pi_{elec} + \sigma_{GEC} \\ & + \varphi_{elec}{}^* \, \pi_{elec,avoid} \big\rangle + 0.5{}^* \big\langle (1 - \varphi_{heat}){}^* \, \pi_{heat} + \sigma_{GHC} \\ & + \varphi_{heat}{}^* \, \pi_{heat,avoid} \big\rangle \Big] \end{aligned} \tag{4}$$

$$OC = 115,846 + 110 * \sum_{i,t'} q_{i,t'} - 691,794 \tag{5}$$

The total biogas yield $\sum_{i,t'} Y_{i,t'}$ (m^3) is generated by the sum of the separate yields $Y_{i,t'}$ from all inputs i inserted at a time t' (*days*) (Equation (6)). $Q_{i,t'}$ ($m^3 \cdot day^{-1}$) represents the absolute quantity of an input i, inserted at a time t' while $Q'_{i,t',t}$ ($m^3 \cdot day^{-1}$) represents the relative quantity of the originally inserted $Q_{i,t'}$ that still remains in the digester after a time t (*day*). Indeed, the insertion of new input material into the digester implies that part of the older material is removed (as reactor volume θ (m^3) is a constant), hence equally removing part of the biogas potential of that original quantity $Q_{i,t'}$. This assumption is translated into the calculation of biogas yield $Y_{i,t'}$ for each individual input i inserted at a time t'. More specifically, constraint (6) is derived from the cumulative biogas yield reaction (1) described above, with β_i (m^3 $CH_4 \cdot ton^{-1}$ *input added*) the maximum methane yield, and μ_i (day^{-1}) the first-order rate constant. For each day t after the insertion of the original

Table 1
Feedstock parameters used for model simulations.

Feedstock	Quantity (ton)	Gate fee paid by AD operators ($euro.ton^{-1}$)	Density ($ton.m^{-3}$)	TS (%)	VS (% of TS)	TKN (g N. l $feedstock^{-1}$)	Na^+ (g.l $feedstock^{-1}$)	K^+ (g.l $feedstock^{-1}$)	B_{max} (Nl $CH_4 \cdot kg$ VS $added^{-1}$)	β (m^3 $CH_4 \cdot ton$ feedstock $added^{-1}$)	μ (day^{-1})
OBW	3333*	10**	0.51+++	28***	86***	1.62***	0.33***	0.44***	353***	85+	0.06+
Manure	1388.75*	−17**	1†	14***	80***	0.69***	0.11***	0.36***	242***	27+	0.12+
Maize	833.25*	35**	0.9††	31++	95++	0.30†††	0.01†††	0.45†††	502++	147+	0.03++

* model assumption, ** personal communication with biogas AD operator, *** [25], + calculations based on collected data, ++ [26], +++ [29].
† [27], †† [28], ††† [35].

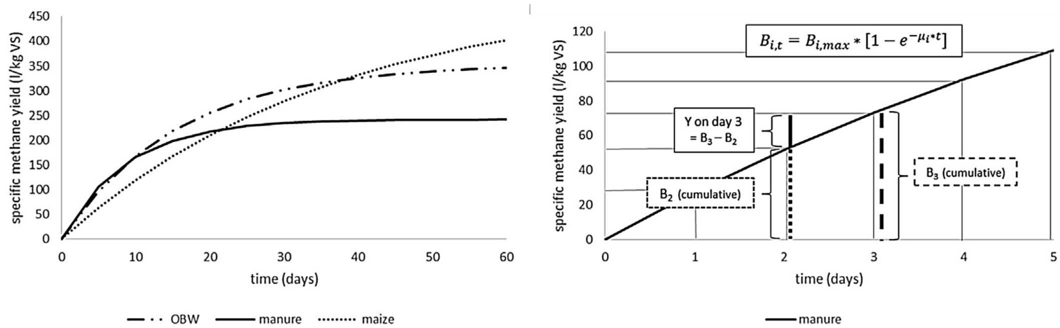

Fig. 1. Graphical representation of the main assumptions of the model (adapted from Refs. [25] and [26]).

quantity $Q_{i,t'}$ of feedstock (on day t'), the model calculates how much of that original feedstock $Q'_{i,t',t}$ remains in the reactor (relative to the original quantity) and how much biogas the remaining quantity will produce that specific day. Equation (6) states that for all times $t \geq t'$, $Y_{i,t'}$ equals the quantity $Q_{i,t'}$, multiplied by the sum over time of the amount $Q'_{i,t',t}$, which is, in turn, multiplied by the cumulative input-specific biogas yield equation. Equation (6) differs from the original reaction (1) in the way that it calculates the daily discrete yield generated by each $Q'_{i,t',t}$, instead of cumulative yield, as explained in Fig. 1.

$$Y_{i,t'} = Q_{i,t'} * \sum_t \left[Q'_{i,t',t} * \beta_i * [(1 - \exp(-\mu_i * (t - t'))) - (1 - \exp(-\mu_i * (t - (t' - 1))))] \right] \quad \text{for } t \geq t' \tag{6}$$

Constraint (7) indicates that every $Q'_{i,t',t}$ is to be seen as a relative value, with a maximum of 1.

$$Q'_{i,t',t} = 1 \quad \text{for } t \geq t' \tag{7}$$

Equation (8) describes how $Q'_{i,t',t}$ changes over time, and how it is dependent on $Q'_{i,t',t-1}$, i.e. the relative value of the same input, inserted at the same time t', remaining in the digester the previous day t-1, and on the sum of all inputs $\sum_i Q_{i,t}$ inserted at the same time t, and the digester capacity θ.

$$Q'_{i,t',t} = Q'_{i,t',t-1} * \left(1 - \sum_i Q_{i,t}\right) \Big/ \theta \tag{8}$$

To ensure the stability of the operation, we added a number of additional constraints which are defined based on knowledge of the AD process and on typically available substrate characteristics. Firstly, in order to avoid an OLR which is too high and digester wash-out, constraint (9) was inserted which prohibits the model from inserting more than a certain percentage α (%) of digester capacity in new input material at a certain time t.

$$\sum_i Q_{i,t} / \theta < \alpha \tag{9}$$

Secondly, based on the study by García-Gen et al. [31] on substrate blend optimization, a number of other parameters were defined. These parameters are total Kjeldahl nitrogen (TKN, in $g.l^{-1}$) (Equation (10)), and salinity as Na^+ concentration ($g.l^{-1}$) (Equation (11)) and K^+ concentration ($g.l^{-1}$) (Equation (12)). The values for these parameters are determined for each input, and for each time t the overall value is calculated in $g.l^{-1}$. For each parameter, a minimum γ and maximum Γ limit ($g.l^{-1}$) can be fixed within the model, depending on the specific case in question.

$$\gamma_{TKN} < \frac{\left(\sum_{i,t'} Q'_{i,t',t} * Q_{i,t'} * TKN_i\right)}{\left(\sum_{i,t'} Q'_{i,t',t} * Q_{i,t'}\right)} < \Gamma_{TKN} \tag{10}$$

$$\gamma_{Na^+} < \frac{\left(\sum_{i,t'} Q'_{i,t',t} * Q_{i,t'} * Na^+_i\right)}{\left(\sum_{i,t'} Q'_{i,t',t} * Q_{i,t'}\right)} < \Gamma_{Na^+} \tag{11}$$

$$\gamma_{K^+} < \frac{\left(\sum_{i,t'} Q'_{i,t',t} * Q_{i,t'} * K^+_i\right)}{\left(\sum_{i,t'} Q'_{i,t',t} * Q_{i,t'}\right)} < \Gamma_{K^+} \tag{12}$$

Equation (13) limits the total quantity of inputs present in the digester at a time t to the digester capacity θ and Equation (14) states that after 60 days a specific input will have passed through the system completely, hence Q' after 60 days equals 0. This constraint was inserted mainly due to computational limitations. Equation (15) sets the time period over which the model runs to 365 days.

$$\theta > \sum_{i,t'} \left(Q'_{i,t',t} * Q_{i,t'}\right) \tag{13}$$

$$Q'_{i,t',t} = 0 \quad \text{for } t \geq 60 \tag{14}$$

$$Q_{i,t'} = 0 \quad \text{for } t' \geq 365 \tag{15}$$

Finally, we were able to calculate the HRT and OLR of all inputs inserted at time t'. $HRT_{t'}$ (*day*) was calculated as the quotient of the sum of daily feedstock mass and the digester capacity θ [32] (Equation (16)) and $OLR_{t'}$ ($kg\ VS.m^{-3}\cdot d^{-1}$) as the quotient of total daily mass of volatile solids (VS) in the feedstock and the digester capacity (Equation (17)). The total daily mass of VS was calculated, for each input, by multiplying $Q_{i,t'}$ ($m^3 \cdot day^{-1}$) with the density δ_i ($ton.m^{-3}$), the total solid content TS_i and the volatile solid content VS_i as a relative fraction of TS_i. To calculate the total daily mass of VS, the sum of the absolute VS_i over all the inputs was taken and the unit was transformed from ton $VS.m^{-3}.d^{-1}$ to kg $VS.m^{-3}.d^{-1}$.

$$HRT_{t'} = \theta \Big/ \sum_i Q_{i,t'} \tag{16}$$

$$OLR_{t'} = \left(\sum_i (Q_{i,t'} * \partial_i * TS_i * VS_i) \right) \Big/ \theta \tag{17}$$

To complete the economic analysis, a comparative Net Present Value (NPV, €) of the AD installation was undertaken to compare the different scenarios. Equation (18) provides the formula for calculating the NPV, where T represents the number of years, I_T (€) and OC_T (€) the respective income and operating costs for each year, r the discount rate (%) and IC (€) the initial capital investment cost of the installation. The investment costs are dependent on the capacity of the digester and the CHP and are calculated using Equation (19). Equation (19) was partly derived from the same case-study as Equations (4) and (5) [21], and partly from the study of Szarka et al. and a survey of CHP manufacturers in Germany in 2011 [33,34]. The first part of the equation (i.e. 388,500 €) incorporates all investment costs related to the digestate centrifuge, storage tank, hygienisation, evaporation and air scrubber units, civil works, permits and grid connection. The second part of the equation (i.e., 184.42*θ + 64,975 €) is linearly dependent on the volume of the digester and incorporates all investment costs relating to the digester itself. The third part of the equation i.e. $CHP_t*(15,648*CHP_t^{-0.5361}$ €) relates to the CHP installation, where CHP stands for the daily engine capacity needed (*kWe*) to transform biogas into electric power and heat. Increasing the capacity of CHP units decreases the specific prices, particularly for units with an installed capacity between 30 and 500 kWe [33,34]. In Equation (20), the CHP_t (*kWe*) is calculated by multiplying the total daily methane yield $\sum Y_{i,t}$ with ε*1000 to transform m^3 CH_4 into kW. This amount is then divided by 24 to calculate the hourly capacity needed, followed by a multiplication with the electrical efficiency factor 0.35 to transform kW into kWe. About 55% of the total investment cost relates to the purchase of the digester and CHP.

$$NPV = -IC + \left(\sum_T (I_T - OC_T) \Big/ (1+r)^T \right) \tag{18}$$

$$IC = 388,500 + 184*\theta + 64,975 + CHP_t * \left(15,648 * CHP_t^{-0.5361}\right) \tag{19}$$

$$CHP_t = \left(\sum_i Y_{i,t} \right) * \varepsilon * 1000 \; / \; 24 * 0.35 \tag{20}$$

2.2. Model parameterization and assumptions

The model can be adapted to different cases by changing parameters and assumptions. A specific case is further developed to show the capacities and limitations of the model more clearly and to highlight potentially interesting management strategies for that specific case. We have chosen a Flemish case with three types of feedstock in the same ratio as they are currently being digested in Flanders. These feedstocks comprise OBW – more specifically food waste, manure (cattle slurry) and silage maize as an energy crop, at a ratio of 60%, 25% and 15% respectively [2]. Specific feedstock parameters were adapted from the literature (Table 1, [25–29,35]). In each scenario, the same amount of feedstock was used in order to keep the operational costs constant, as these costs, in our case, are based solely on the amount of feedstock used (Equation (5)). As we use the same amount of feedstock we did not take into account the transportation costs of biomass. However, when the model is used to compare scenarios with different amounts of feedstock, it is important to include these, as biomass exhibits high transportation costs per unit of energy ultimately generated. Moreover, because different types of biomass have different biogas-generating properties, the design of the supply logistics system can be the determinant factor for the economic viability of energy generation from an AD plant [36]. The gate fee per ton of feedstock is listed in Table 1. Manure has a negative value, as AD operators get paid for accepting manure. This is because the Flanders region has a very high livestock density and, since the implementation of the Nitrates Directive, it has to manage a manure surplus. Furthermore, the capacity of the digester was set at 1000 m^3 and the model was run for a total of 365 days. The conclusions derived from this case are not affected by the digester capacity or its shape, although the shape could also be optimized [37]. For our calculations, α was varied to create different levels of OLR. In order to make comparison possible between the different scenarios, we added an additional constraint stating that all feedstock needed to be used completely in each scenario. This is because if the total tonnage of incoming feedstock is equal for each scenario, the operational costs are also constant for all scenarios. This allowed us to see whether a higher biogas yield could be achieved, with exactly the same amount of feedstock, merely by playing with the operational parameters. The quantities of feedstock were chosen in a way that they did not, in any scenario, pose limitations or infeasibilities with regard to determining the optimal HRT and substrate inlet mass flow rate. Moreover, the total amount of feedstock available for the simulation was determined based on the digester volume, realistic feedstock volumes that are fed on a yearly basis to such a digester, and a realistic OLR for full scale digesters [21]. Feedstock quantities have to be divided by their respective densities to obtain their volumes, as these form part of the restrictions for our model. For each scenario, the OLR was also calculated to ensure that it was kept within realistic limits (see Section 2.3 and Table 2) and restrictions regarding minimum and maximum TKN, Na^+ and K^+ levels were adhered to, based on the levels proposed by García-Gen et al. [31] (see Table 2). Specific feedstock values for TKN, Na^+ and K^+ were converted from $g.kg\ TS^{-1}$ to $g.l\ feedstock^{-1}$ using data on TS content and density (see Table 1).

With regard to the income calculation, in Flanders, π_{elec} equals around 45 €.$MWhe^{-1}$, π_{heat} 45 €.$MWhth^{-1}$, σ_{GEC} 93 €.$MWhe^{-1}$, σ_{GHC} 31 €.$MWhth^{-1}$, $\pi_{elec,avoid}$ 140 €.$MWhe^{-1}$, and $\pi_{heat,avoid}$ 45 €.$MWhe^{-1}$ [21]. Moreover, we set φ_{elec} at 0.2 and φ_{heat} at 0.35. However, as determining the overall electricity price including subsidies is a complex issue and very case-dependent, we assume a lump sum of 185 €.$MWhe^{-1}$ produced. We calculate the comparative NPV for a period of 10 years (T = 10) and a discount rate of 5% (r = 0.05).

As our model focuses on strategic options for increasing profit, and hence, improving biogas yield, we do not take into account the time it takes to start up a new biogas installation and develop the required microbial communities and assume the digester is operating in a steady-state. After all, digester start-up may take months, as temperature, pressure, and mixing all affect the efficiency of digester operation [38] and this type of research is outside the scope of our study.

2.3. Model scenarios

In this study, we have simulated three different main scenarios. The first, default, scenario simulates the conventional way co-digesters currently work, i.e., inserting volumes of different

Table 2
Overview of the optimized variables for the five different sub-scenarios.

	HRT (days)	OLR (kg $VS.m^{-3.d-1}$)	TKN (g N. l feedstock^{-1})	Na^+ (g.l feedstock^{-1})	K^+ (g.l feedstock^{-1})	Total CH_4 yield (m^3 produced)	Increase in yield as compared to scenario 1 (%)
scenario 1 conventional	46	2.93	1.34	0.26	0.43	539,921	
scenario 2-a equal shares	40	3.39	1.34	0.26	0.43	555,273	2.8
scenario 2-b equal shares	25	5.43	1.34	0.26	0.43	557,593	3.3
scenario 3-a free choice	40	2.75–3.07	0.39–1.62	0.03–0.33	0.17–1.55	574,804	6.5
scenario 3-b free choice	25	2.60–4.92	0.39–1.62	0.03–0.33	0.17–1.55	580,257	7.5

feedstock in the same ratio every day. The second scenario keeps the ratio of the different feedstocks constant but allows the model to maximize the cumulative biogas yield by choosing the optimal time to insert these inputs (but always simultaneously and in a constant ratio) while the third scenario lets the model freely decide which volume of a certain feedstock to insert at which optimal time in order to obtain a maximum cumulative biogas yield. Both the second and third scenarios have two sub-scenarios each, based on variations in the OLR. These OLRs were based on results reported in the literature. In a full-scale case study, Lindorfer et al. [5] reported stable working conditions for an anaerobic digester with an OLR of 4.25 kg VS. $m^{-3}.d^{-1}$. Comino et al. [39] even reached an OLR of 7.78 kg $VS.m^{-3}.d^{-1}$ before experiencing system breakdown. Moreover, both studies reported an increase in biogas productivity as a consequence of increasing the OLR.

For scenario 1, the magnitude of α was irrelevant, as we forced the model to insert inputs in the same ratio every day for a period of one year to simulate real-life conditions. The OLR that resulted from this simulation was 2.93 kg $VS.m^{-3}.d^{-1}$, which falls within the normal, realistic range. For scenarios 2 and 3, we selected two values for α, namely 2.5 and 4%. These values are translated into a respective OLR of 3.39 and 5.43 kg $VS.m^{-3}.d^{-1}$for the second scenario, and, from 2.75 to 3.07 and from 2.60 to 4.92 kg $VS.m^{-3}.d^{-1}$ respectively for the third scenario.

3. Results and discussion

3.1. Technical results of scenarios

The outcome of the model simulation is presented below in Fig. 2 and Table 2. The results for all five sub-scenarios are provided and compared.

Fig. 2 shows $Q_{i,t'}$ as a function of the time t′ and $\sum Y_{i,t}$ as a function of the time t. To provide a better view on which quantities are inserted when, we opted to reduce the scale of the vertical axis. As a result of this decision, the quantities of inputs inserted at day 1 are not shown in the figure. The quantities and ratio of feedstocks on the first day are the same for scenarios 1, 2-a and 2-b, i.e. 739, 157 and 105 m^3 for OBW, manure and maize respectively, due to the constraint of equal ratios. When we look at the initial quantities inserted for the third, ‘free choice’ scenario, we can see that the model opts to insert 100%, or 926 m^3, of all available maize feedstock at the outset of the simulation, as maize has the highest biogas potential of all three types of feedstock and inserting it at the start will allow for the maximization of biogas production. Apart from maize, the model opts to insert 74 m^3 of OBW and no manure in the third scenario.

Fig. 2 shows the differences between the scenarios. When comparing scenarios 1 and 2, the output clearly indicates that it would be economically more advantageous to insert larger amounts of feedstock spread over a greater time interval, instead of smaller ones every day. This time interval ranges from inserting input the very next day to leaving a maximum intermission of 1 day for scenario 2-a, and a maximum of 3 days for scenario 2-b, apart from the longer period after the start, to allow the large amounts of feedstock to reach their optimal biogas production, and the period towards the end, where the last inputs are inserted around day 345. The latter is, of course, the result of constraining the model's running time to 365 days. Inserting inputs later would not provide an optimal biogas yield, as time is limited. The increase in biogas yield that can be achieved by adopting this approach is 2.8–3.3% depending on the scenario (see Table 2).

Similar to the second scenario, the simulation in scenario 3 indicates that higher profits can be attained if inputs are inserted in relatively higher quantities at greater time intervals. These time intervals range from a maximum of 1 day for scenario 3-a to a maximum of 4 days for scenario 3-b. The main difference, however, from scenario 2 is that the different feedstocks are inserted separately in the digester, as a ‘batch’, rather than in equal quantities, as typically happens in a co-digester. This is associated with the difference in biogas potential for the different feedstocks. Fig. 1 illustrates that manure reaches its BMP before OBW and maize. Therefore, maize is inserted on the first day of digestion to allow for it to get as close to its BMP as possible. Then OBW is inserted, followed by manure, which reaches its BMP the quickest. Moreover, maize displays the highest SMY, followed by OBW and manure (Table 1). Therefore, when looking at the biogas yield, it doesn't make much sense to have a long HRT, as most of biogas production would be achieved after 20–40 days. However, it makes more sense to increase organic loading in the reactor, as this will increase the volumetric methane production (VMP, in m^3 $gas.m^{-3}$ $digester.day^{-1}$, [40]) while at the same time reducing the HRT, because the amount of feedstock inserted must increase to satisfy the organic load. This approach can result in an increase in biogas yield of 6.5–7.5% depending on the scenario (see Table 2).

In conclusion, it can be derived from the simulation outcome that higher biogas production results from batch feeding, and higher relative feedstock quantities, coupled with greater time intervals, which coincide with higher levels of α and OLR. In this way, anaerobic digester plants can increase their profitability, based on the same total quantity of inputs, simply by making a small change to their operational strategy.

3.2. Economic results of scenarios

Table 3 displays the economic outcome of the model simulations.

The operational costs are the same for all scenarios and amount to €35,102. The economic profit increases by 3–8% compared to the conventional scenario, depending on the scenario used. This

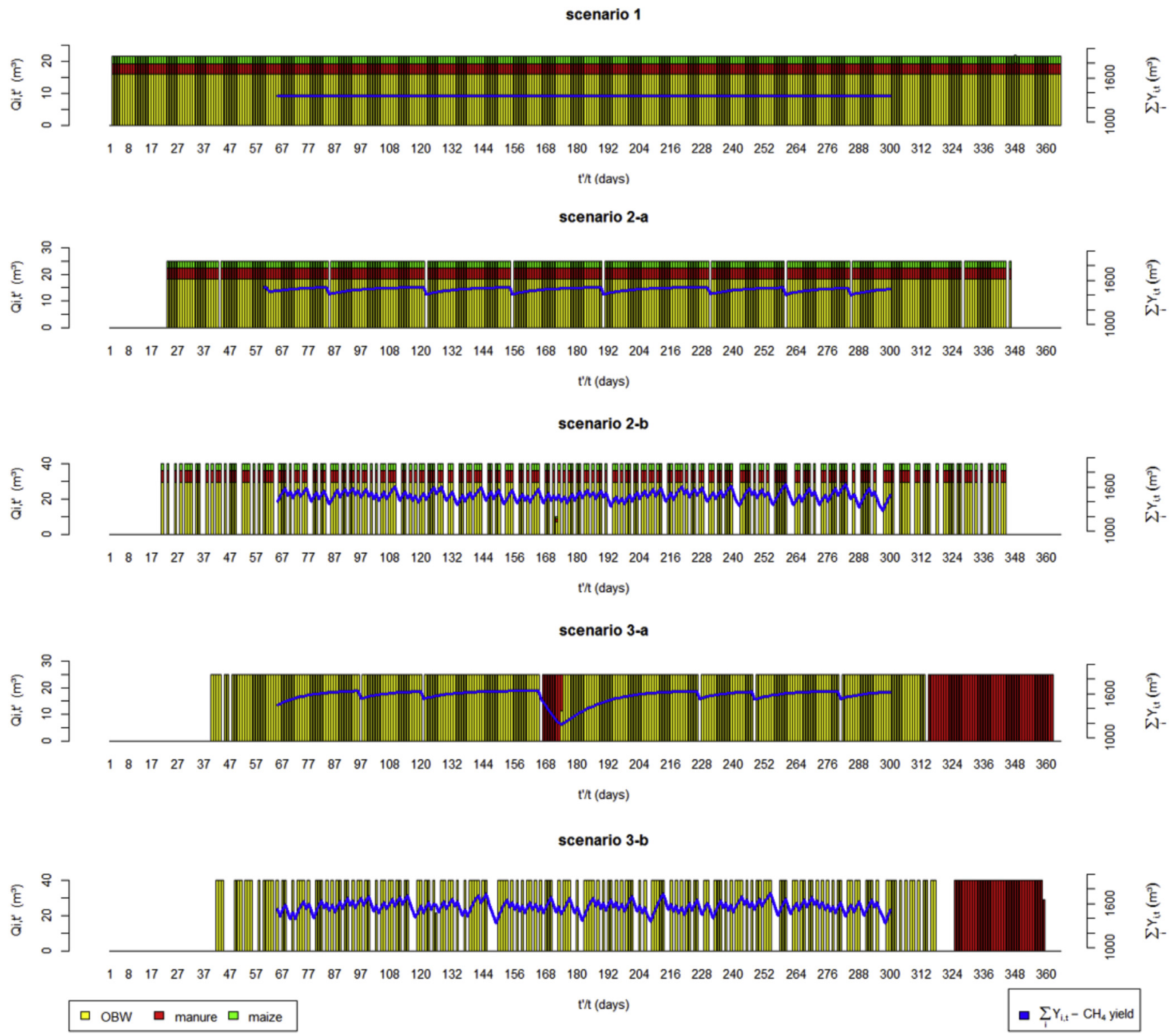

Fig. 2. Overview of input quantities $Q_{i,t'}$ (m^3) in function of input timings $t^{'}$ (days) for different types of feedstock and of CH_4 production $\sum_i Y_{i,t}$ (m^3) in function of time t (days) for the five sub-scenarios.

Table 3
Economic results for the five different sub-scenarios, calculated for a time period of one year.

	Income (€)	Profit (€)	Increase in profit compared to scenario 1 (%)	CHP capacity (kWe)	Investment cost (€)	NPV (€)	Increase in NPV compared to scenario 1 (%)
scenario 1 conventional	349,599	314,497		197	818,969	1,609,493	
scenario 2-a equal shares	359,539	324,437	3.2	220	828,508	1,676,710	4.2
scenario 2-b equal shares	361,041	325,939	3.6	240	836,377	1,680,441	4.4
scenario 3-a free choice	372,186	337,084	7.2	239	835,992	1,766,878	9.8
scenario 3-b free choice	375,716	340,614	8.3	255	842,050	1,788,084	11.1

increase is therefore solely due to the increase in biogas yield and related income from electricity sales.

Furthermore, assuming operational conditions and costs remain unchanged over the period, the comparative NPV was calculated. When it comes to the calculation of investment cost, it is important to note that, for the same digester capacity, there are differences in total biogas production between the scenarios, as well as variations in daily biogas production within the scenarios (see Fig. 2). In the case of pulse feeding (scenarios 2 and 3), additional CHP capacity is required, compared to continuous biogas production (scenario 1), to handle the peaks in electricity production, otherwise the total amount of electricity is reduced in proportion to the CHP-downtime [33]. We therefore selected the appropriate CHP capacity for each scenario by using Equation (20) and taking the maximum daily CHP_t value as the required capacity. We only looked at the period of stable operation – we selected day 65–300 as benchmark values -, hence excluding the start phase as it is not representative of the rest of the operational period. The selected CHP values and corresponding investment costs are displayed in Table 3. As higher NPV values imply greater economic benefits, the numbers in the table indicate that, increases ranging from 4 up to 11%, as compared to the conventional scenario, could be attained by applying the changes in operational management proposed by the model.

It is important to note that, as the OC in this study do not include all the costs incurred by the biogas installation, such as the costs of the supply logistics system, the NPV is used only to compare the different scenarios with one another. Neither the model nor the paper provides a judgment on whether the biogas plant in itself is profitable or not.

3.3. Discussion

Although the analysis based on our NLP model yields useful insights into the optimal performance of a biogas plant, it holds some limitations and is based on a number of assumptions.

Firstly, the performance of commercial biogas plants should ideally be improved by focusing on a number of different areas (see Section 1.2, [6]). We have, however, chosen to focus on only one specific aspect, i.e. the optimization of OLR and HRT.

Secondly, the feedstocks chosen for the model have significantly different first-order kinetic constants – as can be seen in Fig. 1, leading to a significant difference in optimal HRT for maximizing methane production. This means that varying the HRT can result in significant biogas yield increases. However, if the kinetic constants for different feedstocks in an AD are similar, there is one constant optimal HRT depending on the prices of inputs and outputs. Varying the HRT and the feeding mix would not, in that case, increase biogas yields. Moreover, biogas operators would need to have a clear idea about the BMP and kinetic constants of the specific feedstock they are using: Angelidaki et al. [41] and Triolo et al. [42] found that data on BMP may vary between laboratories, as these data cannot usually be compared due to differences in experimental design, equipment used and variations in temperature and experimental conditions. Moreover, the inoculum to substrate (IS) ratio should be recognized as one of the major parameters affecting the results of anaerobic assays [43–45], as it is clearly shown that IS ratio can affect not only the biodegradability but also the CH_4 production rate or hydrolysis rate, calculated from first-order kinetics models [44]. A lower than optimal IS ratio can cause inhibition, while a higher one can cause a BMP overestimation [46]. For our study, we assume an optimal IS ratio was used to determine the BMP, and as new feedstock is inserted in much lower quantities than are already present in the digester, and hence inoculated, we assume there will be no inhibition and biogas production will be similar to the predictions from the BMP test.

Thirdly, we use a simplified cumulative biogas yield function and assume that the digester has already reached an equilibrium state of digestion, implying that biogas production is already taking place optimally. However, at the start of the model simulation, the digester is filled with feedstock as if it is in start-up phase. This means there is a discrepancy between the assumptions. However, we assume this will not greatly affect the overall results. Additionally, as indicated in Section 3.1, at the start of the third scenario, the digester is 90% filled with maize. We acknowledge that this is not a feasible operational start-up for a biogas plant. However, starting the scenario 3 in a currently running operation should be theoretically feasible because the most important restrictions for a stable AD operation are satisfied in the model.

Fourthly, the model does not take microbiological AD parameters into account, but rather looks at operational parameters for profit optimization. Therefore, the model does not provide details for microbiological reactions. This comment also applies to the cumulative biogas yield function used as the basis for the model. The function describes the yield for individual feedstocks, but does not take into account the synergetic effects a co-digestion might have on the mixture. However, the improvement in methane production is mainly a consequence of the increase in OLR, rather than those synergetic effects [7]. This is confirmed in our simulations. Therefore, we assume no negative side-effects would take place.

Moreover, the analysis takes into account a variety of OLRs, some of which are close to rates that have been reported, in the literature, to cause system breakdown. Therefore, it needs to be kept in mind that some of the OLR rates used in our exercise might be overestimated, resulting in an overestimation of digester performance and economic outcomes. Nevertheless, Banks and Heaven [40] studied the effect of increasing OLR in a CSTR and found that the SMY for a substrate with constant VS content remains relatively constant, as the loading is increased up to a certain OLR threshold level. Increasing loads above this level would overreach the metabolic capacity of the digester, with a resulting decline in SMY. According to that same study, little information is available for maximum OLR, as this requires a large experimental effort and most commercial digesters work within empirically established ranges.

Additionally, in the second and third scenarios, feedstock is not necessarily inserted every day, as is the current common practice for commercial digesters, but a time lag of a couple of days may exist, resulting in 'pulse feeding'. De Vrieze et al. [47] demonstrated that stable operation can be maintained in anaerobic digestion when stronger pulse feeding patterns are applied, albeit at the cost of increased daily operational variation. Furthermore, changing feeding patterns can change the evenness, dynamics and richness of the bacterial community. Also, the regular application of a limited pulse of organic material and/or a variation in the substrate composition might promote higher functional stability (i.e. stable methane production and a certain redundancy towards stress) and hence higher tolerance to high levels of ammonium and organic overloading in anaerobic digestion.

Furthermore, there can be a potential variation in the composition of the biogas which can impact the down-stream processes, mainly the engine performance. On the one hand, the value and richness of the biogas depend on the amount of hydrocarbon components present – in this case CH_4 – and this amount varies depending on the type of feedstock used [30]. This is particularly important in the third scenario, as this is the scenario where the relative feedstock input ratios change, and hence also the concentration of the different compounds in the biogas. On the other hand, biogas contains impurities such as Sulphur and siloxanes which have to be removed through biological, physical, or chemical techniques [48]. We assumed engines of small, farm-scale digesters are sufficiently robust to deal with fluctuations in CH_4 concentrations and we did not take into account the possible need to invest in biogas purification units.

Finally, at this stage, the model only considers a single digester, without post-digestion in a second digester. In practice, however, some digesters are equipped with a second or even third digester where post-digestion can take place. This alters the outcome of the model, as the feedstock would have more time to reach its biogas potential in the post-digesters. As mentioned previously, post-digestion can increase biogas yield by 5–15% [22].

4. Conclusions

This paper presents an NLP model to optimize economic profit from an anaerobic farm-scale co-digester through the maximization of biogas production. The model consists of a combination of technical and economic equations. Five scenarios were simulated, differing with regard to substrate inlet mass flow rate, OLR and HRT. The impact on biogas production was investigated and an economic analysis was undertaken based on the concepts of profitability and comparative NPV.

Higher yields than in the conventional scenario were realized under scenarios with higher OLRs and increased time intervals between points of feedstock insertion. Under these scenarios, between 2.8 and 7.5% more biogas was produced than under the conventional one. The results of the technical analysis were extended in the economic analyses where those same scenarios resulted in economic profit and NPV increases of between 3.3 and 8.7, and 6.0 and 15.7% respectively. It can be concluded that varying substrate inlet mass flow rate and OLR, either by increasing the time between feedstock inputs, or by feeding individual streams of feedstock separately into the system, and at the same time reducing HRT, can have a positive impact on the profitability of pocket co-digesters.

The model simulations were carried out under a number of assumptions, including optimal biogas production, looking solely at operational AD parameters, a variety of OLRs, some of which were close to border values, fluctuations in these OLRs, and single stage digesters.

The analysis yields useful insights into the performance of a small, farm-scale co-digester and demonstrates the implications of making small adjustments to the operational management of such a digester. However, it must be emphasized that this exercise is a theoretical optimization and that, even though the technical constraints are adhered to, model verification would have to be conducted to validate the results.

The model and optimized feeding patterns could be adapted by commercial biogas operators, who, due to financial restrictions, might be limited to a certain quantity and type of feedstock, and who could, without additional investments, see their biogas production and profits increase. Even if adapting feeding patterns is more difficult to implement, it is important to determine the kinetic behavior of the feedstock that is being used. Based on this kinetic behavior, biogas operators should co-digest types of feedstock with similar kinetic constants in order to maximize biogas production as opposed to feedstock with dissimilar kinetic constants.

In further research, this model can be used as a base module in which techno-economic optimization can be conducted by taking into account variability in feedstock availability and prices, and adding additional modules such as a post-digester and an ammonia stripper and scrubber. Another option would be to use this model as a base for flexible power generation by steering biogas production through an adapted feeding regimen, in order to link biogas production to electricity prices in the day-ahead or continuous intraday market [33].

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