Abstract: Co-digestion is a well-established strategy to maximise the capacity of anaerobic digestion in wastewater treatment plants (WWTPs). Many tools have been developed to optimise the blend composition. However, the logistics associated with each component of the blend remain a relatively unexplored field, which can yield significant planning challenges. In this paper, an ant colony optimisation based approach is proposed to address these challenges. The proposed algorithm maximises an objective function composed of a first term related to the quality of the sludge and a second term related to the distance between the sludge generator and the anaerobic co-digester. The algorithm successfully optimises the blend composition by considering the related logistics, achieving an optimum blend with an approximately 18 % volume of co-substrate. The approach presented here has been used to plan co-digestion using real data from an actual sanitation network composed of 13 WWTPs in the area of the *Besòs* river basin in Catalonia, and an optimised co-digestion planning strategy with a waste management cost reduction of 77 % was obtained.

Keywords: anaerobic co-digestion; ant colony optimisation; waste management; environmental impact assessment; wastewater treatment; circular economy

1. Introduction

The anaerobic digestion process in wastewater treatment plants (WWTPs) plays an important role amongst potential circular economy technologies since it is one of the most well-established and promising processes in these installations, as stated by [1–3]. Furthermore, the co-digestion of sewage sludge and organic wastes has arisen as a promising strategy in the circular economy due to its capability of merging both wastewater and waste valorisation value chains. However, further work is required to fully achieve the optimisation and improvement of the anaerobic co-digestion process [4–6]. To this end, a remarkable number of anaerobic digestion optimisation tools

Abbreviations

ACO: Ant colony optimisation
CBT: *Consorci Besòs Tordera*
COD: Chemical oxygen demand
C1-C7: External co-substrate generators
ST: Single anaerobic treatment
WWTP: Wastewater treatment plant
W1-W12: Sewage sludge waste generators
HRT: Hydraulic retention time
Alk: Alkalinity
Max-Min: Maximum-minimum
Tox: Toxicity

have been recently developed, as reported by [7]. These tools are focused on the modelling and control of the optimum co-substrate blend and operation, as shown in ([8], [9], [10], [11], [12]). For example, [8] and [10] focused on the identification and modelling of critical parameters for co-digestion, such as volatile fatty acid production and particle size, and concluded that co-digestion is highly feasible; [9] developed control schemes for anaerobic digesters based on the composition qualities; and [11] and [12] implemented optimised control strategies according to the blend composition parameters, such as the organic and nitrogen content and the inhibition thresholds of the anaerobic digestion processes (which have been identified by previous biochemical modelling efforts [13–15]).

However, to the best knowledge of the authors, the complex logistics—and their related economics—associated with both co-substrates and sewage sludge have not been assessed mainly due to the ad hoc nature of each study case and the lack of data in the literature from the organic waste transportation sector. In addition, there are underlying critical factors for co-substrate selection not only at the characterisation-related level but also with respect to the associated logistics. Some undesired impacts of non-optimised transportation routes of co-substrates are as follows: increases in route length, time, costs and emitted greenhouse gases (GHG); increases in traffic density (which can be an issue for highly populated and busy areas); and additional odours, noise and air pollution in urban areas (which is a major issue for pedestrian and recreational zones, such as parks and the main streets of urban areas). Logistics optimisation may provide a useful approach to tackle and avoid the aforementioned social, environmental and economic impacts.

Regarding the optimisation method, combinatorial optimisation problems such as the one presented here can be solved using the ant colony optimisation (ACO) algorithm ([16],[17],[18],[19]). ACO is a metaheuristic approach that has been shown to be effective in solving a variety of NP-hard combinatorial optimisation problems [20], and is based on the as the well-known concepts of the travelling salesman problem (TSP) and the knapsack problem (KP). The TSP [20] is referred to the optimisation problem posed by the need to optimise (specifically, minimise) the distance that a traveller must do to reach a set of locations; such problem can be expressed as a distance minimisation, restricted by the geographical position of each location of the set, which constitutes the problem definition. On the other hand, the KP [20] is a traditional combinatorial optimisation problem, where a knapsack with limited weight must be filled with a set of items with a given weight and value each; however, since the knapsack has a weight restriction, the optimisation lies at filling the knapsack with a subset of items so that the accumulated value of the knapsack would be the highest possible. For example, the ACO algorithm has been used to optimise operational parameters for wind power generating facilities [21,22] and also to enhance the performance of energy transfer in solar power systems [23]. The ACO algorithm searches for a solution using a probabilistic and iterative procedure that emulates the behaviour of a real colony of ants in their search for food (pheromone trails are used and updated in the algorithm). Further methods may be applied to tackle NP-hard problems, e.g., genetic algorithms (GA). GA is a metaheuristic based on the mechanics of natural selection and natural genetics; GA has also become an important tool in combinatorial optimisation problems and has been used to solve different problems of combinatorial optimisation, e.g., hydraulic model calibration [24] and sensor placement for leak detection in water distribution networks [25]. In [26], the relation between GAs and ACO is noted. Some drawbacks of GAs are noted in [24]; e.g., achieving a global optimum for large and complex systems is not guaranteed, which is also a drawback for ACO. However, the ACO algorithm uses strategies to avoid rapid stagnation of the solution in the search space of solutions. A successful approach to ACO implementation is the max-min ant system [27], which consists of limiting the pheromone trails τ within the range $[\tau_{min}, \tau_{max}]$. With this strategy the search space of solutions does not rapidly exhibit significant differences in the pheromone amounts deposited in each zone. A high local concentration of ants at the beginning of the search process could generate a bad quality solution because many zones could remain without being explored by ants. As observed above, the ACO approach was originally applied to solve the TSP, outperforming other nature-inspired algorithms, e.g., GAs [27]. In [28], it is noted how ACO is successfully applied not only to different NP-hard academic combinatorial optimisation problems but also to some real-world problems of the same kind as the one presented here, e.g., in [29], to optimise the truck routes of a gasoline distribution company in Switzerland. ACO can also be conveniently used to solve the multidimensional knapsack problem, as introduced in [30]. In the context of the current problem, the search space of solutions is represented by a bipartite graph. The set of nodes is the sludge generators and their possible volumetric contributions, and the edges are the connections between each generator and its feasible contributions of sludge. Overall, ACO is an EA that can be complemented by local optimisation, with similar drawbacks to other evolutionary algorithms as explained previously and pointed out in [24]. The max-min approximation and the use of strategies to avoid rapid stagnation of the solution in the search space have both been applied for the ACO algorithm to enhance its features and minimise the drawbacks of the use of an evolutionary algorithm.

Moreover, applications of such an enhanced algorithm have already been made for real-world cases of the waste sector ([30,31]). The optimisation problem presented in this publication is inspired by prior optimisation problems approached by the ACO algorithm: here, it not only is applied to optimise co-digestion strategies but also takes into account the potential impact of the logistics associated with the transportation route of each co-substrate. The additional features increase the problem complexity (due to the increase in variables considered by the combinatorial optimisation), so the cost function is reformulated according to the problem stated. Achieving a single global optimum with this problem is not possible. Thus, the cost function is not a convex function, and the number of local optimums is increased by the increase in complexity. The framework presented here is an approach for assessing real conditions based on a previous work [31], which focused on synthetic results. Here, the co-substrate details are obtained by considering real data from an actual sanitation network in the area of the *Besòs* river basin in Catalonia.

The application of the ACO algorithm allows optimisation of co-digestion strategies, enhancing biogas production and minimising associated risks to the anaerobic digestion operation (e.g., overdosing and acidification); furthermore, the novel implementation of the logistics in the algorithm allows more accurate selection of co-substrates in a real substrate multi-source/multi-receptor case study, allowing cost and impact minimisation whilst maximising biogas production with the optimal set of resources, e.g., by taking into account the impacts derived from the derived logistic routes. This is achieved in this work by a novel strategy based on the simultaneous optimisation of both the substrate composition and characterisation of their transport routes provided by the ACO algorithm. The novel application for co-digestion strategies considering the logistics and volume distribution may contribute to the state-of-the-art of existent anaerobic co-digestion tools as shown in [7–12] that have been explained previously, which were more focused on the optimisation of blending and the anaerobic digestion process.

The objective of this work was to develop a new co-digestion optimisation tool based on an enhanced version of the ACO algorithm that improves the constructed solution and avoids its rapid stagnation using two local search heuristics. The optimisation problem includes both substrate biochemical characterisation (for biogas production maximisation) and logistics characterisation (for route optimisation). The effect of centralised anaerobic co-digestion is evaluated from both technical and economic perspectives. This method is applied in a real case study composed of 16 different WWTPs—4 of which include anaerobic digesters—that are managed by *Consorci Besòs Tordera* (CBT), a local water authority in charge of these facilities.

2. Material and methods

ACO is an algorithm aimed at finding an optimal solution of the optimisation problem posed, which consists in the selection of the best substrates and volumes according to a set of restrictions related to the operation of the anaerobic digester. Thus, the problem statement considers a set of substrate generators $w \in \{1, \ldots, N\}$. The N different substrate generators are located different distances (d_w) from a single anaerobic digester (ST). Each generator has the capacity to store its own substrate until it is transported to the ST. Each substrate is characterised by its volume V_w and a set of values C_w^c, where C_w^1 is the chemical oxygen demand (COD) concentration, C_w^2 is the ratio of chemical oxygen demand and total nitrogen (COD/TN), C_w^3 is the alkalinity (Alk) concentration, and C_w^4 is the toxicity (*Tox*) level. Each volume of stored substrate V_w can be selected as a substrate contribution to be transported to the ST. The selection is performed according to different volumetric possibilities (V_w^s, with $s \in \{0 \ldots, l_w\}$) that are determined as a multiple of a number (e.g., 1000) such that $1000 l_w = V_w$. The selection of each volumetric possibility is determined by the corresponding value of the binary decision variable, y_w^s, where $y \in \{0,1\}$, with $y_w^s = 0$ when the corresponding volumetric configuration is not selected, and $y_w^s = 1$ when it is selected. Note that for each waste generator w there are l_w different volumetric configurations in y_w^s, but only one is selected at a time, i.e., $\sum_{s=1}^{l_w} y_w^s = 1 \, \forall \, w \in \{1 \ldots, N\}$ (e.g., a waste generator with $l_w = 5$ would have five different volumetric configurations, but only one is selected at each optimisation iteration). The conveyance of the selected volumes implies a travel distance d_w with a social impact I_w and an economic cost x_w.

The blend of all transported substrate contributions constitutes the ST input. This input must be bounded by a certain set of restrictions, namely, the maximum acceptable volume V in the ST, the COD/TN ratio within the range $[C^2_{min}, C^2_{max}]$, the *Alk* concentration within the range $[C^3_{min}, C^3_{max}]$ and the toxicity level $Tox < C^4_{max}$.

The objective is to minimise a cost function *B*, expressed as follows (note that the cost function is expressed as a quotient because the algorithm is intended to be maximised):

$$B = 1/\left\{\sum_{w=1}^{N}\sum_{s=0}^{l_w} y_w^s\, V_w^s T_w \left[(\textstyle\sum_{c=1}^{3} F_w^c)\rho_q + \frac{\rho_x}{X_w d_w I_w}\right]\right\}, \quad (1)$$

where y_w^s is the binary decision variable; V_w^s is the substrate contribution of generator W_w (in L); T_w is the sludge toxicity level (dimensionless); F_w^c is the set of coefficients corresponding to the substrate composition (dimensionless); ρ_q is the quality coefficient (dimensionless); ρ_x is the logistics coefficient (dimensionless); X_w is the unit cost (in €/km) of substrate transport; d_w is the distance between generator w and the anaerobic digester (in km); and $I_w = 1, \ldots, 3$ is a coefficient related to the social impact of substrate transport (dimensionless); the higher the value of I_w, the higher the social impact of the related route. The value of I_w is assigned qualitatively depending on different criteria e.g. route traffic density or proximity to pedestrian/sensitive areas where air pollution could impact human health. Hence, the use of routes involving critical areas—e.g., city centres or highly dense roadways—is related to a higher social impact factor (with a maximum value of 3). Consequently, a value for I_w is assigned for each sludge/substrate generator depending on its route to the ST.

The coefficients F_w^c ($c = 1, \ldots, 3$) and T_w are related to the role of the components (C_w^c, with $c = 1, \ldots$,3) in the anaerobic process under the following conditions:

- F_w^1 is defined as the coefficient related to the potential biodegradation according to the COD content, following eq. 2. Such an equation has been drawn from [31], where it is used to quantify the organic content of the substrate and, hence, potential biogas production. Further calculations of biogas production have been made assuming a conversion factor of 0.268 m^3 biogas/kg DQO (a parameter estimated from the current performance of the anaerobic digester of the case study and assuming minimal variations in retention time).

$$F_w^1 = 0.00001 * C_w^1 - 0.01 \qquad (2)$$

- F_w^2 is determined according to the ratio of COD/TN (eq. 3). Its value must be in the range 20–60, with a maximum value $F_w^2 = 1$ at C_w^2=40. This equation is used in [31] to assign the optimum COD/TN ratio and penalise higher or lower ratios, which has been proven suboptimal for the anaerobic digester performance in the aforementioned reference.

$$F_w^2 = e^{-\left(\frac{(C_w^2-40)^2}{450}\right)} \qquad (3)$$

- F_w^3 is related to the alkalinity concentration (eq. 4), ranging from 3000 to 6000 g/m^3 (which achieves maximum biogas production according to[31]). Then, the maximum value $F_w^3 = 1$ (i.e., optimum alkalinity) corresponds to C_w^3=4500, which is related to the optimum alkalinity (high enough to prevent acidification but low enough to prevent salts precipitation), as used in [31].

$$F_w^3 = e^{-\left[\frac{(C_w^3-4500)^2}{8*10^6}\right]} \qquad (4)$$

- T_w is a coefficient linked to the toxicity level. The Tox level is established according to the USEtox 2.1 toolbox toxicity estimation for a set of metals, expressed in total equivalent mg/L of lead (Pb). T_w has the highest values at the minimum toxicity levels. Hence, T_w=1 for a Tox level=0, and $T_w \cong 0$ for a Tox level ≥2.1.

$$T_w = e^{-\left[\frac{(C_w^4)^2}{0,6}\right]} \qquad (5)$$

The cost function presented in this work is adapted from [31], where the ACO algorithm is used for waste management optimisation in a similar fashion as here. The coefficient T_w is located outside the substrate biochemical characterisation to increase the importance of toxicity minimisation, which is a major risk for an anaerobic digestion operation [32] . The first term in eq. 1 is related to the quality composition of the substrate, and the second term in eq. 1 is related to the transport to the digester (the logistics term). The sum of both terms in eq. 1 is weighted by the coefficients ρ_q and ρ_x, allowing the assignment of different importance to each term. This enables stating whether the case study priorities are more focused on logistics or on maximising the anaerobic digester performance.

The cost function in eq. 1 is constrained by the decision variable y_w^s and the substrate characteristics (i.e., volume, composition, and toxicity level) that are acceptable for input to the anaerobic process.

Optimisation will provide a sequence that includes all the generators, where each generator is associated with its substrate contribution (including zero contribution) to the ST input. This optimised sequence may be interpreted as logistic planning based on the average travels per month: all transportation routes assume that a truck of 20 metric tonnes capacity is fully loaded with substrate from the waste generator, disregarding the truck waiting time before starting each route; once fully loaded, the truck would go directly to the waste receptor (assuming it always follows the same route). It is assumed that for all the co-substrate discharges made within a time frame equal to or less than the digestion hydraulic retention time (usually approximately 20 days) a blending effect would occur (otherwise, for the conducted case-study, equalisation tanks are available to hold different loads for a limited amount of time). On the other hand, the specific hour of the day where routes would start and finish has not been considered. This issue does not affect the solution of the algorithm, although it has been noted that this would be a significant issue for real-world implementation (due to potential social impacts for practitioners).

The ACO algorithm executes an iterative procedure that uses a population of ants, initially placed in a random location of the search space of solutions. Each ant traces a path through the search space following the probabilistic rule known as state transition, in order to construct a solution.

The state transition rule is defined by eq. 6.

$$p_{ws}^m(t) = \frac{[\tau_{ws}(t)]^\alpha [\eta_{ws}(t)]^\beta}{\sum_{l=0}^{l_w} [\tau_{wl}(t)]^\alpha [\eta_{wl}(t)]^\beta} \quad (6)$$

where at iteration $t, p_{ws}^m(t)$ is the probability that the mth ant chooses the volume V_w^s; $\tau_{ws(t)}$ is the pheromone trail; α is the importance assigned to the pheromone trail; $\eta_{ws}(t)$ is the specific heuristic information; and β is the importance assigned to the heuristic information. The new heuristic information η_{ws}, defined in eq. 7, is used in the computation of a solution; the search seeks solutions by considering higher volumes, convenient substrate characteristics and shorter distances. This heuristic information provides an additional help to guide the paths of ants.

$$\eta_{ws} = \frac{V_w^s \sum_{c=1}^{3} F_w^c}{d_w} \quad (7)$$

After each iteration, the pheromone trails are updated following eq. 8 [27].

$$\tau_{ws}(t+1) = \rho\tau_{ws}(t) + \Delta\tau_{ws}^{best} \quad (8)$$

where $\tau_{ws}(t+1)$ is the pheromone trail at the beginning of iteration $t+1$; ρ is the persistence of pheromone in the trails (with $0 < \rho < 1$) corresponding to iteration t, and $\Delta\tau_{ws}^{best}$ is the amount of pheromone added to the trail of the ant that has achieved the best solution (B^*) at iteration t. The value assigned to this amount is defined in eq. 9 [31].

$$\Delta\tau_{ws}^{best} = B^* \quad (9)$$

The rest of paths followed by the ants that have not achieved the best solution do not increase their pheromone trails. At the beginning of iteration t+1, their amounts are those corresponding to iteration t decreased by the value of the persistence ρ (1-ρ models the pheromone evaporation).

In this procedure of the algorithm, only the pheromone trails of the ants that has achieved the best solutions increase, and the evaporation mechanism helps to avoid unlimited accumulation [27]. For all iterations, all pheromone trails have values in the range [τ_min,τ_max].

3. Results

3.1 Case study

The case study included a network of 13 WWTPs which are part of the wastewater treatment system managed by *Consorci Besòs Tordera* (CBT), a public local water administration composed of 64 municipalities in four different regions of Catalonia (Spain) with a population of approximately 470,000 inhabitants. The area served by these WWTPs features a contrast between high anthropic-pressure areas (urban and industrial, relatively close to the metropolitan area of Barcelona) and other rural areas.

The sanitation network under study is composed of 12 WWTPs (W1-W12) that produce undigested sewage sludge and an additional WWTP with anaerobic digestion where the produced sludge would be treated. Figure 1 show a map of the full wastewater system where the case study is located. Additionally, seven co-substrate generators from industries of the region (whose location is not included in Figure 1 for data privacy reasons) have been identified by CBT practitioners as potentially viable substrates for co-digestion (C1-C7). Due to regional legislation constraints, the maximum volume of co-digestion with industrial substrates has been set at 9,000 L by day.

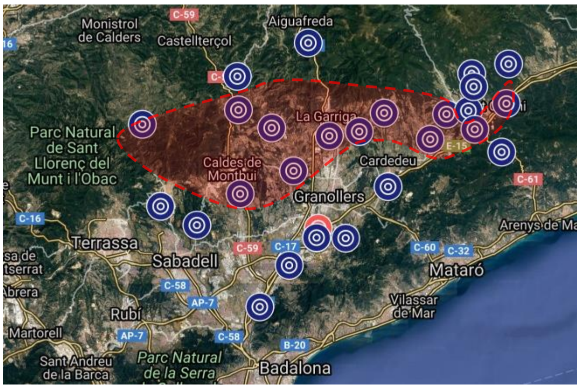

Figure 1. Map of the wastewater treatment system under study, where each dot corresponds to a WWTP. The specific sanitation network under study corresponds to the 12 dots under the red-shaded area (the WWTP with undigested sludge) and the red dotted WWTP (that corresponds to the receptor WWTP with anaerobic digestion) [single column fitting image]

The algorithm used in this work is programmed in Java. The simulations of the case study were performed with an HP EliteBook 840 G4 x64 using the OS Microsoft Windows 10 Pro and an Intel(R) Core(TM) i7-7500U CPU processor (2.70 GHz, 2904 MHz) consisting of two main processors and four logic processors.

Each simulation consists of 10 repetitions of the algorithm execution (their resulting values were averaged because of the probabilistic nature of the methodology), 500 iterations per repetition and 100 ants per iteration. All the repetitions start with a maximum pheromone trail on all the nodes to assign the same probability of selection to each node. The values used for the algorithm parameters are $\alpha = 1, \beta = 2$ and $\rho = 0.98$ ([20,27]).

The methodology was applied to a set of 19 substrate generators (12 WWTPs and 7 industrial substrate generators, which contain higher loads of organic matter than the 12 WWTPs and hence have higher potential for co-digestion strategies). The data corresponding to each generator are summarised in Table 1 and have been gathered as part of a real case study on the wastewater treatment infrastructure of CBT, a local water administration composed of 64 municipalities in four different regions of Catalonia (Spain) with a population of approximately 470000 inhabitants. In this area, 12 WWTPs (W1–W12 in Table 1) without anaerobic digestion have been identified, and characterisations of their sewage sludge have been performed. Additionally, seven external waste generators have been identified (C1–C7 in Table 1), whose substrate flows have been tested and validated as technically feasible for co-digestion purposes by CBT (by applying an internal co-substrate homologation process for WWTP anaerobic digestion).

A social impact factor I_w ranging from 1 to 3 was assigned to each route according to the corresponding social impact related to the route considered for each substrate.

ID	Vw (L by day)	COD (mg/L)	C/N	Alk (mg/L)	Tw (mg/L)	d (km)	X (€/km)	Iw
GR	359000	26900	20.3	2500	1.12	0	0	0
W1	27600	19900	17.8	4300	1.55	5.3	25.7	1
W2	47000	16900	20.6	3200	1.36	35.9	20.1	1
W3	46300	18600	19.4	10100	1.42	21.8	16.2	1
W4	20200	23400	15.6	3400	1.38	30.4	13.9	1
W5	38400	21100	17.9	4500	1.35	19.7	13.8	2
W6	34400	18800	14.0	3800	1.61	14.8	19.3	2
W7	13800	22600	15.3	2700	1.57	32.1	13.1	1
W8	4400	22100	15.2	1800	2.30	26.5	11.3	2
W9	10800	21700	15.1	5300	0.93	20.3	19.4	3
W10	9500	20400	15.5	2500	1.28	30	15.4	1
W11	17000	23300	14.8	7800	0.98	36.9	16.6	1
W12	6500	20100	16.5	3100	1.40	20.5	16.6	1
C1	9000	667400	42.5	250	0.01	15.9	15.4	1

C2	9000	497400	461.8	330	0.01	7	21.4	3
C3	9000	155900	3118.1	60	0.02	27.9	11.7	1
C4	9000	459100	274.1	660	0.10	16.2	12.6	1
C5	9000	657200	2330.6	630	0.01	52.8	11.6	1
C6	9000	266200	2832.4	20	0.01	56.1	10.4	1
C7	9000	262100	32768.4	110	0.01	5.6	19.4	1

Table 1. Waste generator dataset used for the simulations of the ACO algorithm. Each waste generator (W1-W12 and C1-C7) distance is related to the correspondent waste generator to the anaerobic digester receptor system. GR is referred to the sewage sludge produced within the same WWTP that includes the centralised anaerobic digestion system to be optimised.

In the approach presented here, one scenario is simulated based on the waste generator data in Table 1 and considering a single waste receptor. As specified in the case study section, the sanitation system under study is comprised of 12 WWTPs without anaerobic digestion and one additional WWTP with anaerobic digestion, and 7 cosubstrate generators. For all of those 19 waste generators (i.e. the 12 WWTPs without anaerobic digestion and the 7 cosubstrate generators) it is optimised the addition to the single anaerobic system of one of the main WWTPs managed by CBT, the *Granollers* WWTP (GR WWTP), whose own sludge properties have been introduced in Table 1. For that anaerobic digestion system, a volume constraint of 141 m^3/d is used (corresponding to a retention time limit of 20 days). More details on the properties of the anaerobic digestion system under study can be found in Table 2.

Anaerobic digestion properties	Value
Inflow sludge flow (m^3/d)	366
Inflow dry matter content (% w/w)	3.57
Inflow volatile matter content (% dm)	72
Outflow sludge flow (m^3/d)	220
Outflow dry matter content (% w/w)	2.5
Outflow volatile matter content (% dm)	54
Biogas production (Nm^3/d)	3600
Digester volume (m^3)	10000
Hydraulic Retention Time (days)	27.2
Organic Loading Rate (kg COD/m^3)	1.2
Heating demand (thermal kW/d)	11200

Table 2. Properties of the anaerobic digestion system under study. Where “%w/w” refers to percent weight-weight; “% dm” refers to percent over dry matter

The effect of the logistics on the optimised volume distribution is also assessed: two scenarios are simulated—O1 and O2, with 0 % and 50 % weight given to the logistics term ρ_x in eq. 1, respectively. Hence, in scenario O1, the optimisation is only focused on the quality of the blend—i.e., without considering the logistics impact on the optimal solution—whilst in scenario O2, the quality of the blend and the corresponding logistics are given the same importance to obtain the optimal solution.

Each simulation is repeated 10 times, consisting of runs of 100 ants and 500 iterations, since the ACO algorithm search is a probabilistic, iterative-based method. Once the optimised volume distributions are obtained, further calculations are performed to characterise the corresponding logistics and the resulting anaerobic digestion balances. At this stage, the data of the variables detailed in Table 3 are obtained. It must be noted that the operating expense (OPEX) balance in Table 3 is obtained by considering integral waste management; hence, the related cost analysis considers not only the receiving system ST (i.e., the *Granollers* WWTP) but also the waste management costs related to W1–W12.

Data description	**Units**
Digester operating data	
HRT	Day^{-1}
OLR	kg COD/m^3·d
Biogas production	Nm^3/d
Electricity production	kWh/d
Non-digested biosolids	kg/d
Digested biosolids	kg/d
Digester flows and quality composition data	
External sewage sludge addition	m^3/d
External industrial waste addition	m^3/d
Centralised non-digested sludge (treated anaerobically)	%
Logistic requirements for sludge centralisation	Journeys/month
Logistic requirements for co-digested industrial waste	Journeys/month
Average COD of digester input	mg/L

Average ratio COD/N of digester input	-
Average alkalinity of digester input	mg CaCO3/L
Average toxicity of digester input	mg eq Pb/L
OPEX balance	
Dehydration system cost for external sludge generators	€/y
Non-digested sludge management cost	€/y
Non-digested sludge logistics cost (for centralised digestion)	€/y
Biogas valorisation benefits	€/y
Dehydration system cost after centralised digestion	€/y
Digested sludge management cost	€/y
Total cost-benefit analysis balance	€/y

Table 3. Variables used for the characterisation of logistics and digester balance from the volume distribution. HRT is the hydraulic retention time; OLR is the organic loading rate.

The data obtained for the two optimised scenarios O1 and O2 (each comprising 10 repetitions of the ACO algorithm) are compared to those obtained for the additional non-optimised scenarios, for which the volume distributions of W1–W12 and the substrates C1–C7 are fixed. These scenarios correspond to the following: 1) Scenario M: manual volume distribution (according to expert knowledge criteria and the same volume constraints as in scenarios O1 and O2); 2) Scenario T: no volume constraint is considered (thus, all external sludge is processed by the receiving digester with no regard to retention time); and 3) Scenario C: control scenario according to the actual operating parameters of the receiving digestion system.

An additional constraint is considered, related to the valorisation of the biogas—set at 3800 Nm3/d of biogas, according to the current cogeneration capacity of the *Granollers* WWTP (which performs centralised co-digestion) for biogas valorisation. Thus, scenarios with and without this biogas valorisation restriction (referred to as biogas valorisation restriction, or BVR) are compared.

3.3 Scenario analysis

Volume distributions for each scenario are shown in Figure 2. Scenario C only involves the digestion of an external flow of 8000 L/day of industrial waste (C2), while scenario T involves the digestion of all the sewage sludge flows (waste generators W1–W12) but only the co-digestion of industrial waste C2. These pre-set scenarios are considered to compare the effect of absolute centralisation without the potential biases caused by industrial high-organic-load external wastes. In addition, optimised scenarios O1 and O2 (each consisting of 10 repetitions of the ACO algorithm described in the Material and Methods section) both involve the volume distribution generated by the application of the ACO algorithm to the set of 19 substrate generators. A summary of the results is presented in Table 4.

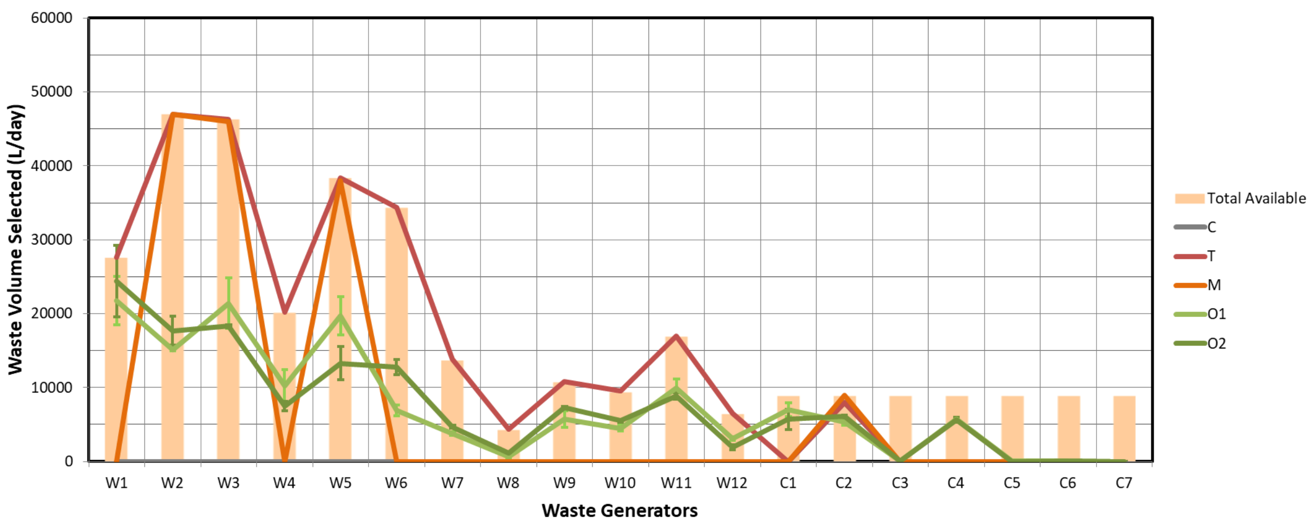

Figure 2. Volume distribution for each scenario (C: Current scenario; T: Total centralisation scenario; M: Manual scenario; O1: Optimised scenario with 0 % logistic weight; O2: Optimised scenario with 50 % logistic weight) without BVR. [2 column fitting image]

Scenario	**OPEX (TEUR/y)**	**HRT (days)**	**OLR (kg COD/m^3·d)**	**Biogas (Nm^3/d)**	**Industrial Waste Dosage (m3/d)**
			without BVR		
C	-480	27.2	1.2	3600	8
T	-93	15.6	1.8	5100	8
M	-300	20	1.5	4500	8
O1	-107 ± 8	20	2.1 ± 0.2	6700 ± 400	18 ± 0.7
O2	-125 ± 11	20	2.0 ± 0.2	6400 ± 300	18 ± 0.4
			with BVR		
C	-480	27.2	1.2	3600	8

T	-202	15.6	1.8	5100	8
M	-354	20	1.5	4500	9
O1	-350 ± 10	20	2.1 ± 0.2	6700 ± 400	18 ± 0.7
O2	-346 ± 14	20	2.0 ± 0.2	6400 ± 300	18 ± 0.4

Table 4. Summary of results for each scenario, where O1 and O2 correspond to ACO-based optimisations and the C, T and M scenarios correspond to pre-set scenarios (current, total centralisation and manual distribution scenarios, respectively). OPEX is expressed as TEUR (thousand euros) per year.

As observed in Table 4, scenario T results in the highest (i.e., best) CBA balance but with a low retention time (HRT) trade-off. On the other hand, the optimised scenarios (i.e., O1 and O2) result in the highest production of biogas (and highest organic load rates) and the second and third best CBA balances while keeping the retention time at 20 days. Scenario M results in a balanced performance between the optimised scenarios and scenarios C and T.

Considering BVR in Table 4, almost no significant differences can be noted amongst the different scenarios: the lack of capacity to valorise all the produced biogas worsens all CBA balances except that for the current scenario (where biogas production is below the BVR). Moreover, little difference is observed between the M, O1 and O2 scenarios for all restriction combinations (the CBA balance is approximately −350000 €/year for the scenarios considered).

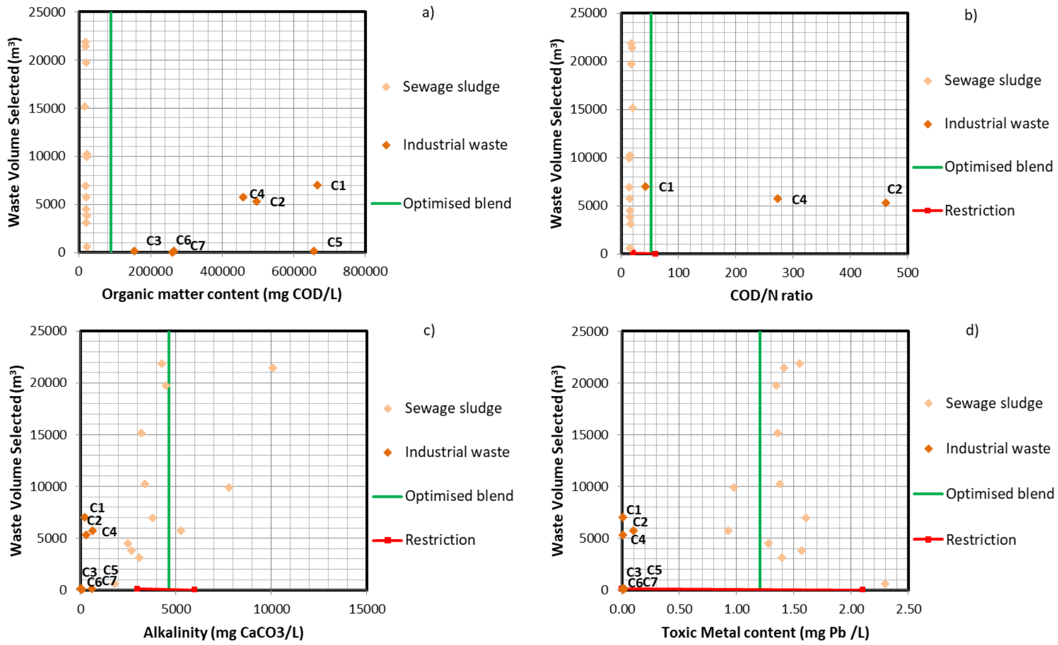

Figure 3. Waste generator volume selection for scenario O1 according to a) organic matter content, b) C/N ratio, c) alkalinity and d) associated metal toxicity. Note that only average values are shown here (deviations of volume selection can be checked in Figure 2) [2 column fitting image]

Figure 3 depicts the details of the optimisation results for scenario O1. To maximise biogas production, the algorithm optimises the combination of wastes with the highest organic content (Figure 3) while keeping the restrictions on nitrogen content, alkalinity and toxicity (Figure 3).

For sewage sludge wastes (W1–W12), relatively similar organic and nitrogen contents are noted (approximately 20000 ± 2000 mg/L COD and 16 ± 2 COD/N ratio, respectively); however, the COD/N ratio (ranging from 14 to 20, as seen in Table 1) is below the low limit constraint of the ACO algorithm (set at 20). On the other hand, the COD/N values of the industrial co-substrates have much higher values and wider ranges (from 42 for C1 to 32700 for C7). The COD/N constraint is the limiting factor when composing the blend since the algorithm seems to prioritise industrial wastes with the lowest ratio of COD/N (C1, C2 and C4, as seen in Figure 3; C3, C4, C5, C6 and C7 are beyond the chart limits, but their contribution to the blend is minimal).

Regarding alkalinity and toxicity (Figures 3.c and 3.d, respectively) industrial wastes show less alkalinity (300 ± 260 mg/L alkalinity) and less metal toxicity (0.02 ± 0.03 mg/L equivalent Pb) than sewage sludge (4000 ± 2400 mg/L alkalinity and 1.4 ± 0.3 mg/L equivalent Pb). Hence, it may be noted that from a toxicity perspective, these industrial substrates would be safe for co-digestion strategies (although their high COD/N ratio limits their usage due to the COD/N ratio restriction over value 60).

As for the energy balance, a cogeneration system with 40% thermal efficiency and 35% electrical efficiency has been assumed. Scenarios C, T and M do not provide enough thermal energy to sustain the thermal demand of the anaerobic digester, thus requiring that part of the biogas should be valorised in a boiler to exclusively produce heat. On the contrary, both optimised scenarios O1 and O2 would provide enough thermal energy via cogeneration to sustain the thermal demand of the anaerobic digester process. Table 5 shows the energy balance for each scenario applying 100% valorisation of biogas via cogeneration.

Scenario	**Biogas (Nm^3/d)**	**Digestion thermal demand (thermal kW/d)**	**Thermal energy production (thermal kW/d)**	**Electric energy production (electric kW/d)**
C	3600	11200	8600	7600
T	5100	16600	12200	10700
M	4500	13800	10800	9500
O1	6700	13800	16000	14000
O2	6400	13800	15300	13400

Table 5. Energy balance of the anaerobic digestion system under study for each scenario, assuming 100% valorisation of biogas via cogeneration and 40% thermal efficiency and 35% electrical efficiency.

4. Discussion

The employed ACO algorithm allows an optimised logistic planning proposal to be obtained in terms of the average volume extracted from each waste generator. This, together with data from the case study, allows average travels per month, biogas production and the resulting OPEX balance to be estimated. Other existent optimisation algorithms regarding anaerobic co-digestion that were introduced previously in this paper have been focused on separate aspects of anaerobic co-digestion (always with the objective of maximise biogas production): in [10], the focus is placed on linear optimisation of the feed composition through the detailed conversion routes of each compound of the feed (e.g., carbohydrates, lipids, proteins); in [11], linear optimisation of the feed is also performed, taking into account the potential effects of the pretreatment technologies, so the output also considers a technology assessment about substrate pretreatment processes; and in [33], the focus is to study the anaerobic digestion dynamics of the main metabolic reactions and the biochemical transformation pathways for various organic compounds, so that it allows a deeper analysis of the transition from mono-digestion to co-digestion (since such transitions always depend on the type of microbiota in the digester and their adaptability to the organic load increase). Additionally, algorithms focused on logistic optimisation already exist, e.g., in [29], where an ACO algorithm is applied to optimise truck routes (but not considering other properties of the transported materials, such as the biochemical properties of sewage sludge in the case study of this work), or in [34], where GIS-based optimisation is carried to address faecal sludge logistics. Other methods of anaerobic digestion optimisation can be found in literature, which includes multi-objective oriented works as in [35] and other works driven by nature-inspired techniques [36]. Also, prediction of the biogas flow rate is a significant issue, which has been recently addressed by other researchers by means of artificial neural networks, genetic algorithms and the ACO algorithm [37,38]. The novel ACO algorithm developed in this work is an approximation to tackle most of the aforementioned issues from a holistic perspective (such as considering logistics, volume distribution, and cosubstrate blend optimisation, working within the operative restrictions of volume, alkalinity and nitrogen loading).

Without BVR (Table 4), the optimum scenario is O1, despite having a slightly lower CBA (−107000 €/y) than scenario T (−93000 €/y). This difference in CBA is because all variants of scenario T consider the total centralisation of all the non-digested sewage sludge (from W1–W12), and hence, the HRT is drastically reduced to approximately 15 days. Since these operation conditions are at the edge of conventional and convenient anaerobic digestion management conditions, this strategy implies a relatively risky shift in operation conditions. In addition, less efficient biogas production, a decreased buffer capacity of the digester in the case of metal toxicity, and an increased risk of acidification would be expected. The precise motivation of the optimisation problem (approached herein by the ACO algorithm) is the need to set a limit on the acceptance of external wastes to avoid these undesired conditions of operation.

For the manual distribution approach, as observed in Table 4, the pre-set scenario M results in a lower CBA than the optimised scenarios O1 and O2 (without BVR, scenario M has a CBA of −300000 €/y, while scenarios O1 and O2 have CBAs of −107000 €/y and −125000 €/y, respectively). This is because scenario M adds less industrial, high-load organic waste (from 8 to 18 m3/d) and thus allows less production of biogas (4500 Nm3/d, in comparison to the 6400–6700 Nm3/d of O1 and O2). However, the O1 and O2 scenarios allow for more biogas production than the manual scenario since the optimisation process allows for the control of critical factors such as alkalinity and the COD/N ratio. The monitoring of these parameters is paramount to avoid acidification of the digester, which may have an important impact on its performance and may be avoided using appropriate diagnosis and optimised blending strategies, such as the one presented here.

On the other hand, potential legislation and other policy-based limitations on the addition of industrial substrates (such as those corresponding to C1–C7) have been identified, but they have not been considered in this study. If enacted, these additional restrictions could reduce the effectiveness of a co-digestion strategy below its full technical potential, as shown by the ACO algorithm approach.

Besides, a significant environmental impact is provided by centralised anaerobic digestion. Although it is not the main focus of the study, it has been estimated that centralised digestion can reduce about 27% emissions generated from sewage sludge management: the current system without centralised anaerobic digestion generates about 1120 tonnes CO_2/year, while digesting external sewage sludge according to the optimisation procedure reduces the total emissions generated up to 810 tonnes CO_2/year. These results have been calculated assuming that undigested sludge sent to composting has a net environmental impact of 79 kg of CO_2 equivalent greenhouse gas (GHG) emissions per tonne of undigested sewage sludge sent to composting, and 33 kg of CO_2 equivalent GHG emissions for the case of digested sludge sent to land application as agricultural fertiliser (according to data extracted from IPCC Guidelines and used in the ECAM open source tool [39] for assessing the urban water cycle). Note that for this estimation no other sources of GHG have been estimated;

thus, further work should be addressed to perform an exhaustive life cycle analysis (LCA).

Regarding the impact of the logistic term on optimisation in the CBT case study, minor differences are observed between scenarios O1 and O2 (as seen in Table 4). Scenario O2 shows a slightly lower CBA balance than O1. Hence, in this particular case, increasing the weight of the logistic term to 50 % of the cost function does not provide a better CBA balance. This result may indicate that external substrate waste generators with higher biomethanisation capacity are geographically closer to the anaerobic digester receptor ST (*Granollers WWTP*) than those with less potential to produce biogas. Note that the case study involves waste generators with logistic distances below 30 km. Without loss of generality, for different scenarios with higher logistic distances, the logistic term might be more significant, but it is not the case here, where the distance between co-substrate generators and receptor do not seem to be significant for optimisation purposes. This logistic term, however, could be significant for the present case study if stronger restrictions and/or penalties would be considered regarding, e.g., social impact factors, CO_2 emissions penalisations, or a different geographic configuration of external substrate generators.

A comparison of the scenarios with and without BVR shows that lower differences are observed with BVR in the CBAs of scenarios M, O1 and O2. This result indicates that the added value of the optimised scenarios comes particularly from those scenarios with a higher ability to produce biogas, i.e., when biogas valorisation is not constrained, as with BVR. Hence, the limitation on biogas valorisation blocks most of the benefits obtained from the application of optimisation strategies for co-digestion.

Accordingly, to maximise the CBA of the co-digestion strategies, the capacity of biogas valorisation should be increased to 7000 Nm3/h for the *Granollers* WWTP, and the volume distribution in scenario O1 should be followed; under these conditions, industrial co-substrate volume addition would comprise 18 % of the total input to the digester, and a potential cost reduction of 77 % in CBA could be obtained (from −480000 €/y for scenario C to −107000 €/y for the proposed scenario O1).

It may also be noted that optimal digester operation is paramount to achieve good performance; such optimisation can be achieved by using tools such as the one in [9], and significant operational costs may be saved when optimising the blend, as detailed here, and when assuring optimal digester conditions, e.g., via properly optimising alkalinity, toxicity and COD/N while maximising the organic content and thus biogas production. The ACO algorithm presented herein allows for the optimisation of the co-substrate blend and logistic planning.

Hence, implementation of this tool in actual installations should allow significant co-digestion performance improvement, with a potential reduction in waste management costs of 77 % for the 13 WWTPs involved in the case study. Moreover, if this tool is used together with an on-line digester monitoring and diagnosis system, digester stability is assured, and possible risks such as digester acidification or intoxication will be minimised.

5. Conclusions

In this work, the optimisation of the co-digestion strategy in a real case study in the waste management sector is considered by means of the implementation of an ACO algorithm in a novel fashion, considering both the quality and the logistics of each co-substrate, obtaining an optimised planning strategy for a real multi-plant case study. The main conclusions of this study are as follows:

- The application of an ACO algorithm has proved a useful method to optimise the blend of anaerobic digestion, resulting in the successful simulation of different co-digestion optimised scenarios O1 and O2.
- Logistic-related parameters of each waste generator (i.e., distance, cost and social impact) have been adapted from the approach presented in [40], which was originally conceived for sewage sludge biochemical properties.
- The results obtained show how an increasing logistics weight in the optimisation provides a lower expected distance (hence, lower transportation costs) and lower social impact factors, even though this does not have a significant impact on CBA in the case study considered.
- An optimised blend of sewage sludge with an 18 % volume co-substrate is achieved, allowing an increase in organic matter content of +188 %, a C/N ratio upgrade from 16 to 59, a reduction in toxicity from 1.61 mg Pb/L to 1.36 mg Pb/L and a potential waste management cost reduction of 77 %.

- The significant improvement from the manual scenarios to the optimised scenarios when no limit on biogas valorisation is imposed suggests the importance of optimised blending to attain improved performance.

Further work may include the consideration of multiple anaerobic digesters as sludge and co-substrate receptors to increase the current limit on biogas valorisation (i.e., when the blend optimisation process yields better performance) and to optimise the current overall potential of CBT for co-digestion. In addition, implementing methodologies to objectively quantify the social impact factor would allow better characterisation of the logistic impact of each substrate generator.

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