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Navigating Environmental, Economic, and Technological Trade-Offs in the Design and Operation of Submerged Anaerobic Membrane Bioreactors (AnMBRs)

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Abstract

Anaerobic membrane bioreactors (AnMBRs) enable energy recovery from wastewater while simultaneously achieving high levels of treatment. The objective of this study was to elucidate how detailed design and operational decisions of submerged AnMBRs influence the technological, environmental, and economic sustainability of the system across its life cycle. Specific design and operational decisions evaluated included: solids retention time (*SRT*), mixed liquor suspended solids (*MLSS*) concentration, sludge recycling ratio (*r*), flux (*J*), and specific gas demand per membrane area (*SGD*). The possibility of methane recovery (both as biogas and as soluble methane in reactor effluent) and bioenergy production, nutrient recovery, and final destination of the sludge (land application, landfill, or incineration) were also evaluated. The implications of these design and operational decisions were characterized by leveraging a quantitative sustainable design (QSD) framework which integrated steady-state performance modeling across seasonal temperatures (using pilot-scale experimental data and the simulating software DESASS), life cycle cost (LCC) analysis, and life cycle assessment (LCA). Sensitivity and uncertainty analyses were used to characterize the relative importance of individual design decisions, and to navigate trade-offs across environmental, economic, and technological criteria. Based on this analysis, there are design and operational conditions under which submerged AnMBRs could be net energy positive and contribute to the pursuit of carbon negative wastewater treatment.

Keywords

Anaerobic MBR; biomethane; global warming potential; life cycle analysis; renewable energy; carbon neutral.

1. Introduction

Wastewater treatment plants (WWTPs) predominantly utilize aerobic bioprocesses, which rely on the delivery of air (or oxygen) to achieve contaminant degradation to meet effluent standards. This approach has been highly effective at achieving organic carbon removal from municipal wastewaters, but has resulted in resource-intensive treatment that has broad environmental consequences. Wastewater management in the United States, for example, is estimated to represent roughly 3% of U.S. electricity demand (USEPA, 2006). With an estimated 0.3-0.6 kWh of electricity consumed per m^3 of wastewater treated (Judd and Judd, 2011), this energy demand equates to roughly 0.4-0.8 tonnes of CO_2 emitted per day by a WWTP treating 10 $ML \cdot d^{-1}$ (assuming the 2012 Spanish electricity mix). In addition to impeding progress toward carbon neutral (or negative) WWTPs, these high levels of electricity consumption inflate operating costs and incur a diverse set of life cycle environmental impacts stemming from electricity production processes.

In recent years, there has been increasing interest in the development of mainstream (i.e., main liquid stream) anaerobic treatment processes. In particular, submerged anaerobic membrane bioreactors (AnMBRs) have gained attention for their ability to produce methane-rich biogas during the treatment of urban wastewaters (Giménez et al., 2011; Robles et al., 2012; Raskin, 2012; Smith et al., 2013). AnMBRs circumvent several critical barriers to the environmental and economic sustainability of wastewater treatment by eliminating aeration, reducing sludge production, and generating methane (a usable form of energy) from organic contaminants in the wastewater (Shoener et al., 2014). However, given the early stage of development and uncertainties around AnMBR performance, it is unclear how detailed design and operational decisions influence the environmental and economic impacts of AnMBR (Smith et al., 2014).

Recent studies (e.g., Smith et al., 2012) have identified the need to focus future research efforts on achieving sustainable operation of AnMBRs treating urban wastewater. Although environmental and economic criteria have been used to evaluate submerged AnMBRs relative to alternative aerobic technologies (Smith et al., 2014), a critical barrier to advancing AnMBR development has been the lack of understanding of how detailed design decisions influence system sustainability; a barrier stemming from the lack of a calibrated and validated AnMBR process model to predict system performance under various design and operational scenarios. Ferrer et al. (2008) implemented a computational software called DESASS for designing, simulating, and optimizing both aerobic and anaerobic technologies. The simulation software incorporates a plant-wide model, biological nutrient removal model No. 2 (BNRM2) (Barat et al., 2013), and has been calibrated and validated across a wide range of operating conditions in an industrial-scale AnMBR system (Durán et al., 2013). By leveraging semi industrial-scale data and modeling, Ferrer et al. (2015) and Pretel et al. (*Submitted*) have established an economic basis for the minimum cost design of AnMBRs suitable for implementation in full-scale WWTPs by considering the key parameters affecting membrane performance. However, the environmental impacts of design and operational decisions, as well as the resulting trade-offs across environmental and economic dimensions of sustainability, have not been characterized.

The aim of this study was to elucidate and navigate sustainability trade-offs in the detailed design of submerged AnMBRs by evaluating the full range of feasible design alternatives using technological, environmental, and economic criteria. To this end, the implications of AnMBR design and operational decisions were characterized using a quantitative sustainable design framework (QSD; Guest et al., 2009) integrating a calibrated and validated process performance model with life cycle assessment (LCA) and life cycle costing (LCC) under uncertainty. By integrating pilot-scale performance data into this QSD framework, our goal was to characterize the relative importance of individual design and operational decisions of submerged AnMBR, while also shedding light on key elements of the system that warrant further research and development. Finally, QSD was used to optimize a submerged AnMBR system to demonstrate how this methodology can be leveraged to navigate sustainability trade-offs in the design and operation of treatment systems, including low energy and energy-producing wastewater technologies.

2. Methodology

2.1 Experimental AnMBR Plant

This study was carried out using five years of data from an AnMBR system featuring industrial-scale, hollow-fiber (HF) membrane units. The influent to the pilot-scale system is the effluent from the pre-treatment (screening, degritter, and grease removal) of the Carraixet WWTP (Valencia, Spain), with wastewater at ambient temperature (*T*) from 15 to 30 ºC. The AnMBR consists of an anaerobic reactor with a liquid volume of 0.9 m^3 (total volume of 1.3 m^3) connected to two membrane tanks each with a liquid volume of 0.6 m^3 (total volume of 0.8 m^3 each). Each membrane tank features an ultrafiltration HF membrane commercial system (PURON®, Koch Membrane Systems, 0.05 µm pore size, 30 m^2 total filtering area, and outside-in filtration). One 0.5 mm rotofilter screen, one equalization tank (0.3 m^3), and one clean-in-place (CIP) tank (0.2 m^3) are also included as main elements of the pilot plant. Further details of this AnMBR system can be found in Giménez et al. (2011) and Robles et al. (2012).

2.2 Design and Operational Decision-Making

Recent work leveraging this pilot-scale system has identified that costs of the system are most sensitive to the following parameters (Ferrer et al., 2015; Pretel et al., *Submitted*): sludge retention time (*SRT*); mixed liquor suspended solids in the membrane tank (*MLSS*); sludge recycling ratio (*r*; the ratio of recycled sludge to forward flow); 20 ºC-standardized critical fluxes (*J*); and specific gas demand per membrane area (*SGD*). These parameters influence both the design (i.e., reactor/pump/membrane sizing and construction; Section 3.3.1) and operation (Section 3.3.2) of submerged AnMBR. Based on extensive experimental data from the AnMBR plant and DESASS modeling (Section 2.3), acceptable ranges of these critical parameters were identified to be the following: *SRT* from 13 to 70 days (minimum *SRT* values were set based on treatment efficacy, effluent standard, and sludge stabilization criteria); *r* from 0.5 to 8; *MLSS* entering the membrane tank from 5 to 25 $g \cdot L^{-1}$; *SGD* from 0.05 to 0.3 $m^3 \cdot m^{-2} \cdot h^{-1}$; and *J* from 80 to 120% of the respective critical flux (J_C). To enable more detailed discussion of decision-making, the evaluation of the AnMBR system is divided into its two sub-components: (i) the *biological process*, which includes the anaerobic reactor and its hydraulic connection with the membrane tank, and (ii) the *filtration process*, which includes the membranes and any related maintenance or fouling mitigation.

Beyond these continuous decision variables, three discrete choices/options were also considered in the design of the AnMBR system: the decision of whether to release or recover methane (both biogas and soluble methane in the effluent) for energy production (via a microturbine); whether or not treated effluent is used for fertigation (i.e., irrigation with nutrient-rich water) to offset fertilizer needs; and the final fate of wasted sludge (land application to achieve fertilizer offsets, incineration, or landfilling). The process flow diagram of the submerged AnMBR is shown in

Figure S1 of the Supplementary Data (SD), and the full range of design and operational decisions can be found in Table S1 (also in the SD).

2.3 Performance Modeling

The simulated AnMBR system was designed to treat an influent flow of 50,000 $m^3 \cdot d^{-1}$, with a chemical oxygen demand (COD) of 600 $mg \cdot L^{-1}$ and low sulfate content (10 $mg \cdot L^{-1}$). The full characterization of the sewage entering the AnMBR plant can be found in Ferrer et al. (2015). The system was simulated using DESASS (Ferrer et al., 2008) with BNRM2 (Barat et al., 2013). A total of 80 simulations were executed in DESASS and leveraged to characterize system performance across 43,200 scenarios using an Excel-based model that also incorporated an energy consumption tool, enabling the calculation of the overall energy balance (OEB) of the different units at the WWTP. The methodology for the OEB followed the approach of Pretel et al. (2013), which includes procedures for mechanistically calculating mechanical energy demand and energy recovery from biogas.

2.4 LCA Implementation

Implementation of a LCA framework was conducted in accordance with ISO 14040 (2006) and following industry best practices (Corominas et al., 2013). In order to define the goal and scope, the environmental impacts of the AnMBR system associated with water line operations (i.e., primary and secondary wastewater treatment as well as final discharge of the treated effluent) and sludge line treatment (i.e., stabilization to comply with discharge standards) were evaluated. A functional unit of one m^3 of treated wastewater was used for the comparison of the different design alternatives (i.e., the combinations of the SRT, MLSS, J, SGD, and r simulated under four temperatures resulting in a total of 43,200 scenarios; Table S1). Figure 1 shows the system boundary used for the LCA and LCC, including the inventory data of the individual materials and processes in this study. As shown in Figure 1, the construction, operation, and demolition phases of the WWTP as well as transportation of the materials, reagents, and sludge were all included, but structural concrete and pipes were excluded from the demolition phase because their useful life was greater than that of the project itself. A maximum useful membrane life of 20 years was assumed, with operational fluxes higher than J_C resulting in decreased membrane life (for detailed discussion, see Ferrer et al., 2015). Briefly, membrane life was set from 8 years (when J = 120% of J_C) to 20 years (when J = 80% of J_C), according to the maximum total contact with chlorine permissible (500,000 ppm·hours cumulative) and the interval for membrane chemical cleaning. Following the recommendations of Judd and Judd (2011), 9.5 months was set as the interval for membrane cleaning with chemicals when operating under critical filtration conditions and with a SGD value of 0.1 $m^3 \cdot m^{-2} \cdot h^{-1}$. Cleaning frequency was adjusted based on the flux (80-120% of the J_C) and SGD by leveraging experimental data extracted in the semi-industrial AnMBR system (e.g., Robles et al., 2012; as described in Ferrer et al., 2015). Pre-treatment processes (e.g., screening, grit removal, and grease removal), rotofilter use, equalization tanks, and CIP were not included in this study because their design and operation (and thus, their costs and environmental impacts) were not influenced by the design and operational decisions of the AnMBR process itself. As a result, these supporting processes would not influence the comparative assessment of AnMBR design and operation, and were subsequently placed outside the system boundary. Final effluent was either discharged to natural surface waters or re-used for fertigation. Fugitive CH_4 emissions were accounted when methane was not captured and recovered for energy production. The CML characterization factor of 23 kg CO_2 eq. per kg of CH_4 was used for evaluating the climate implications of fugitive methane. Direct CO_2 releases (i.e., fugitive CO_2 emissions) during sludge dewatering and biogas capture were not quantified because the released CO_2 is classified as biogenic according to IPCC guidelines (Hobson, 2000). Direct emissions to air (e.g., CO, SO_2, NO_2, non-methane volatile organic compounds) resulting from methane combustion through a microturbine-based CHP system were excluded because of a lack of information.

The life cycle inventories (LCI) of individual materials and processes were compiled using the Ecoinvent Database v.3 accessed via SimaPro 8.01 (PRé Consultants; The Netherlands). The Centre of Environmental Science (CML) 2 baseline 2000 methodology was used to conduct the impact assessment. The impact categories considered in this study were as follows: eutrophication (kg PO_4 eq.), global warming potential with a 100-year time horizon (GWP_{100}; kg CO_2 eq.), abiotic depletion (AD, kg Sb eq.), and marine aquatic ecotoxicity (kg 1,4-DB eq.). No grouping, weighting, or aggregation of impact categories was used.

2.5 LCC Implementation

In order to determine the LCC of the system, all costs were converted to uniform annual cost. Capital costs were annualized assuming a discount rate of 10% and a project lifetime of 20 years. Annual operating and maintenance (O&M) costs were estimated based on energy and reagent consumption, sludge handling and disposal, as well as the replacement of the equipment required. Unit costs and further details about the LCC methodology can be found in Table S2 as well as Ferrer et al. (2015) and Pretel et al. (*Submitted*).

2.6 Characterization of the Relative Importance of Design and Operational Decisions

In order to elucidate the relative importance of individual design and operational decisions on AnMBR system sustainability, a sensitivity analysis was conducted in two stages (Figure 2): Stage 1 evaluated the full decision space, and Stage 2 focused only on the designs that were likely to be chosen by decision-makers based on economic and environmental criteria (i.e., design and operational decisions resulting in costs below the 15^{th} percentile; see Figure 2, left-center panel). The uncertainty around absolute values of cost and LCA results, as well as the relative sensitivity of results to key assumptions (including discount rate, membrane cost, electricity cost, concrete cost, energy for stirring, microturbine efficiency, transportation distance, and percent of produced methane dissolved in the effluent), were also evaluated, with details in the SD (Table S3).

To setup the sensitivity analysis, continuous (*MLSS*, *SRT*, *r*, *SGD*, and *J*) and discrete (fate of methane, fate of effluent, and fate of sludge) decisions were sampled from across the decision space, resulting in a total of 10,800 scenarios – where a *scenario* is a single, unique combination of design and operational decisions – at each of four temperatures (totaling 43,200 total simulations; see Table S1 in the SD for the values sampled from each continuous decision). The costs and GWP_{100} stemming from capital, O&M_{15} (O&M at 15 ˚C), and O&M_{30} (O&M at 30 ˚C) were then quantified for each scenario. To quantify the effect that individual decisions had on environmental and economic criteria, the results were segregated across the decision space for each individual parameter. For Stage 1 of the sensitivity analysis, the median, 5^{th}, 25^{th}, 75^{th}, and 95^{th} percentiles were then calculated for a given parameter value or discrete decision, as was the global median (i.e., the median of all the results). The range between the maximum and minimum value for each percentile was then normalized to the global median in order to quantify how much the range and absolute value of output metrics change across the full decision space for each individual parameter (see the top panel of Figure 2 for a visual representation of this methodology).

Recognizing that design and operational decisions resulting in costs below the 15th percentile are most likely to be chosen (so long as they meet treatment objectives) by WWTP designers and decision-makers, these scenarios were the focus of Stage 2 of the sensitivity analysis. Once this subset of scenarios was identified (consisting of the “practical” scenarios most likely to be chosen for implementation), the *practical* average and standard deviation of cost and GWP_{100} across all continuous decisions were determined. Next, the *local* average and standard deviation were calculated for each simulated value across the range of an individual design or operational decision (e.g., *MLSS* = 5, 10, 15, 20, and 25 $kg \cdot m^{-3}$). For a given decision, the greatest difference between a *local* and the *practical* average was then used to calculate the maximum percent shift from the practical average stemming from that decision (this calculation of the maximum percent shift was repeated for the *practical* standard deviation using *local* standard deviations; bottom-left graph in Figure 2). The relative importance of each continuous decision variable on a given metric (costs and GWP_{100} stemming from capital and average O&M) was determined by taking the sum of the percent change in average and percent change in standard deviation and ranking those sums in descending order (bottom-right graph in Figure 2), similar to the ranking process of Morris’ one-at-a-time method (Saltelli *et al*., 2004). As a final step in the Stage 2 sensitivity analysis, Monte Carlo simulation was conducted with 10,000 trials to examine the change in rank of the five continuous decision variables in order to characterize the robustness of these rankings.

3. Results and Discussion

Four main sections have been established in order to elucidate and navigate sustainability trade-offs stemming from detailed decision-making for submerged AnMBR: the relative importance of individual design and operational decisions (Section 3.1), navigating trade-offs across dimensions of sustainability (Section 3.2), optimization of the AnMBR process (Section 3.3), and uncovering how and why individual design/operational decisions impact AnMBR sustainability (Section 3.4). Taken altogether, these sections demonstrate how QSD can be used to optimize wastewater treatment technologies, including those targeting energy and broader resource recovery from wastewater. Results and discussion presented here are centered on linking design decisions to costs and life cycle environmental impacts, with a focus on global warming potential with a 100 year time horizon (GWP_{100}) as a representative example of broader environmental impacts. It should be noted, however, that most environmental impact categories followed similar trends as those of GWP_{100}.

3.1 Relative Importance of Design and Operational Decisions to AnMBR Sustainability

Figure 3 shows the effect of the continuous (*MLSS*, *SRT*, *r*, *J*, and *SGD*) and discrete (methane fate, effluent fate, and sludge fate) decisions on costs and environmental impacts across capital, $O\&M_{15}$, and $O\&M_{30}$. Considering continuous variables, all five influenced costs to a similar degree, although *MLSS* and *J* were most responsible for the variance in the LCC results stemming from capital and O&M costs, respectively (Figure 3A). The variables *r*, *MLSS*, and *SGD* were the most significant contributors to the variance in LCA results, mostly due to O&M (Figure 3C). For almost all parameters, the largest variance in economic and environmental performance was observed at the 95th percentile and the lowest variance at the 5th percentile. Discrete variables had similar cost implications as the design and operational parameters (Figures 3A and 3B), but disproportionately high GWP_{100} consequences (one to two orders of magnitude higher; see y-axis scales in Figures 3C and 3D). This observation stemmed from the climate implications of fugitive methane (23 kg of CO_2 eq. per kg of fugitive CH_4), energy offsets (0.13 kg of CO_2 per kWh produced), and fertilizer offsets (2.68 kg of CO_2 equivalents per kg of N). In comparison to the baseline set of discrete decisions (recovery of biogas and soluble methane for electricity production, effluent reuse, and land application of biosolids), allowing fugitive methane emissions and managing sludge through incineration were the least preferable options in terms of cost (Figure 3B). Regarding LCA results, eliminating energy recovery from methane and final disposal of the sludge into landfill were the least preferable options (Figure 3D).

In order to provide insight into the role of individual design and operational decisions on the relative sustainability of practical designs (i.e., the final set of designs likely to be considered by decision-makers), Stage 2 of the sensitivity analysis focused on the scenarios below the 15th percentile for costs (as shown in Figure 2). The relative importance of the five continuous decision variables was evaluated across four categories: influence on costs and GWP_{100} stemming from capital and average O&M (i.e., average of O&M at 15 and 30˚C; Figure 4). The results of the Monte Carlo simulation (Figure 4 and Table S4) show that *MLSS* consistently (71-

100%) had the largest impact on capital costs and both LCA categories, and was ranked second for its impact on LCC O&M across all simulations. *SRT* only had a high impact on LCA Capital (ranked second), which is a result of its effect on tank volume, which in turn determines construction material requirements. *r* was most often ranked second for LCC Capital, which was due mainly to its effect on tank volume when building the plant. *SGD* consistently impacted LCA O&M (ranked second) because of electricity demand from blower operation. *J* was ranked first for LCC O&M (across all simulations) because of its effect on membrane operation and replacement cost. Thus, the factors driving environmental impacts were tankage and electricity for gas sparging, while costs were driven by tankage and membranes. In comparison to Figure 3 and the analysis of the full decision space, the results presented in Figure 4 provide much more meaningful insight for decision-makers by focusing on the scenarios most likely to be chosen. This analysis eliminates observations that are irrelevant (e.g., stemming from scenarios that would never be chosen), and also allows decision-makers to prioritize individual design and operational decisions as part of a participatory planning process incorporating locality-specific factors (Guest et al., 2010).

3.2 Navigating Trade-Offs Across Dimensions of Sustainability

In order to develop a final set of parameters, it becomes necessary to characterize the interactions among design and operational decisions. To this end, we evaluated relationships among decision variables to identify trade-offs and synergies, where *trade-offs* exist when adjusting a decision variable produces tension between sustainability metrics (i.e., to get better in one, you must get worse in the other), and *synergies* occur when changing a given decision variable moves sustainability metrics in the same direction (either both become more desirable, or both become less desirable).

When synergies exist between LCC and LCA results, it can be expected that designers would seek to simultaneously improve both costs and environmental impacts by adjusting the decision variable. If the LCC and LCA results follow opposing trends, trade-offs can be considered by comparing the ratio of additional costs (€) to the tonnes of CO_2 equivalents that are saved (i.e., not released to the environment). This approach to quantifying the tension between sustainability metrics enables the comparison of a given decision to an external benchmark – the carbon emissions trading system – which enables the purchase of carbon offsets (€·t CO_2^{-1}). In general, emissions trading seeks to reduce pollution by providing economic incentives for companies to limit their emissions (Stavins, 2003). The largest international framework for greenhouse gas emissions is the European Union Emission Trading Scheme, which currently spans power plants and industrial plants across 31 countries (EU, 2013). By using market prices for carbon offsets as a benchmark (e.g., in Spain the emissions trading system is currently around 6 €·tonne CO_2 saved^{-1} (REE, 2012)), the rationality of having a WWTP incur additional costs to reduce carbon emissions can be evaluated.

Figure 5 shows the effect of *MLSS* (Figure 5A), *J* (Figure 5B), *SRT* (Figure 5C), and *SGD* (Figure 5D) in order to illustrate the potential for trade-offs and synergies between costs and environmental impacts. Although simulations were performed across the full range for all continuous decision variables, four illustrative examples (the min-max combinations of two other decision variables) are plotted in each figure. In Figure 5A, *MLSS* was varied from 5-25 g·L^{-1} for four possible design/operational scenarios at the min-max of J (80 and 120% of J_C) and r (0.5-8). For these example scenarios, costs and GWP_{100} were synergistic below $MLSS$ values of 15 $g \cdot L^{-1}$. In Figure 5B, flux was varied from 80-120% of J_C for four possible design/operational scenarios at the min-max $MLSS$ (5 and 25 $g \cdot L^{-1}$) and SGD (0.05 and 0.30 $m^3 \cdot m^{-2} \cdot h^{-1}$). At a flux below 97% and above 112%, synergy occurs between the LCA and LCC results, which indicates that both impacts can be lessened by increasing or decreasing the flux in the direction of the synergy arrows shown in Figure 5B. However, between 97-112% of J_C, tension exists between economic and environmental impacts, thus requiring the navigation of trade-offs. In Figure 5C, SRT was varied from 13 to 70 days across combinations of $MLSS$ (5 and 25 $g \cdot L^{-1}$) and r (0.5-8) (when methane is not recovered), and was shown to be synergistic at all values examined, which indicates that LCC and GWP can be lessened by minimizing SRT across the entire decision space. In contrast, Figure 5D demonstrates that SGD often results in trade-offs across the full range of values considered (0.05 to 0.30 $m^3 \cdot m^{-2} \cdot h^{-1}$), shown with combinations of $MLSS$ (5 and 25 $g \cdot L^{-1}$) and J (80 and 120% of J_C).

As one proposed approach to identify an optimal design, Figure 6 benchmarks the ratio of €$\cdot$tonne-CO_2 saved^{-1} for the WWTP against the Spanish emissions trading system across the feasible range of J values (for this analysis, SGD = 0.30 $m^3 \cdot m^{-2} \cdot h^{-1}$ and $MLSS$ = 25 $g \cdot L^{-1}$). Across the bulk of the design space where trade-offs exist, the cost of mitigating carbon emissions at the WWTP was drastically higher than the market-based benchmark, with costs of up to 30,000 €$\cdot$tonne-CO_2 saved^{-1} at the treatment plant. In this particular case, therefore, treatment plants seeking to lower their carbon footprint beyond leveraging synergies with cost may achieve a more meaningful environmental benefit at much less cost if they were to purchase credits on the trading market (if such an action is possible). In the future, however, this QSD framework may provide additional support for the creation of carbon crediting systems for the wastewater sector (proposed by Wang et al., 2011 in the context of reducing nitrogenous greenhouse gas emissions); such a transition could enable utilities to take a more proactive posture and secure additional financial resources for the installation of low-energy and energy positive treatment technologies.

3.3 Optimization of Submerged AnMBR

We propose that the optimization of AnMBR design should minimize costs subject to effluent water quality constraints, and only consider further reducing greenhouse gas emissions when (i) there are no readily available, less expensive alternatives for GHG reduction, and (ii) it is part of a transparent, inclusive planning and design process that addresses locality-specific factors in decision-making (Guest et al, 2009, 2010). For the submerged AnMBR system evaluated here, costs and GHG emissions were largely in synergy (reducing one reduced the other), and design conditions that resulted in trade-offs between costs and GWP_{100} had incurred costs for CO_2 mitigation that far exceeded the European Union Emission Trading Scheme (except for a very narrow band in which carbon could be offset at an expense to the utility of < 6 €·tonne-CO_2 saved^{-1}). Thus, the optimization of the submerged AnMBR system (detailed below) focused on cost minimization, with all potential designs subject to year-round treatment requirements with treatment efficacy confirmed through DESASS modeling under summer and winter conditions. It should be noted that this methodology leveraged pilot-scale experimental data for the design and simulation of a full-scale treatment process, and that additional scale-up challenges – although outside the scope of this study – may influence system sustainability.

3.3.1 Optimizing the Construction of the Submerged AnMBR System

Capital costs represented a meaningful fraction of life cycle costs across the full range of AnMBR design alternatives (with typical values of 45 ± 8%; average ± standard deviation), whereas life cycle environmental impacts were largely dominated by the O&M phase (e.g., 74 ± 14% for GWP_{100} when total methane is recovered, 99% if methane is released as fugitive emissions). Following the approach to optimization outlined immediately above (Section 3.3), the anaerobic reactor and membrane area were sized by selecting the configuration (based on 10,800 evaluated combinations of MLSS, SRT, r, J, and SGD) that resulted in the minimum LCC while enabling the plant to meet treatment requirements across all simulated temperatures (from 15 ºC to 30 ºC). In this respect, winter conditions (15 ºC) governed the sizing of the constructed system. *J* was set slightly above the critical flux (105% of J_C, based on the least favorable *SGD* and *MLSS* values), *r* was set to 3 and the anaerobic reactor volume was set in 35,190 m^3. By selecting the minimum cost values for these parameters as opposed to the minimum or maximum (17,800 m^3 or 373,440 m^3 for volume, 80% or 120% for *J*, and 0.5 or 8 for *r*, respectively), the overall LCC reduced by 35/70% (minimum/maximum) for volume, 17/47% for *J*, and 22/4% for *r*. When considering the LCA, there was no obvious benefit to selecting the optimum values for construction-phase elements because their impact on the life cycle environmental impacts was minimal.

3.3.2 Optimizing the Operating Submerged AnMBR

In the O&M phase, an operational volume (calculated from *r* and required to be below the constructed volume), an operational membrane area (calculated from the operating *J* for each *SGD* and *MLSS* value at a flux of 105% J_C, and required to be smaller than constructed area), and an operating *r* value (at or below the constructed *r* capacity) have been considered for the full range of feasible design alternatives in order to assess the overall LCC and LCA results for the AnMBR system. Further details on the interactions among the detailed design calculations with decision variables can be found in Ferrer et al. (2015). Based on economic and environmental criteria, the optimum operating parameters of the AnMBR design (*MLSS*, *r*, *SRT*, *SGD*, and *J*) were determined at different temperatures (see Table 1). Details of the mechanisms governing the selection of individual parameters is discussed in more detail in Section 3.4.

The uncertainty analysis was conducted on LCC and LCA results at 15 ºC (taking the scenario with the optimum operating parameters from Table 1), and an additional sensitivity analysis was performed to better understand the influence of individual assumptions. Based on the LCC considering fugitive methane emissions, the input parameters affecting the output were (in descending order): membrane cost, discount rate, energy for stirring and electricity cost. When methane was recovered, the microturbine efficiency became more important than the stirring energy and the electricity cost. Based on the LCA, when methane was not recovered, the only input parameter affecting the output was the percentage of dissolved methane emitted to air (where the balance of dissolved methane is assumed to be degraded to CO_2). When total methane recovery was considered, the efficiency of the microturbine became the most important (approximately 50%), followed by transportation distance (35%), and stirring energy (15%). The results showed that although there was uncertainty surrounding model outputs (Figure S2 in the SD), alternative values for these assumed parameters would not have changed the observed trends and narrative surrounding the sustainable design of submerged AnMBR.

3.4 Connecting Design and Operational Decisions to Sustainability Metrics

3.4.1 The Impact of SGD and MLSS on Membrane Filtration

In order to better understand the mechanisms governing the impact of *SGD* and *MLSS* on LCA and LCC results, these values were varied across the decision space at a temperature of 15 ˚C. Other parameters corresponding to biological processes (i.e., *r* and *SRT*) were fixed at 3 and 41 days, respectively. Total methane recovery, nutrient recovery from effluent, and agricultural application of sludge were considered for the discrete decisions. Based on the LCC results, gas sparging was the most significant process at high *MLSS* and *SGD*, contributing nearly 62% of the total operating cost. However, reagent consumption had an increased impact when operating at high *MLSS* and low *SGD* values – representing up to 41% of the total operating cost – due to the increased membrane cleaning requirement.

When *MLSS* was held constant, *SGD* had a positive correlation with filtration costs, increasing the filtration operating cost by up to 0.063 €·m^{-3} (representing a 19% increase), but had no effect on biological costs. Similarly at a given *SGD* value, increasing *MLSS* increased filtration costs, but it also decreased costs associated with biological processes. Based on this, the optimum parameters for this study were the optimum value for *SGD* (0.10 $m^3 \cdot m^{-2} \cdot h^{-1}$) and *MLSS* = 10-15 $g \cdot L^{-1}$ (Table 1). This value was chosen for *MLSS* because at larger values, the increase in filtration costs was not offset by a decrease in biological costs. Similarly, lower *MLSS* values increased biological costs much more than the filtration costs decreased (up to 85% of the total operating costs).

Methane recovery was not affected by changes in *MLSS* and *SGD*. Based on the LCA results, reagent consumption did not have a significant environmental impact (GWP_{100} = 0.003 kg $CO_2{\cdot}m^{-3}$ and marine ecotoxicity = 0.428 kg 1,4-DB$\cdot m^{-3}$). Gas sparging presented the greatest environmental impact based on GWP at high *MLSS* and *SGD*, increasing GWP to 0.051 kg $CO_2{\cdot}m^{-3}$ and marine ecotoxicity to 21.479 kg 1,4-DB$\cdot m^{-3}$. Biological processes had a beneficial impact on reducing GWP_{100} because of the decreased emissions from methane and by enabling nutrient recovery, achieving values as low as -0.039 kg $CO_2{\cdot}m^{-3}$ for GWP_{100} and -19.0 kg 1,4-DB$\cdot m^{-3}$ for marine ecotoxicity.

3.4.2 The Impact of r and MLSS on the Bioprocess

To better understand the underlying relationships among *r*, *MLSS*, and LCA and LCC outputs, these values were varied across the decision space while *SGD* and *J* were fixed at their optimum values (0.10 $m^3{\cdot}m^{-2}{\cdot}h^{-1}$ and 105% of J_C, respectively). Based on the LCC results, mixer operation was the most significant cost – comprising up to 80% of the total operating cost of 0.11 €$\cdot m^{-3}$ – and was highest at low *MLSS* and *r* values. The sludge recycling pump accounted for a small fraction of the operating cost (approximately 8%).

At a given *MLSS* value, decreasing *r* increased the cost of biological processes; at lower *MLSS* values, this increase was even more pronounced, raising the biological operating cost up to 0.091

€·m^{-3} (representing a 48% increase). Conversely, the filtration process costs was not affected by *r*. When *r* was fixed, *MLSS* had a similar trend in terms of biological process cost, but filtration costs also decreased. Therefore, the lowest total cost occurred at r = 2-3 and *MLSS* = 10-15 g·L^{-1} (Table 1).

Changes in *r* and *MLSS* had no effect on methane recovery. Based on the LCA results, the sludge recycling pump contributed very little to overall environmental impact (i.e., increases in GWP_{100} by 0.002 kg CO_2·m^{-3} and marine ecotoxicity by 1.14 kg 1,4-DB·m^{-3}). Mixer operation had a much greater impact overall. At low *MLSS* and *r* values, GWP_{100} increased by 0.077 kg CO_2·m^{-3} and marine ecotoxicity increased by 40 kg 1,4-DB·m^{-3}. When considering methane and nutrient recovery, however, GWP_{100} decreased to -0.039 kg CO_2·m^{-3} and marine ecotoxicity to -17.9 kg 1,4-DB·m^{-3}.

3.4.3 The Impact of SRT and T on the Bioprocess

For the LCA, the effects of sludge disposal (agriculture), methane production, and effluent discharge were also evaluated by varying *SRT* across temperatures (*T*). At high *SRT* and *T*, biogas production and nutrient solubility were large. Sludge disposal, stirring, and sludge recycle pumping all contributed significantly to marine ecotoxicity (up to 13.1 kg 1,4-DB·m^{-3} for sludge disposal, which corresponded with the lowest value of SRT and up to 10.6 kg 1,4-DB·m^{-3} for the latter two, which corresponded with the highest value of SRT). When neither nutrients nor methane are recovered, emitted methane represented almost 100% of the GWP (increasing it up to 1.61 kg CO_2·m^{-3}) and discharged nutrients increased eutrophication up to 0.042 kg PO_4^{-3}·m^{-3}. However, if nutrients, biogas, and soluble methane are all recovered, this system achieved carbon offsets through resource recovery (up to -0.059 kg $CO_2\cdot m^{-3}$ for methane recovery and up to -0.067 kg $CO_2\cdot m^{-3}$ for nutrient recovery) as well as reductions in marine ecotoxicity (up to -18.6 kg 1,4-DB$\cdot m^{-3}$ for methane recovery and up to -37.3 kg 1,4-DB$\cdot m^{-3}$ for nutrient recovery). In terms of eutrophication, a reduction of around 50% can be achieved as a result of recovering nutrients in the effluent.

3.4.4 Energy, Nutrient, and Residuals Management

Regarding methane recovery, three options were considered: no recovery, only recovering biogas, or total methane recovery (recovery of both biogas and methane dissolved in the effluent). The LCC results show that cost savings of up to 16 and 36% (at 15 ˚C and 30 ˚C, respectively) are possible. By accounting for the energy offsets through on-site production, greenhouse gas savings up to 76-104% (at 15˚C and 30˚C, respectively) can be achieved. These calculations were made assuming both biogas and dissolved methane in the effluent stream were recovered and utilized for energy generation. The total cost of the technologies needed for these processes (degassing membrane for dissolved methane and microturbine-based CHP for energy generation) were also considered. Based on this analysis, there may exist submerged AnMBR design/operational scenarios that have the potential to generate energy in excess of what is required to run the AnMBR system, making them net energy positive.

The framework in this study examined whether or not treated effluent is used for fertigation (i.e., irrigation with nutrient-rich water) to offset fertilizer needs. Note that calculations of fertilizer offsets from fertigation included assumptions of nitrogen and phosphorus bioavailability (50% and 70%, respectively), consistent with other studies (Gallego et al., 2008; Rodriguez-Garcia et al., 2011; Garrido-Baserba et al., 2013; Pretel et al., 2013). Based on the LCA data, nutrient recovery reduced eutrophication by approximately 50% and significantly reduced marine toxicity (around -37 kg 1,4-DB$\cdot$m^{-3}), GWP (-0.07 kg $CO_2\cdot m^{-3}$) and AD (-0.0005 kg Sb eq) due to the fertilizer avoided. For sludge disposal, three options were considered in this study: agricultural application, incineration, or landfilling. Based on the LCC results, there were savings of 50% or 90% using agricultural application over landfilling or incineration, respectively. Based on the LCA results, incineration could be a better option over agriculture in terms of GWP_{100} and eutrophication, because while agricultural application offsets fertilizer use, it still results in direct emissions to air (e.g., N_2O, NH_3), water (e.g., PO_4), and soil (heavy metals). Although the approach used to estimate emissions from land application and fertilizer offsets were consistent with other studies (Gallego et al., 2008; Rodriguez-Garcia et al., 2011; Garrido-Baserba et al., 2013; Pretel et al., 2013), this approach does not account for direct fugitive emissions to air and water that stem from synthetic fertilizers. The negative consequences of land application in terms of GWP_{100} and eutrophication, therefore, would be reduced if direct emissions from synthetic fertilizers were included in the system boundary, since a portion of these emissions would be offset. Beyond GHG and nutrient emissions, agriculture also had the fewest negative impacts in AD and marine toxicity.

4. The Role of AnMBR in Carbon Neutral Wastewater Treatment

The main challenge of AnMBR technology is optimizing design and operation of the process in order to improve the sustainability of the technology to treat wastewaters. The AnMBR system may be suitable to treat most municipal wastewater streams, since it can achieve high quality effluent (Smith et al., 2012; Lin et al., 2013) while also achieving meaningful steps toward sustainable wastewater treatment: lower inherent energy demand stemming from no aeration and energy recovery through methane production. Although conventional activated sludge treatment plants consume roughly 0.2-0.6 $kWh \cdot m^{-3}$ (McCarty et al., 2011; Judd and Judd, 2011; Fenu et al., 2010), a sub-set of design scenarios here achieved on-site energy production in excess of estimated on-site energy demands. However, consistent with findings from other energy assessments of AnMBRs (Smith et al., 2014; Shoener et al., 2014; Martin et al., 2011), sparging remains a critical challenge as it accounts for the majority of AnMBR energy demand (with typical values of 52 ± 21%; average ± standard deviation), in this study). Fouling mitigation (during operation) and membrane capital costs – as well as anaerobic reactor construction and mixing – remain the dominant sources of costs, which are critical challenges to enable AnMBR to overtake activated sludge in practice (Lin et al., 2011; Ferrer et al., 2015). Additionally, maximizing the capture of methane is another key component of AnMBR technology for achieving energy savings and reducing the overall WWTP carbon footprint in a way that is financially viable. Particularly in this study, greenhouse gas savings up to 76-104% (at ambient temperature of 15 ˚C and 30 ˚C, respectively) were achieved by accounting for energy offsets through on-site production when methane (from both biogas and effluent streams) is captured and utilized for energy generation.

As we pursue improved designs of submerged AnMBR systems, the greatest opportunities for simultaneously improving economic and environmental performance will be through reduced energy consumption. Based on the QSD results presented here, it is also worth highlighting the importance of (i) reducing energy-intensive sparging, (ii) increasing flux to decrease required membrane area, and (iii) developing efficient dissolved methane recovery processes in order to maximize energy recovery and avoid direct greenhouse gas emissions. In any case, these pursuits to reduce life cycle environmental impacts should not jeopardize effluent quality – the primary responsibility of WWTPs. The high quality effluent provided by AnMBRs is one of the technology's greatest strengths. The membranes help ensure robust treatment and can enable safe nutrient recovery through fertigation, the latter of which can have significant economic and environmental benefits through fertilizer and freshwater offsets.

5. Conclusions

A quantitative sustainable design process has been leveraged to develop a detailed design of submerged AnMBR by evaluating the full range of feasible design alternatives using technological, environmental, and economic criteria. Results showed that *J, SGD*, *MLSS,* and *r* required the navigation of sustainability trade-offs, but minimizing *SRT* simultaneously improved environmental/economic performance. Moreover, *MLSS* and *J* had the strongest influence over LCA results and capital costs, with *J* governing O&M costs. Based on this analysis, there are design and operational conditions under which submerged AnMBRs could be net energy positive at higher operating temperatures and contribute to the pursuit of carbon negative wastewater treatment. More broadly, this work demonstrates the use of QSD, which can be leveraged to quantify and navigate sustainability trade-offs in the optimization of wastewater treatment and resource recovery systems.

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Tables

Table 1. Optimum operating parameters at different ambient temperatures of the AnMBR design and total cost.

Optimum Operational Parameters							Scenarios for Sludge Disposal			Scenarios for Methane Recovery	
T, ºC	MLSS, $g \cdot L^{-1}$	SRT, days	r	SGD, $m^3 \cdot m^{-2} \cdot h^{-1}$	J, % of J_C (in LMH)	Total cost†, $€ \cdot m^{-3}$	Land application‡, $€ \cdot m^{-3}$	Incineration‡, $€ \cdot m^{-3}$	Landfilling‡, $€ \cdot m^{-3}$	Biogas recovery*, $€ \cdot m^{-3}$	Total CH_4 recovery*, $€ \cdot m^{-3}$
15	15	41	3	0.10	105 (16)	0.130	0.001	0.049	0.006	- 0.021	- 0.005
20	15	28	2.5	0.10	105 (16)	0.125	0.001	0.049	0.006	- 0.022	- 0.004
25	10	19	2.5	0.10	105 (23)	0.094	0.001	0.049	0.006	- 0.024	- 0.004
30	10	13	2	0.10	105 (23)	0.079	0.001	0.050	0.006	- 0.026	- 0.002

† *Cost of the AnMBR system, excluding sludge disposal and methane recovery.*
‡ *Cost of sludge management and disposal assuming 100% of sludge is managed with a single method.*
* *Cost of 100% biogas or total methane (biogas and soluble methane) recovery (capital and operating cost of the technology are included). Negative values represent net profit.*

Figure captions

Figure 1. System boundary for the LCA and LCC of the submerged AnMBR.

Figure 2. Sensitivity analysis methodology used to characterize the relative importance of individual design decisions on (Stage 1) the full range of possible designs or (Stage 2) the range of practical designs (where *practical* designs are those combinations of design and operational parameters that resulted in the lowest 15^{th} percentile of cost or environmental impact, believed to be the most likely to be chosen by decision-makers for implementation). Results of this sensitivity analysis can be found in Figures 3 and 4.

Figure 3. Effect of the continuous (*MLSS*, *SRT*, *r*, *J*, and *SGD*) and discrete (methane recovery, nutrient recovery, and sludge disposal) decisions on the outputs (LCC and LCA) stemming from capital, $O\&M_{15}$, and $O\&M_{30}$ and considering 5^{th}, 25^{th}, 75^{th}, and 95^{th} percentiles. The range between the maximum and minimum for each percentile was normalized by the global median. Discrete selections are listed as †methane fate (*fugitive* emission, *biogas* recovery for electricity production, total *methane* recovery – including biogas and soluble methane – for electricity production), ‡effluent fate (*reuse* for fertigation, direct *discharge*), and *residuals fate (*land* application, *landfill*, *incineration*).

Figure 4. Radar plot showing the average relative importance of five continuous decisions (*MLSS, SRT*, *r*, *J*, *SGD*) on four outputs (LCC Capital and O&M, LCA Capital and O&M). The influence of each decision on LCC and LCA outputs was ranked from 1–5 – with one having the highest impact on each result – across 10,000 trials. The size of the green area represents the magnitude of the decision's impact. Average ranks and standard deviations (from the 10,000 trials) can be found in Table S4 in the SD.

Figure 5. LCC (€$\cdot m^{-3}$) and GWP (kg-CO_2 eq$\cdot m^{-3}$) results of a subset of AnMBR scenarios showing trade-offs and synergies between economic and environmental criteria across the decision space for: (A) *MLSS* ($g\cdot L^{-1}$); (B) *J* (% J_C); (C) *SRT* (days); and (D) *SGD* ($m^3\cdot m^{-2}\cdot h^{-1}$).

Figure 6. Evaluation of the ratio of €·tonne-CO_2 saved^{-1} in the selection *J* values (when *SGD* = 0.30 $m^3\cdot m^{-2}\cdot h^{-1}$ and *MLSS* = 25 $g\cdot L^{-1}$) and comparison with the Spanish emissions trading system (6 €·t CO_2^{-1}) as a benchmark.