*Highlights

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- Average costs of €0.047 (UWW) and €0.067 per m^3 (UWW and FW) were obtained
- Energy costs accounted for 59.6% and 69.0% of the total costs respectively
- Average reversible fouling removal downtimes were 0.4% and 1.6% respectively
- Control strategy efficiently minimized filtration costs for both substrates

Real-time optimization of the key filtration parameters in an AnMBR: urban wastewater mono-digestion *vs.* co-digestion with domestic food waste

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Abstract

This study describes a model-based method for real-time optimization of the key filtration parameters in a submerged anaerobic membrane bioreactor (AnMBR) treating urban wastewater (UWW) and UWW mixed with domestic food waste (FW). The method consists of an initial screening to find out adequate filtration conditions and a real-time optimizer applied to a periodically calibrated filtration model for minimizing the operating costs. The initial screening consists of two statistical analyses: (1) Morris screening method to identify the key filtration parameters; (2) Monte Carlo method to establish suitable initial control inputs values. The operating filtration cost after implementing the control methodology was €0.047 per m^3 (59.6% corresponding to energy costs) when treating UWW and €0.067 per m^3 when adding FW due to higher fouling rates. However, FW increased the biogas productivities, reducing the total costs to €0.035 per m^3. Average downtimes for reversible fouling removal of 0.4% and 1.6% were obtained, respectively. The results confirm the capability of the proposed control system for optimizing the AnMBR performance when treating both substrates.

Keywords

Anaerobic membrane bioreactor (AnMBR); process control; food waste; fouling; modelling; urban wastewater

1. Introduction

Submerged anaerobic membrane bioreactors (AnMBRs) are amongst the most promising technologies for treatment of urban wastewater (UWW) (Ben and Semmens, 2002). When compared with traditional processes, such as conventional activated sludge system, AnMBRs offer several advantages (Judd and Judd, 2011; Raskin, 2012): (i) decoupling of hydraulic retention time (HRT) and solids retention time (SRT), (ii) improvement of organic matter removal efficiency, (iii) reduction of the environmental footprint of the treatment process, (iv) production of a solids-free purified effluent, (v) smaller amounts of sludge produced due to the low biomass yield of anaerobic microorganisms, (vi) lower energy demands (no aeration needed), and (vii) energy recovery by biogas production. In addition, the co-digestion in AnMBRs of UWW with domestic food waste (FW) is a very interesting option which may serve to enhance the biogas productivities (*i.e.* by increasing the organic loading rate and the influent COD/SO_4^{2-} ratio), thus improving the general economics of the treatment process (Becker et al., 2017). Moreover, this approach creates an opportunity for recycling energy and nutrients from both wastes (Kibler et al., 2018). This strategy also allows the valorization of domestic FW, whose anaerobic mono-digestion is known to be associated with several complications, such as accumulation of NH_3 and volatile fatty acids (VFAs) (Capson-Tojo et al., 2017, 2016).

However, a key issue exists that affects the economics of membrane filtration processes and therefore its industrial applicability: membrane fouling (Deng et al., 2016; Sheets et al., 2015). Fouling reduces the permeability of the membrane, which leads to an increase in the operating and maintenance costs, jeopardizing the global performance (Judd and Judd, 2011). Moreover, previous studies have suggested that fouling issues tend to get worse if adding FW to the UWW (Pretel et al., 2016). Thus, if AnMBRs are to be a competitive alternative for UWW treatment from an economical point of view, minimizing the impact of membrane fouling is of critical importance. Therefore, one of the main challenges of this technology is to optimize the treatment performance (keeping high treatment flow rates) and the energy consumption (small physical cleaning intensities and periods) whilst minimizing the fouling effect. Particularly, avoiding irreversible fouling, which must be removed chemically and eventually determines the lifespan of the membranes, is of critical importance (Drews et al., 2009; Judd and Judd, 2011). Moreover, as the physical cleaning of the membranes can account for more than 75 % of the energetic consumption in AnMBRs (Verrecht et al., 2010), this step must also be optimized, reducing as much as possible its frequency.

In this respect, the development of advanced control systems is crucial for a successful optimization of the process performance in AnMBRs (Jimenez et al., 2015; Nguyen et al., 2015). Different studies have assessed theoretically (and sometimes validated experimentally) the energy and economical savings resulting from the implementation of different types of advanced control systems in aerobic membrane reactors (MBRs) (Drews et al., 2007; Huyskens et al., 2011). Mannina and Cosenza (2013) applied Monte Carlo simulations to compare the energy requirements, the effluent quality and the economic costs of five different scenarios based on an MBR model. Also, an ad-hoc platform constructed over the COST/Benchmark Simulation Model No. 1 (BSM1) (Coop, 2002) was applied to evaluate different control strategies in MBRs, using the energy requirements to assess the performances (Maere et al., 2011). Gabarron et al. (2014) compared different optimization strategies applied to MBRs, reducing significantly the energy needs and the membrane fouling. Moreover, Ferrero et al. (2011a, 2011b, 2011c) reduced significant the energy requirements due to membrane scouring (up to 21%) by applying a knowledge-based control system based on a supervisory controller. Focusing on model-based control, Drews et al. (2009, 2007) created a control system based on a mathematical model that successfully improved the filtration efficiency. In addition, Busch et al. (2007) developed a run-to-run control system to optimize the filtration performance by adjusting the filtration variables after each filtration cycle. Recently, computational fluid dynamics simulations have also been applied to optimize membrane scouring and the hydrodynamics in airlift external circulation MBRs (Yang et al., 2017, 2016). These studies allowed a significant reduction of reversible fouling due to cake formation, thus maximizing the MBR performance.

However, so far few control strategies have been developed and validated to optimize the performance of AnMBRs for the treatment of UWW (Robles et al., 2013a). In Robles et al. (2013a), an upper layer fuzzy-logic controller efficiently kept low fouling rates, improving the process performance. In addition, a model-based optimization method has also been applied to improve the performance of AnMBRs treating UWW (Robles et al., 2014a). This method was effectively used for optimization of an advanced control system (consisting of an upper-layer fuzzy-logic controller), obtaining energy savings of up to 25 %. Nevertheless, to improve the economic viability of these systems, it is necessary to develop new control strategies that allow the filtration system to work under optimal conditions. These new strategies should be easy to handle and computational-cost effective to facilitate plant engineers to optimize the process performance.

Among the different options that exist, the use of model-based control systems is of interest, not only to control the process performance, but also to predict it, allowing eventually its optimization from an energetic and/or economical approach (Batstone et al., 2015; Gernaey et al., 2004; Martin and Vanrolleghem, 2014). Nonetheless, the predictions based on models are never totally free of uncertainty because models are always a conceptual representation of reality and are based on assumptions. Moreover, models need to be calibrated, a process that can be arduous. In this context, sensitivity analysis is a powerful tool that can be used for two main purposes: (i) quantifying the effects of the inputs on the outputs of the model and (ii) identifying the most relevant factors and those that can be disregarded, thus simplifying the calibration process (Pianosi et al., 2016).

Therefore, the objective of this study was to develop a model-based control strategy for real-time optimization of the performance of AnMBRs fed with UWW and a mixture of UWW and FW. This strategy aimed at optimizing the operating mode of the filtration process in an AnMBR system by dynamic simulations using a previously validated filtration model..

Specifically, the new model-based control strategy consists of an initial screening to find out the adequate filtration conditions and a real-time optimizer of the filtration operation mode. As for the initial screening, two sequential statistical methods were applied only once as a prior step: (i) a sensitivity analysis to find an identifiable input subset for the filtration process (Morris screening method) (Morris, 1991) using the trajectory-based random sampling technique, and (ii) a Monte Carlo procedure to find adequate initial conditions. This initial screening was based on an approach previously used for optimizing the input parameters of an advanced control system for filtration in AnMBRs (Robles et al., 2014a). Regarding the real-time optimizer, an optimization algorithm applied to a filtration model is run to obtain the optimum values of the identifiable subset for the filtration process that minimize the operating costs of the system. This new-model-based controller is more straight-forward when compared to the previous control strategy (Robles et al, 2014b) based on coupling model-based control systems with fuzzy-logic advanced supervisory control, since only a model must be calibrated.

2. Materials and methods

To accomplish the besought goal the first approach of the process, which is carried out only once as a prior step, consisted of: (i) a sensitivity analysis that considers the different parameters that are likely to be optimized in a previously chosen model (Robles et al., 2013c, 2013d), thus selecting highly-influential parameters conforming the identifiable input subset to be optimized and (ii) the selection of adequate initial conditions (those leading to local minimal operational costs) of the identifiable input subset was performed via the Monte Carlo method. Knowing these values, the real-time optimization of the highly-influential operational parameters was carried out. With this purpose, an optimization algorithm was defined. This real-time optimizer stablished, at every control time (CT), the set points for the operational parameters leading to the lowest costs of the filtration process. Finally, the reduction of the total costs of the filtration process after the implementation of the control system was assessed (with and without FW in the substrate).

2.1. Description of the AnMBR plant

The data used in this study to calibrate and validate the filtration model was obtained from an AnMBR that mainly consisted of an anaerobic reactor with a working volume of 0.9 m^3 connected to two membrane tanks. Each membrane tank had a working volume of 0.6 m^3 and included one ultrafiltration hollow-fiber membrane commercial system (PURON®, Koch Membrane Systems, 0.03 µm pore size, 31 m^2 total filtering area and outside-in filtration). The plant was fully automated and monitored online in real-time. In addition, the anaerobic sludge was sampled once a day to assess the filtration performance. The concentration of mixed liquor total solids (MLTS) was determined according to the Standard Methods (APHA, 2005). A more precise description of the plant and its instrumentation (as well as the corresponding flow diagrams) can be found elsewhere (Robles et al., 2015, 2013b).

2.1.1. Lower-layer controllers

The lower-layer controllers implemented in the system that interact with the proposed optimization method are: (i) three proportional-integral-derivative (PID) controllers that adjust the rotating speed of the sludge recycling pump, the permeate pump and the biogas recycling blower used for membrane scouring by gas sparging, in order to keep the desired flow-rate set-points; and (ii) one on–off controller that regulates the membrane operating stage by changing the position of the respective on–off valves and the flux direction of the permeate pump. A more precise description of the plant control system can be found elsewhere (Robles et al., 2015).

2.2. Characteristics of the substrates

As aforementioned, the proposed model-based optimization strategy was validated for an AnMBR treating UWW and a mixture of UWW and FW. To this aim, a filtration model was calibrated and validated using data from an AnMBR system that treated UWW and a mixture of UWW and FW. The UWW was the effluent from the pre-treatment step of the Carraixet WWTP (Valencia, Spain) and the FW was collected from canteens in the university (Moñino et al., 2016). The UWW was characterized by a low COD/SO_4-S ratio and the mixture of UWW and FW was set to different penetration factors (PF, defined as the percentage of the population having a kitchen disposer). The COD/SO_4-S ratio of the UWW was around 6.6 kg COD·kg^{-1} SO_4-S while the COD/SO_4-S ratio of the UWW was around 9.6 kg COD·kg^{-1} SO_4-S. The FW was grinded by an experimental set-up simulating a household grinding system. This set-up consisted on a grinded InSinkErator, model Evolution 100. Afterwards, the FW was pre-filtered using a mesh of 0.5 mm, similar to the one used for the UWW. Further details can be found elsewhere (Moñino et al., 2017).

2.3. Description of the filtration model

The filtration model used in this study is a semi-empirical model based on a classical resistance-in-series model (Robles et al., 2013c). This model is able to represent the dynamic evolution of the transmembrane pressure (TMP) by equations 1 and 2.

$$TMP(t) = J_{net} \cdot \mu_p \cdot R_T \qquad \text{(Eq. 1)}$$

Where, TMP (t) is the TMP at time t, μ_p is the dynamic viscosity of the permeate and R_T is the total filtration resistance.

$$R_T = R_M + R_C + R_I = R_M + \omega_C \cdot \alpha_C + \omega_I \cdot \alpha_I \qquad \text{(Eq. 2)}$$

Where, R_M is the resistance intrinsic to the membrane, R_C is the resistance of the cake that is formed on the surface of the membrane due to solid deposition, R_I is the added resistance due to irreversible membrane fouling, ω_C is the mass of solids deposited on the membrane per membrane area, α_C is the average specific resistance of the cake created, ω_I is the mass of irreversible fouling normalized per membrane area and α_I is the average specific resistance of the irreversible fouling.

The dynamics of ω_C and ω_I were modelled using a black-box approach. With this purpose, three different components were defined: X_{TS} (MLTS), X_{mC} (cake dry mass in the membrane surface), and X_{mI} (irreversible fouling dry mass on the membrane surface). In addition, four kinetic physical processes were included in the model: (i) cake layer formation during filtration, (ii) cake layer removal by biogas sparging for membrane scouring, (iii) cake layer removal by back-flushing and (iv) irreversible fouling formation. A more precise description of the structure of the filtration model can be found elsewhere (Robles et al., 2014a).

The selected filtration model was calibrated and validated using experimental data from the above-introduced AnMBR plant when treating UWW and a mixture of UWW and FW.

2.4. Model-based optimization

As aforementioned, the first stage of the model-based control strategy is the selection of the operational parameters associated with the filtration process that are likely to be optimized dynamically. These variables are the biogas recycling flow-rate for membrane cleaning (BRF), the sludge recycling flow-rate into the membrane tanks (SRF), the duration of the filtration, relaxation and back-flushing stages (t_F, t_R and t_{BF} respectively) and the initiation frequency and transmembrane flow of the back-flushing stage (f_{BF}, J_{BF}). It must be commented that the transmembrane flow during filtration (J_F) has not been considered for the optimization. The reason is that this value will be fixed by the influent flow-rate to the system.

Considering these selected variables, the operating mode of the membranes can be represented by Figure 1A. As this figure shows, an alternation is established between the relaxation and the back-flushing stages. More precisely, if the number of filtration cycles (f) is lower than f_{BF}, the system will alternate between filtration and relaxation cycles. However, if f_{BF} is equal or overpasses f, the corresponding relaxation stage will be substituted by a back-flushing stage. Figure 1B shows a schematic representation of the model-based control strategy applied in this study, which is divided in an initial screening and a real-time optimizer of the filtration operation mode. The initial screening is based on a procedure described in Robles et al., (2014a) for screening the input parameters of an advanced control system for filtration in AnMBRs and the real-time optimizer uses the previously introduced filtration model for calculations (Robles et al., 2013c). First of all, the Morris screening method (Morris, 1991) was used to perform a global sensitivity analysis (GSA) of the selected filtration model (step a) to identify the operational parameters with high influence on the cost of the filtration process (step b). Once these parameters were identified, the Monte Carlo procedure (see for instance Saltelli et al. (2000) was applied to determine the optimal initial values of the evaluated parameters (step c). These values are used to update the initial set-points of the operational parameters (step d), which are transferred to the process (step e). After the transmission of the initial set-points, every CT the optimization algorithm is started. In this work CT has been set to 1 hour. This real-time optimizer, calculates the new optimal set-points for the highly-influential operational parameters at each CT (step f), running the periodically calibrated filtration model, and transmits them (step g) to update again the set-points of the process (steps d and e). To this aim, a cost objective function was used.

2.4.1. Description of the costs objective function

To determine the costs related to energy consumption, the energy requirement of each process was calculated and multiplied by the cost of energy (E_{COST}; € per kWh). In this study E_{COST} was set to €0.138 per kWh, which corresponded to average electricity prices in Spain.

The energy requirements of the blower (W_{BRF}) (adiabatic compression), sludge recycling pump (W_{SRF}) and permeate pump for filtration ($W_{filtration}$) or back-flushing ($W_{back\text{-}flusing}$) were calculated as shown in Robles et al. (2014a).

The total energetic costs were lumped in a single variable (C_W), which was calculated as the sum of C_{BRF}, C_{SRF} and C_{STAGE}, as shown in Equation 3:

$$C_W = C_{BRF} + C_{SRF} + C_{STAGE} = W_{BRF} \cdot E_{COST} + W_{SRF} \cdot E_{COST} + W_{STAGE} \cdot E_{COST} \quad \text{(Eq. 3)}$$

Where, C_W is the total energetic cost, C_{BRF} is the operating cost of membrane scouring by biogas sparging, C_{SRF} is the operating cost of pumping the sludge, C_{STAGE} is the operating cost of pumping permeate during the respective operating stage (*i.e.* filtration or back-flushing).

Finally, in order to determine the combination of operational set-points that lead to the minimal value of the total operating costs ($C_{TOTAL;}$ € per m^3), Equation 4 was applied.

$$C_{TOTAL} = C_W + C_{REAGENTS} + C_{LIFESPAN} \quad \text{(Eq. 4)}$$

Where, C_W is the total energetic cost, $C_{REAGENTS}$ is the proportional cost of reagents needed to clean the irreversible fouling produced during filtration and $C_{LIFESPAN}$ is the cost of membrane replacement due to irreversible fouling. $C_{REAGENTS}$ and $C_{LIFESPAN}$ were calculated as shown in Robles et al. (2014a).

2.4.2. Global sensitivity analysis: Morris screening method

In this study the Morris screening method (Morris, 1991) has been applied to perform the GSA. This method is a one-factor-at-a-time process based on the generation of representative matrices of the combinations of values of the parameters to evaluate through a random sampling. In this study, the trajectory-based sampling strategy proposed in Ruano et al. (2012) was applied. From the matrices, it determines the distribution of scaled elementary effects (SEE_i) of each input factor on the model output. Finally, the SEE_i distribution (F_i) for each input factor is analyzed to determine the relative importance of the input factors and obtain a good approximation of a GSA.

The selected statistical parameters to evaluate these distributions were: the standard deviation (σ) and the absolute mean (μ^*) (see for instance Saltelli et al. (2000) and Campolongo et al. (2007)).

In order to elucidate which operational parameters are the most influential on the total filtration cost, the output variable for the GSA in this study was C_{TOTAL} (Eq. 4).

A more precise description of the GSA applied in this study can be found elsewhere (Robles et al., 2014b).

2.4.3. Initial values of the operational parameters: Monte Carlo method

The Monte Carlo method was used for the selection of initial values of the operational parameters close to the minimum (locally) of the function to minimize. This has two main benefits: (i) it improves the results of the dynamical optimization given by the controller and (ii) it gives optimal values of the non-influential parameters, further improving the minimization of C_{TOTAL}. Therefore, the Monte Carlo method was applied as a previous step before the dynamic optimization. The Monte Carlo method consisting on trajectory-based random sampling was used in this study. Hence, the combination of the operational parameters giving the minimum operating cost (Eq. 4) was selected as the initial values of the real-time optimizer.

2.4.4. Simulation strategy and model calibration

MATLAB® was used to simulate the filtration process using the previously-introduced model. The Runge-Kutta method (ode45 function in MATLAB®) was used as integration method for solving the differential equations in the model. The model was calibrated using experimental results from operation with both substrates.

2.4.5. Simulations for real-time dynamic optimization of the filtration process

The dynamic optimization of the filtration process was carried out using the costs equation (Eq. 4) as objective function. The optimization algorithm was applied by using the trust region approach (Coleman and Li, 1996), based on the Newton method (LSQNONLIN function in MATLAB®) and the Runge-Kutta method (ode45 function in MATLAB®).

2.4.6. Implementation of the Morris and Monte Carlo methods

In order to obtain results that could be extrapolated to different situations, MLTS concentrations in the entrance of the membrane tanks was ranged from 10 to 20 $g \cdot l^{-1}$ during simulation. In addition, to take into account the typical fluctuations of the flow rate entering a WWTP, the net transmembrane flow (J_{net}) was also varied. For each concentrations of MLTS, J_{net} was modified from 4 to 12 LMH ($l \cdot h^{-1} \cdot m^{-2}$), following the influent pattern from the model BSM1 (Jeppsson et al., 2006).

The average values of the operational parameters evaluated in this study are shown in Table 1. In addition, the uncertainty considered for the sensitivity analysis (minimum and maximum values) is also presented. The range of values for the set-points of these parameters was established according to a uniform distribution. Finally, the results of the Monte Carlo procedure (which will be discussed afterwards) are also shown in Table 1.

2.4.7. Optimization algorithm

Using both substrates, the performance of the controller (based on the optimization algorithm) was evaluated by simulation using the filtration model described above. The simulation accounted for 24 h of continuous operation and was carried out at four different MLTS concentrations entering the membrane tanks for both feeding strategies (*i.e.* UWW and mixture of UWW and FW): 11, 13, 15 and 17 $g \cdot l^{-1}$.

To simulate the important variations of the influent flow rate that occur in WWTPs, the dynamic of BSM1 influent (Jeppsson et al., 2006) was used in this simulation study, commonly accepted for evaluation of control algorithms in WWTPs (Maere et al., 2011, Rojas et al., 2012; Martin and Vanrolleghem, 2014; Foscoliano et al., 2016). Thus, during the simulations J_{net} varied according to the dynamic of BSM1 influent (see e-supplementary data).

As aforementioned, the CT was set to 1 hour. The computational cost for optimizing dynamically the process was between 1 to 3 minutes (using a PC Intel® CORE™ i5 with 8 GBytes of RAM).

3. Results and discussion

3.1. Overall performance of the AnMBR plant

The AnMBR plant, treating either UWW or UWW mixed with domestic FW, was operated for a long period within a wide range of operating conditions regarding both biological and filtration processes (Robles et al., 2013c; Giménez et al., 2011, Pretel et al., 2016; Moñino et al., 2017).

Generally, COD removal efficiencies above 90 % were obtained, while effluent COD concentration ranged between 23 and 54 $mg \cdot l^{-1}$. The VFA in the reactor showed an average value of 30 mg $HAc \cdot l^{-1}$, which is significantly lower than the common concentrations found in other anaerobic digestion processes. Methane production increased significantly when operating at high SRT and/or when adding domestic FW to the substrate. For instance, 30 and 56 $l_{CH4}\cdot m^{-3}$ were obtained when treating UWW at SRTs of 40 and 70, respectively. These values are not so high due to the significant sulfate concentration in the influent, thus, a considerable amount of influent COD was consumed by sulfate reducing bacteria. Nonetheless, methane production increased up to 119 $l_{CH4}\cdot m^{-3}$ when treating a mixture of UWW and FW with a penetration factor of 80 % and 70 days of SRT.

As for sludge production, lower amounts of wasted sludge were produced when operating at high SRT and/or feeding UWW mixed with domestic FW. The obtained 0.37 kg $TSS\cdot kg^{-1}$ $COD_{REMOVED}$ of wasted sludge at a SRT of 70 days for UWW treatment was reduced up to 0.21 kg $TSS\cdot kg^{-1}$ $COD_{REMOVED}$ when treating a mixture of UWW and FW with a penetration factor of 80 % at the same SRT.

Concerning the filtration process, the fouling rates were mainly governed by the MLTS and the specific demands of gas per square meter of membrane (SGD_m) levels. However other factors should also be considered, such as the characteristics of the sludge (i.e. SMP, EPS, biomass). Mostly, for similar SGD_m values, as MLTS levels surged the fouling rates increased. It is important to note that low values of the fouling rates were observed (below 10 $mbar\cdot min^{-1}$ for negligible levels of irreversible fouling) when treating UWW at an SGD_m of 0.23 $Nm^3\cdot h^{-1}\cdot m^{-2}$ (equivalent to a BRF of 7.1 $m^3\cdot h^{-1}$) and MLTS levels below 25 $g\cdot l^{-1}$ (ranging from 8 to 32 $g\cdot l^{-1}$). Above 25 $g\cdot l^{-1}$ of MLTS, the membrane fouling surged sharply (around 100 $mbar\cdot min^{-1}$) for similar SGD_m values. Nonetheless, these fouling rates were reduced when the SGD_m levels raised up to non-prohibitive levels (from 0.23 to 0.5 $Nm^3\cdot h^{-1}\cdot m^{-2}$, equivalent to BRFs of 7.1-15.5 $m^3\cdot h^{-1}$), taking into account that the effect of the gas sparging intensity was reduced as the irreversible fouling increased. The results obtained during long-term operation of membranes reinforced the need for optimizing the membrane scouring at each operating condition.

When treating UWW and domestic FW, fouling rates surged as the penetration factor in the mixture increased. For instance, a permeability loss of 0.14 LMH $bar^{-1}\cdot m^{-3}$ was obtained when treating UWW at MLTS of 17 $g\cdot l^{-1}$. In contrast, permeability losses of up to 0.38 LMH $bar^{-1}\cdot m^{-3}$ were obtained when feeding a mixture of UWW and FW with a penetration factor of 80 %.

3.2. Calibration of the model

Before the application of the model, it was previously calibrated and validated based on the data obtained in the AnMBR plant treating both UWW and a mixture of UWW and FW. More precisely, the model was validated for different concentrations of MLTS entering the membrane tanks (10-30 $g\cdot l^{-1}$), different J_{net} (4-6 LMH) and different SDG_m (0.1-0.5 $m^3\cdot h^{-1}\cdot m^{-2}$, equivalent to BRFs of 3.1-15.5 $m^3\cdot h^{-1}$). The model was able to predict precisely the behavior of the membrane during the studied operational conditions (R of 0.989). It is important to note that a recalibration of the filtration model must be done periodically to take into account possible fluctuations such as influent load dynamics (*i.e.* heterogeneity of FW and UWW).

3.3. Sensitivity analysis

3.3.1. Treating urban wastewater

The rankings for the operational parameters according to the sensitivity measurements obtained (μ^* and σ) are presented in Table 2. Only the results for the optimized number of evaluated trajectories (r_{opt}) are shown.

Hierarchical clustering analysis (HCA; R software version 3.2.5.) of the μ^* presented in Table 2 and the ones obtained during r_{opt} determination resulted in three differentiated clusters formed according to the influence of the studied parameters on the model output (see e-supplementary data): (i) BRF, with a much higher value of μ^* when compared with the other parameters, indicating its great importance for the process costs; (ii) f_{BF}, t_{BF}, t_F and SRF, with values of μ^* that indicate a significant relative influence on the process costs; and (iii) t_R and J_{BF}, with a low relative importance. According to these results, 5 parameters were identified as highly influential on the process costs: (i) BRF (μ^* = 1.253 and σ = 1.856); (ii) f_{BF} (μ^* = 0.770 and σ = 2.220); (iii) t_F (μ^* = 0.724 and σ = 1.921); (iv) t_{BF} (μ^* = 0.574 and σ = 1.210); and (v) SRF (μ^* = 0.464 and σ = 1.584). To allow a visual identification of these parameters, a graphical representation of the results of the sensitivity parameters (μ^* and σ) at r_{opt} can be found in the Electronic Annex. Both the clustering and the graphical results suggest a high influence of BRF, SRF, t_F, t_{BF} and f_{BF} on the cost of the process. Therefore, in this study they have been optimized dynamically as a function of the operational conditions. On the other hand, as t_R and J_{BF} present low values of μ^* and σ, it can be considered that their influence on the total costs is low. Thus, their set-points were considered to be constant, keeping the initial values given by the Monte Carlo method. In addition, the GSA results allow evaluating the mathematical relationship between each parameter and the total costs. Due to their relative high values of both μ^* and σ, the effects of BRF, SRF, t_F, t_{BF} and f_{BF} can be classified as non-linear.

The huge influence of BRF was related to the high energy consumption of this process. Thus, while an adequate value of BRF allows minimizing the solid cake formation, the irreversible fouling rates, and the costs associated with biogas recirculation, too high values increase greatly the total costs of the filtration process. Concerning SRF, this parameter affects, not only the costs associated with sludge pumping, but also $MLTS_{MT}$ at a given J_{net}. It is important to consider that changes of the $MLTS_{MT}$ modify also the BRF requirements. In addition, t_F affects the amount of solids that are deposited onto the surface of the membranes. t_F also influences the net water treatment flow, thus determining the normalized profitability of the process (expressed in € per m^3). Finally, t_{BF} and f_{BF} modify the extent of permeability recovery of the membranes. This is related to a partial or total removal of the solid cake.

However, it must also be considered that high values of t_{BF} and f_{BF} decrease J_{net} and increase the non-filtration period of the AnMBR.

3.3.2. Treating urban wastewater and food waste

The values of the sensitivity measurements (μ^* and σ) obtained for the optimized number of evaluated trajectories (r_{opt} = 40) when using UWW and FW as substrates are presented in Table 2. The corresponding HCA (see e-supplementary data) resulted in very similar clusters when compared to the process treating only UWW. In this case, 5 main clusters were obtained: (i) BRF, again with a much higher value of μ^* when compared with the other parameters; (ii) f_{BF}, with higher relative values when compared to treatment of only UWW; (iii) t_{BF} and t_F, also with values of μ^* that indicate a significant relative influence; (iv) SRF and t_R, with a low relative influence; and (v) J_{BF}, with a very low relative importance. The similar responses of the systems fed with UWW and the mixture of UWW and FW confirm the applicability of the optimization methodology evaluated in this study to both substrates. In order to allow an un-biased comparison of the performances of the controller using both substrates, the same five operational parameters were identified as influential: BRF, f_{BF}, t_{BF}, t_F and SRF. However, it must be considered that the clustering results suggest that in this case SRF could also be kept constant, reducing even more the computational costs. As for the case using UWW as substrate, a graphical representation of the obtained sensitivity rankings treating the UWW and FW mixture is presented in the Electronic Annex.

3.4. Initial parameter estimation via the Monte Carlo method

As aforementioned, the Monte Carlo method was used to estimate the initial values of the different operational parameters object of study when applying both feeding strategies (*i.e.* UWW and mixture of UWW and FW). The total filtration cost varied greatly, with values ranging between €0.04 per m^3 and €0.40 per m^3. Therefore, it can be concluded that the total costs can be effectively minimized by selecting the proper set-points of the selected operational parameters.

The obtained results, which correspond to the combination leading to minimum local costs, are presented in Table 1 (column Monte Carlo Results). However, it is important to highlight that the Monte Carlo method cannot give an optimal combination of the operational parameters. This occurs because of the discrete variation of the values of the evaluated parameters chosen to carry out the simulations. Nevertheless, as the used sampling procedure aims at covering all the domain of variation of the parameters, the cost is locally minimized. Starting from the initial combination given by the Monte Carlo method, the selected parameters were optimized dynamically throughout the operational period.

3.5. Performance of the real-time optimizer

3.5.1. Treating urban wastewater

Figure 2 shows the values of BRF, SRF, t_F and t_{BF} optimized by the controller during the simulations performed with a MLTS concentration entering the membrane tank of 17 $g \cdot l^{-1}$ and the transmembrane fluxes shown in the e-supplementary data. This condition is presented because it is the worst-case scenario, meaning that in reality the performance should be improved, with less fouling and lower filtration costs when reducing $MLTS_{MT}$.

As shown in Figure 2A, the value of BRF followed a very similar pattern when compared to J_{net}. This occurred because the controller established higher values of BRF in the periods when the treatment flow rate was the highest (10-13 hours). During those flow peaks, the velocity of solid deposition on the surface of the membrane was much higher than at regular operation and therefore the controller had to increase considerably BRF to keep the TMP at appropriate values. In addition, Figure 2A also shows that the value of BRF was reduced when the treatment flow decreased, reaching even the minimum BRF value allowed in the AnMBR plant (4 $m^3 \cdot h^{-1}$). These conditions corresponded to the minimal membrane fouling propensity, but were also associated with low agitation of the sludge in the membrane tanks, leading to a reduction in the efficiency of the process of physical cleaning by biogas sparging. A correlation matrix including the optimized parameters, $MLTS_{MT}$, J_{net}, TMP, the energy requirements and the filtration costs with UWW as substrate (see e-supplementary data; R software version 3.2.5.) verified the positive correlation observed between J_{net}, TMP and BRF.

Regarding SRF, Figure 2A shows a similar behavior to that observed for BRF. The controller increased SRF at higher J_{net} to keep $MLTS_{MT}$ at adequate levels. Again, the correlation matrix verified the correlation existing between BRF and SRF.

Concerning t_F and t_{BF}, it can be observed in Figure 2B that in this case these variables did not follow a pattern similar to that of J_{net}. However, a variation of these parameters occurred through the operational period studied. Interestingly, the periods when t_F and t_{BF} varied the most were those when BRF and SRF showed their lowest values (*i.e.* 5-9 h and 19-24 h). This indicates that, when the controller could not further optimize BRF and SRF, it modified the parameters with lower influence (*i.e.* t_F and t_{BF}) to further minimize the total filtration costs. No linear correlations were observed between t_F and t_{BF} and any other studied parameter/variable (see e-supplementary data). The last parameter to be discussed (f_{BF}) remained relatively constant, around 1 BF every 10 F cycles (see Figure 3).

Figure 3 represents the evolution of the TMP and the sequence of operational stages (F, R and BF) performed during the simulation at 17 $g \cdot l^{-1}$ MLTS entering the membrane tanks.

As it can be observed, the operational mode varied according to the duration of the stages (t_F and t_{BF}). In addition, by increasing SRF and BRF (Figure 2A) during the periods most prone to fouling (hours 10-12), the real-time optimizer was able to keep the TMP under the maximum limits established by the provider (*i.e*. 0.6 bars).

3.5.2. Treating urban wastewater and food waste

Figure 4 shows the values of BRF, SRF, t_F and t_{BF} optimized by the model-based controller when treated UWW and FW. As for the operation with UWW as substrate (Figure 2A), the values of BRF and SRF varied according to the variations in J_{net} (see e-supplementary data). As previously, the controller established higher values of both parameters at the points of highest J_{net} (10-13 hours). This period corresponded to the greatest rates of solids deposition onto the membranes. Therefore, the controller increased BRF to reduce the fouling rate and increased also SRF to minimize $MLTS_{MT}$.

In addition, it can be observed in Figure 4B that the values of t_F are lower than those obtained with UWW as substrate (Figure 2B). Interestingly, the opposite occurred for t_{BF}, whose length was higher with the mixture of UWW and FW. This was related to a more intense fouling caused by the FW, which led to longer BF periods to remove the cake layer from the membrane surface. Moreover, f_{BF} increased from 1 BF every 10 F cycles to 1 BF every 4 F cycles (data not shown). Longer t_{BF} and higher f_{BF} with FW led to an increase of the downtime for reversible fouling removal. The average downtime for reversible fouling removal increased from 0.4 % (UWW) to 1.6 % (UWW and FW) of the total operational period. Nevertheless, it must be considered that these are low values which were achieved as a result of the controller action. As example, previous studies have reported minimum values of 2.4 % of downtime when treating UWW in an automatically-tuned advanced control system for AnMBRs (Robles et al., 2014a).

It must be mentioned that the corresponding correlation matrix (see e-supplementary data) was very similar to that obtained for UWW as substrate, verifying that the controller responded in a similar manner for both substrates. Also, as the evolution of the TMP and the different stages simulated using the substrate mixture were similar to that of UWW treatment (Figure 3), these values are not presented.

3.6. Total energy consumption

Figure 5A shows the evolution of the energy requirements of the filtration process after the implementation of the controller at 17 $g \cdot l^{-1}$ MLTS entering the membrane tank with UWW as substrate. As it can be observed, the main contributor to the energy consumption of the system was W_{BRF}, accounting in average for 80 % of the total energy requirements and up to 87 % at the highest J_{net}. In addition, W_{BRF} (thus W_{TOTAL}) shows a similar pattern to that observed for J_{net}. In fact, both variables were strongly correlated (see e-supplementary data). While during the periods of low inflow to the plant (*i.e.* hours 2-9) W_{TOTAL} reached 0.13 $kWh \cdot m^{-3}$ (with W_{BRF} accounting for 67 %), this value increased up to 0.34 $kWh \cdot m^{-3}$ (with W_{BRF} accounting for 87 %) at high J_{net} (*i.e.* hours 9-12). At this point it must be mentioned that the results shown in this study were obtained with a model calibrated using considerably dirty membranes (i.e. the membranes were already strongly irreversibly fouled). Therefore, the energy requirements presented correspond to a very unfavorable scenario and it can be expected that their values will be considerably lower when operating with clean membranes. Nevertheless, the proposed control strategy allowed keeping the W_{BRF} within low values (around 0.18 $kWh \cdot m^{-3}$). More precisely, the control system led to savings of around 50 % of the energy required for membrane scouring when compared to non-optimized cyclic operation of the same AnMBR plant (0.36 $kWh \cdot m^{-3}$) (Robles et al., 2013a). By coupling model-based control systems with fuzzy-logic advanced supervisory control, consumptions of 0.15 $kWh \cdot m^{-3}$ (Robles et al., 2013a) and 0.12 $kWh \cdot m^{-3}$ (Robles et al., 2014a) were achieved. The value obtained in this study was slightly higher (0.18 $kWh \cdot m^{-3}$). However, it must be considered that in this case only a model must be calibrated, which can be continuously optimized by retrofitting. In addition, if the model is properly calibrated this control strategy is more straight-forward and the control action is faster when compared to the previous control strategies, which require more computational capacity.

When paying attention to the average energy requirements of the AnMBR after the implementation of the control system (Table 3), it can be observed that from the total consumption of 0.20 $kWh \cdot m^{-3}$ (operating at 17 $g \cdot l^{-1}$ MLTS entering the membrane tanks), 79.7 % corresponded to W_{BRF}, 16.9 $kWh \cdot m^{-3}$ to W_{SRF}, 9.53 % to $W_{back\text{-}flushing}$ and 4.77 % to $W_{filtration}$.

The results presented in Figure 5 and Table 3 show that the energy required to clean physically the membranes by biogas sparging (W_{BRF}) represents the main consumption of energy in AnMBRs. Thus, there is a clear need to optimize this particular process.

Figure 5B and Table 3 also show the energy consumption of the filtration process treating UWW and FW. In this case, the average total requirement was 0.34 $kWh \cdot m^{-3}$, with a maximum value of 0.58 $kWh \cdot m^{-3}$. The average proportion of W_{BRF} accounted for 88.5 %, indicating the need of optimizing BRF for each specific process.

The higher average W_{TOTAL} when adding FW (0.34 *vs.* 0.20 $kWh \cdot m^{-3}$) was related to the aforementioned increase of the fouling rate in the membranes, which implied longer non-filtration periods, thus reducing the net volume of water treated per unit of membrane surface. However, it must be considered that the addition of FW also led to a higher energy recovery due to an increase of the biogas production. With a SRT of 70 days at a temperature of 27 ºC, the volumetric methane production was up to 72 $l_{CH4} \cdot m^{-3}$ using UWW as substrate (Pretel et al., 2016). When adding FW, this value increased up to 147 $l_{CH4} \cdot m^{-3}$ which, assuming a percentage of methane recovery of 80 %, was translated into an increase of the energy recovery of 0.20 $kWh \cdot m^{-3}$. Taking this value into account, the energy requirements of the filtration process are lowered from 0.34 $kWh \cdot m^{-3}$ to 0.14 $kWh \cdot m^{-3}$, even when operating with strongly fouled membranes. Thus, the addition of FW led to a global energy saving of 30 % when compared to the treatment of UWW as sole substrate because of the increased volumetric methane production The energy requirements of the filtration process with the controller operating at 11, 13, 15 and 17 $g \cdot l^{-1}$ for both feeding strategies are summarized in the e-supplementary data.

3.7. Total costs

Figure 6A shows the evolution of the operational and maintenance costs of the filtration system after the implementation of the model-based control strategy treating UWW at 17 g·l^{-1} MLTS. As it can be observed, C_W represented the main cost of the process, accounting for an average of 60 % of the total cost. This clearly emphasizes the need to optimize the operational conditions to minimize the energy demand of the system. However, in the period of peak J_{net} (hours 9-10) the ensemble of $C_{REAGENTS}$ and $C_{LIFESPAN}$ represented up to 90 % of the total costs. This was related to a more intense irreversible fouling occurring in this period of high-rate filtration, which caused an increase in the amounts of chemicals required to clean the membranes and lowered the membrane lifespan, raising the associated costs.

Regarding the average costs, the results operating at 17 g·l^{-1} MLTS entering the membranes are presented in Table 4. After the implementation of the control system, C_{TOTAL} was €0.047 per m^3, with C_W, $C_{REAGENTS}$ and $C_{LIFESPAN}$ representing the 59.6, 17.0 and 23.4 %, respectively.

These values corroborate that C_W represents the main filtration costs during regular operation. In addition, as it has been already mentioned, the membranes used in this study were strongly fouled, and therefore lower costs are expected in real operation. Thus, the values of these latter costs should be lower in full-scale plants, further reinforcing the great importance of optimizing the energy requirement in AnMBR plant.

Figure 6B and Table 4 present the costs corresponding to the co-digestion system (UWW and FW). As shown, the obtained pattern was very similar to that obtained for treatment of UWW. However, in this case the average filtration cost corresponded to €0.067 per m^3, with C_W accounting for 69 % of this value. The higher value of C_{TOTAL} when adding FW is again related to a higher fouling rate in the co-digestion system, which led to higher costs associated with the mechanical cleaning of the membrane. This is further suggested by the higher C_W

values (€0.046 per m^3 with FW *vs.* €0.028 per m^3 with only UWW). However, when taking into account the economical profit related to the higher volumetric methane production when adding FW to the UWW, C_{TOTAL} is reduced to €0.035 per m^3, meaning that FW addition led a relative economic saving of 26 % of the filtration costs (when compared with the AnMBR system treating only UWW).

The average costs of the filtration process with the controller operating at 11, 13, 15 and 17 $g \cdot l^{-1}$ for both feeding strategies are summarized in e-supplementary data.

4. Conclusions

The proposed methodology enabled identifying the most influential filtration parameters and selecting proper initial set points for their optimization. The controller allowed a real-time optimization of these set-points, obtaining an energy demand of 0.20 $kWh \cdot m^{-3}$ (79.7% W_{BRF}) and a cost of €0.047 per m^3 (59.6% C_W) when treating UWW. The addition of FW increased the energy demand and the costs (0.34 $kWh \cdot m^{-3}$ and €0.067 per m^3) due to higher fouling intensity, but also led to the production of more biogas. In this respect, further research must be focused on enhancing biological process to surge methane production giving the minimum operating costs, *i.e.* coupling biological with filtration process control. The obtained results confirm the applicability of the proposed control system for optimizing the AnMBR performance when treating both substrates. An automatic recalibration of the filtration model according to the dynamics of the influent characteristics will be necessary to improve the real-time optimizer.

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Figure captions

Figure 1. (A) Sequence of the different operational stages in the membrane modules during the alternative operating mode and (B) flow diagram of the proposed optimization methodology

Figure 2. (A) Values of BRF and SRF and (B) t_F and t_{BF} optimized by the model-based controller. The results were obtained using UWW as substrate

Figure 3. Evolution of the TMPs and different stages simulated. The results were obtained using UWW as substrate

Figure 4. (A) Values of BRF and SRF and (B) t_F and t_{BF} optimized by the model-based controller. The results were obtained using UWW and FW as substrates

Figure 5. Evolution of the energy requirements of the filtration process with the controller operating at 17 $g \cdot l^{-1}$ MLTS entering the membrane tanks. The results for feeding strategies are shown: (A) UWW and (B) mixture of UWW and FW

Figure 6. Evolution of the costs of the filtration process with the controller operating at 17 $g \cdot l^{-1}$ MLTS entering the membrane tanks. The results for feeding strategies are shown: (A) UWW and (B) mixture of UWW and FW

Table captions

Table 1. Average values of the operational parameters evaluated in this study. The intervals of uncertainty, as well as the initial values for the model-based controller (Monte Carlo results) are also presented

Table 2. Sensitivity rankings for r_{opt} with UWW as substrate (r_{opt} = 60) and the mixture of UWW and FW (r_{opt} = 40)

Table 3. Average energy requirements of the filtration process with the controller operating at 17 $g \cdot l^{-1}$ MLTS entering the membrane tanks

Table 4. Average costs of the filtration process with the controller operating at 17 $g \cdot l^{-1}$ MLTS entering the membrane tanks

Supplementary material

Figure S1. Net transmembrane flow (J_{net}) applied during the validation of the model-based controller by simulation. The corresponding values of the MLTS concentrations in the membrane tanks ($MLTS_{MT}$) during the co-digestion experiment at 17 $g \cdot l^{-1}$ are also shown

Figure S2. TMP simulated by the model (TMP_{sim}) vs experimental TMP (TMP_{exp})

Hierarchical clustering analysis based on the absolute means of the selected parameters with UWW as substrate

Figure S3. Hierarchical clustering analysis based on the absolute means of the selected parameters obtained (A) with **(a)** UWW as substrate and (B) with UWW and FW as substrates

Figure S4. Sensitivity measurements (μ^* and σ) obtained (A) with UWW as substrate (r_{opt} of 60) and (B) with the mixture of UWW and FW as substrate (r_{opt} of 40)

Figure S5. Correlation matrix ($\alpha = 0.05$; $n = 999$) of the optimized parameters, the energy requirements and the filtration costs obtained (A) with UWW as substrate and (B) with mixture of UWW and FW as substrate. The $MLTS_{MT}$, J_{net} and TMP are also included

Table S1. Average costs of filtration process and energy requirements with the controller operating at 11, 13, 15 and 17 $g \cdot l^{-1}$ for both feeding strategies.

Abbreviation and symbols

AeMBR - Aerobic membrane bioreactor

AnMBR - Submerged anaerobic membrane bioreactor

BRF – Biogas recycling flow-rate

BF – Back-flushing period

$\mathbf{C_{B}}$ **–** Operating cost of membrane scouring by biogas sparging

$\mathbf{C_{LIFESPAN}}$ – Cost of membrane replacement due to irreversible fouling.

$\mathbf{C_{REAGENTS}}$ – Cost of reagents needed to clean irreversible fouling

$\mathbf{C_{SRF}}$ – Operating cost of pumping the sludge

$\mathbf{C_{STAGE}}$ – Operating cost of pumping permeate

CT – Control time

$\mathbf{C_{TOTAL}}$ **–** Total operating costs

$\mathbf{C_{W}}$ – Total energetic cost

D – Pipe diameter

$\mathbf{E_{COST}}$ – Cost of energy

$\mathbf{EE_{i}}$ – Elemental effects of each input factor on the model output

f – Number of filtration periods

fr – Friction factor

F – Filtration period

$\mathbf{f_{BF}}$ **–** Back-flush frequency

$\mathbf{F_{i}}$ – Scaled elementary effect distribution

g – Acceleration of gravity

GSA – Global sensitivity analysis

HCA – Hierarchical clustering analysis

HRT – Hydraulic retention time

J_{BF} – Transmembrane flow during back-flush

J_{net} – Net transmembrane flow

L – Pipe length

L_{eq} – Equivalent pipe length of accidental pressure drops

M – Molar flow rate of biogas

MBR - Membrane bioreactor

MLTS – Mixed liquor total solids

$MLTS_{MT}$ – MLTS concentration in the membrane tanks

OFMSW - Organic fraction of municipal solid waste

P_1 – Absolute inlet pressure

P_2 – Absolute outlet pressure

q – Volumetric flow rate

R – Relaxation period

R_g – Ideal gas constant

R_C – Resistance of the solid cake formed on the surface of the membrane

R_I – Resistance due to irreversible fouling of the membrane

R_M – Resistance intrinsic to the membrane

r_{opt} – Optimum number of times that the SEE_i should be calculated

R_T – Total filtration resistance

SEE_i – Scaled elementary effect

SDG_m – Specific demand of gas per square meter of membrane

SRF – Sludge recycling flow-rate

SRT – Solids retention time

t_{BF} – Duration of the back-flushing stage

t_F – Duration of the filtration stage

T_{gas} – Biogas temperature

TMP – Transmembrane pressure

TMP_{sim} – Simulated transmembrane pressure

TMP_{exp} – Experimental transmembrane pressure

TS – Total solids

t_R – Duration of the relaxation stage

UWW - Urban wastewater

V – Fluid velocity

V_T – Net volume of treated wastewater

$W_{back\text{-}flusing}$ – Energy requirements of the back-flushing pump

W_{BRF} – Energy requirements of the biogas lower

$W_{filtration}$ – Energy requirements of the permeate filtration pump

W_{SRF} – Energy requirements of the sludge recycling pump

X_{mC} – Dry mass of cake in the membrane surface

X_{mI} – Dry mass of irreversible fouling on the membrane surface

X_{TS} – Concentration of total solids in the mixed liquor

Z_1-Z_2 – difference in height

α – Compression index

α_C – Average specific resistance of the solid cake

α_I – Average specific resistance of the irreversible fouling

σ – Standard deviation

ρ_{sludge} – sludge density

η_{blower} – Overall mechanical and electrical efficiency of the blower

η_{pump} – Overall mechanical and electrical efficiency of the pump

μ – Mean

$\boldsymbol{\mu}^{*}$ – Absolute mean (μ^{*})

$\boldsymbol{\mu}_{\mathbf{p}}$ – Dynamic viscosity of the permeate

$\boldsymbol{\omega}_{\mathbf{C}}$ – Mass of solids settled per membrane area

$\boldsymbol{\omega}_{\mathbf{I}}$ – Mass of irreversible fouling per membrane area

$\boldsymbol{\Delta R}_{\mathbf{I,MAX}}$ – Upper threshold of irreversible fouling resistance at which membrane cleaning starts

Graphical Abstract

Graphical abstract

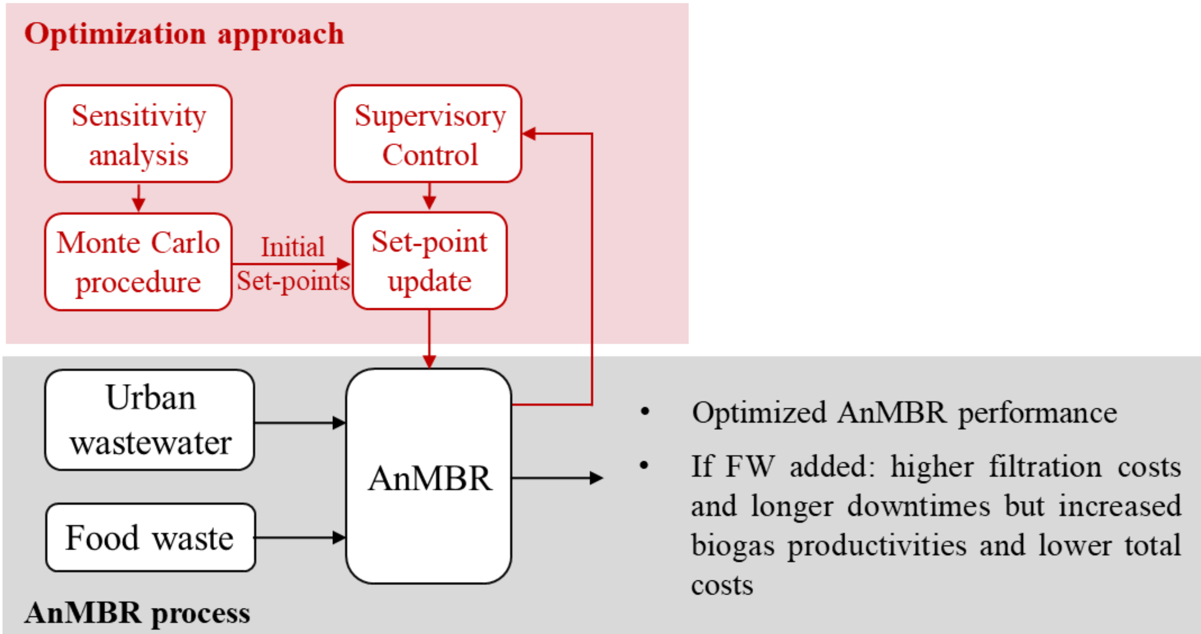

Table 1

Table 1. Average values of the operational parameters evaluated in this study. The intervals of uncertainty, as well as the initial values for the model-based controller (Monte Carlo results) are also presented

Parameter	Units	Substrate	Average values	Minimum	Maximum	Monte Carlo results
BRF	$m^3 \cdot h^{-1}$	UWW	12	3	21	13
		UWW +FW	12	3	21	13
SRF	$m^3 \cdot h^{-1}$	UWW	2.1	1.5	2.7	2.0
		UWW +FW	2.1	1.5	2.7	1.8
t_F	s	UWW	400	200	600	600
		UWW +FW	400	200	600	485
t_R	s	UWW	35	10	60	10
		UWW +FW	35	10	60	10
t_{BF}	s	UWW	35	10	60	17
		UWW +FW	35	10	60	31
f_{BF}	-	UWW	11	1	21	10
		UWW +FW	11	1	21	4
J_{BF}	LMH	UWW	15	10	20	16
		UWW +FW	15	10	20	10

Table 2

Table 2. Sensitivity rankings for r_{opt} with UWW as substrate (r_{opt} = 60) and the mixture of UWW and FW (r_{opt} = 40)

UWW			UWW + FW		
Parameter	**μ^***	**σ**	**Parameter**	**μ^***	**σ**
BRF	1.253	1.856	**BRF**	1.355	2.099
f_{BF}	0.770	2.220	**f_{BF}**	0.579	1.418
t_F	0.724	1.921	**t_{BF}**	0.344	1.059
t_{BF}	0.574	1.210	**t_F**	0.252	0.710
SRF	0.464	1.584	**SRF**	0.163	0.410
t_R	0.057	0.261	**t_R**	0.067	0.138
J_{BF}	0.057	0.268	J_{BF}	0.005	0.018

Table 3

Table 3. Average energy requirements of the filtration process with the controller operating at 17 g·l^{-1} MLTS entering the membrane tanks

Substrate	W_{TOTAL} (kWh·m^{-3})	W_{BRF} (%)	W_{SRF} (%)	W_{Stage} (%)
UWW	0.20	79.7	16.9	14.3
UWW + FW	0.34	88.5	9.6	9.8

Table 4

Table 4. Average costs of the filtration process with the controller operating at 17 $g \cdot l^{-1}$ MLTS entering the membrane tanks

Substrate	C_{TOTAL} (€ per m^3)	C_W (%)	$C_{REAGENTS}$ (%)	$C_{LIFESPAN}$ (%)
UWW	0.047	59.6	17.0	23.4
UWW + FW	0.067	69.0	13.0	18.0

Figure 1

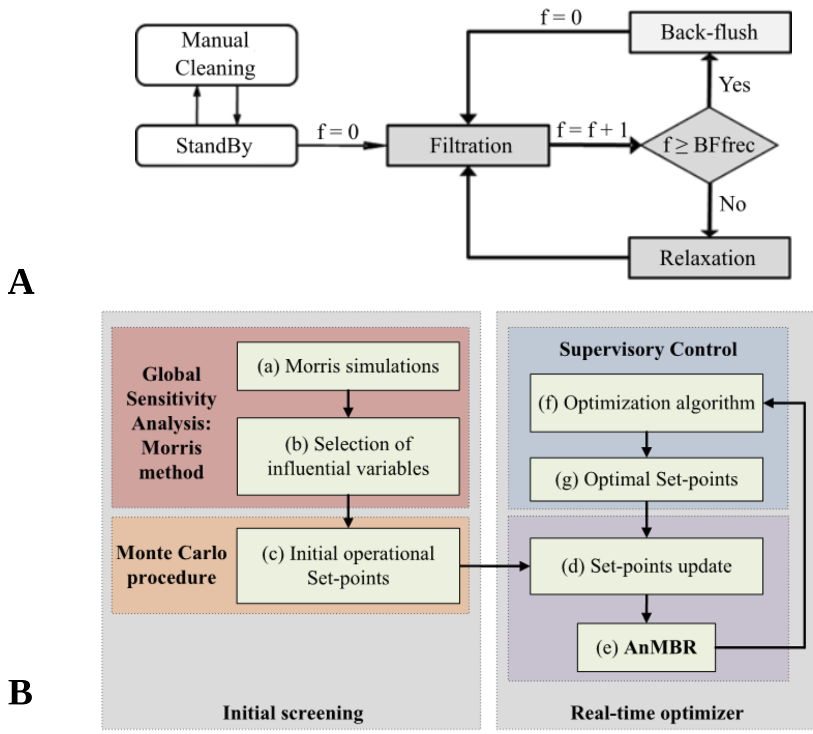

Figure 1. (A) Sequence of the different operational stages in the membrane modules during the alternative operating mode and (B) flow diagram of the proposed optimization methodology

Figure 2

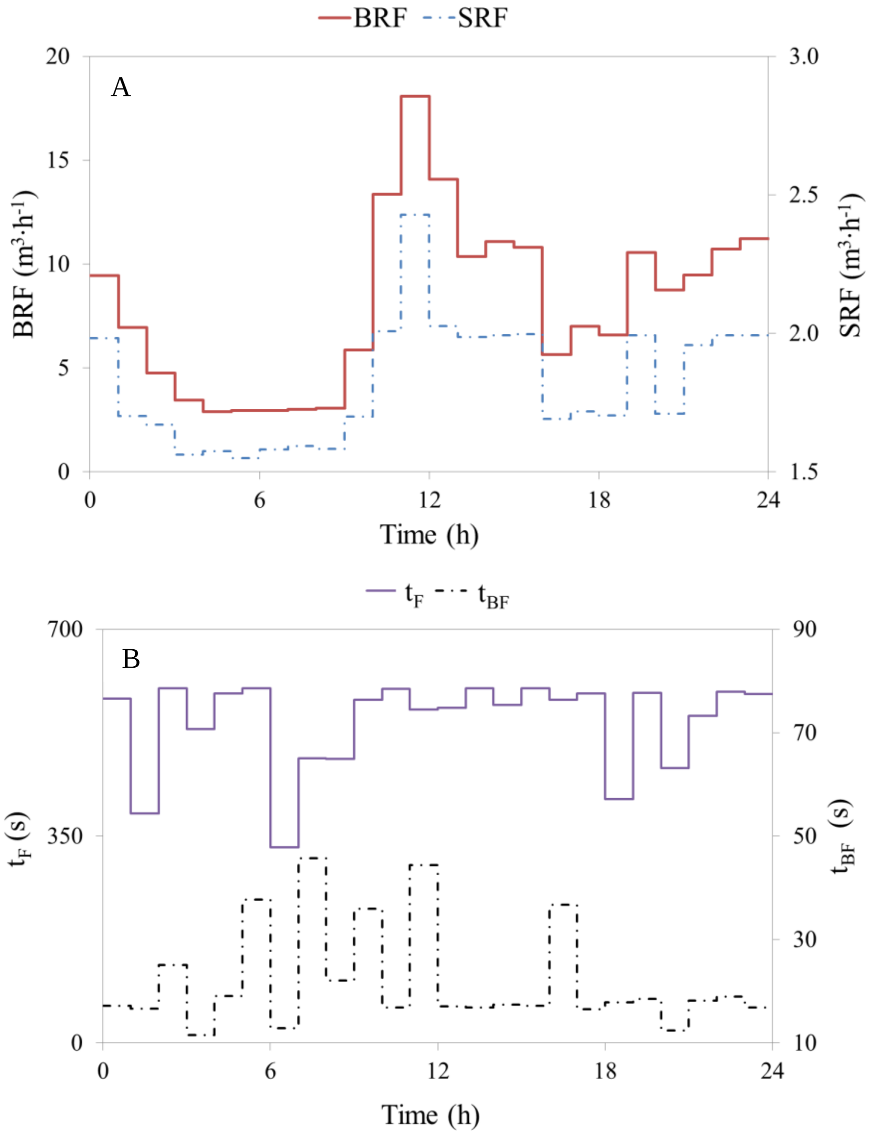

Figure 2. (A) Values of BRF and SRF and (B) t_F and t_{BF} optimized by the model-based controller. The results were obtained by applying the transmembrane flux shown in Figure S1 with a MLTS concentration entering the tanks of 17 $g \cdot l^{-1}$ and using UWW as substrate

Figure 3

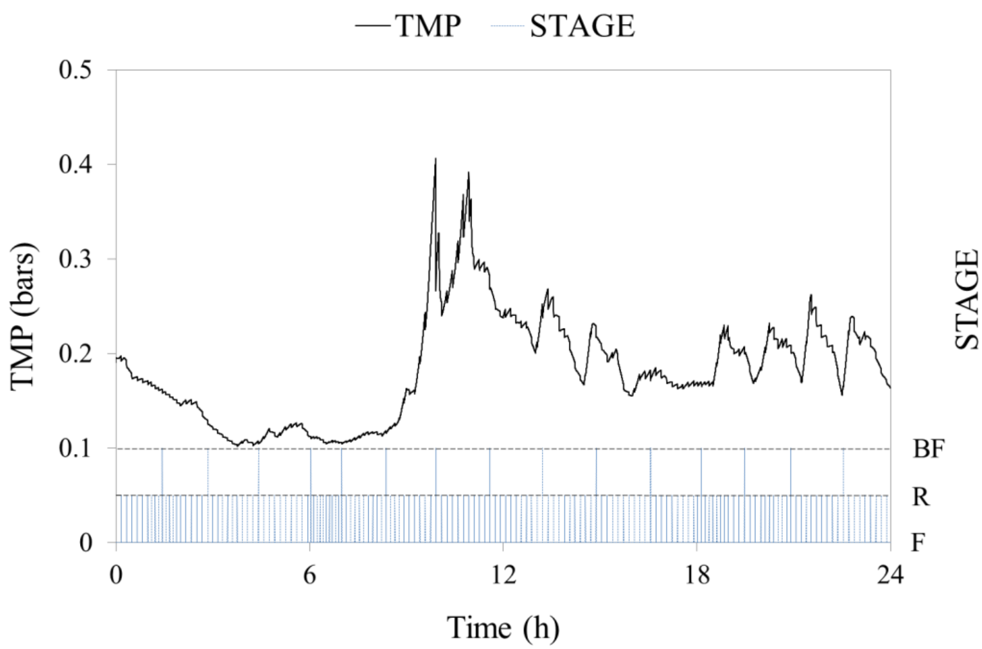

Figure 3. Evolution of the TMPs and different stages simulated. The results were obtained by applying the transmembrane flux shown in Figure S1 with a MLTS concentration entering the tanks of 17 $g{\cdot}l^{-1}$ and using UWW as substrate

Figure 4

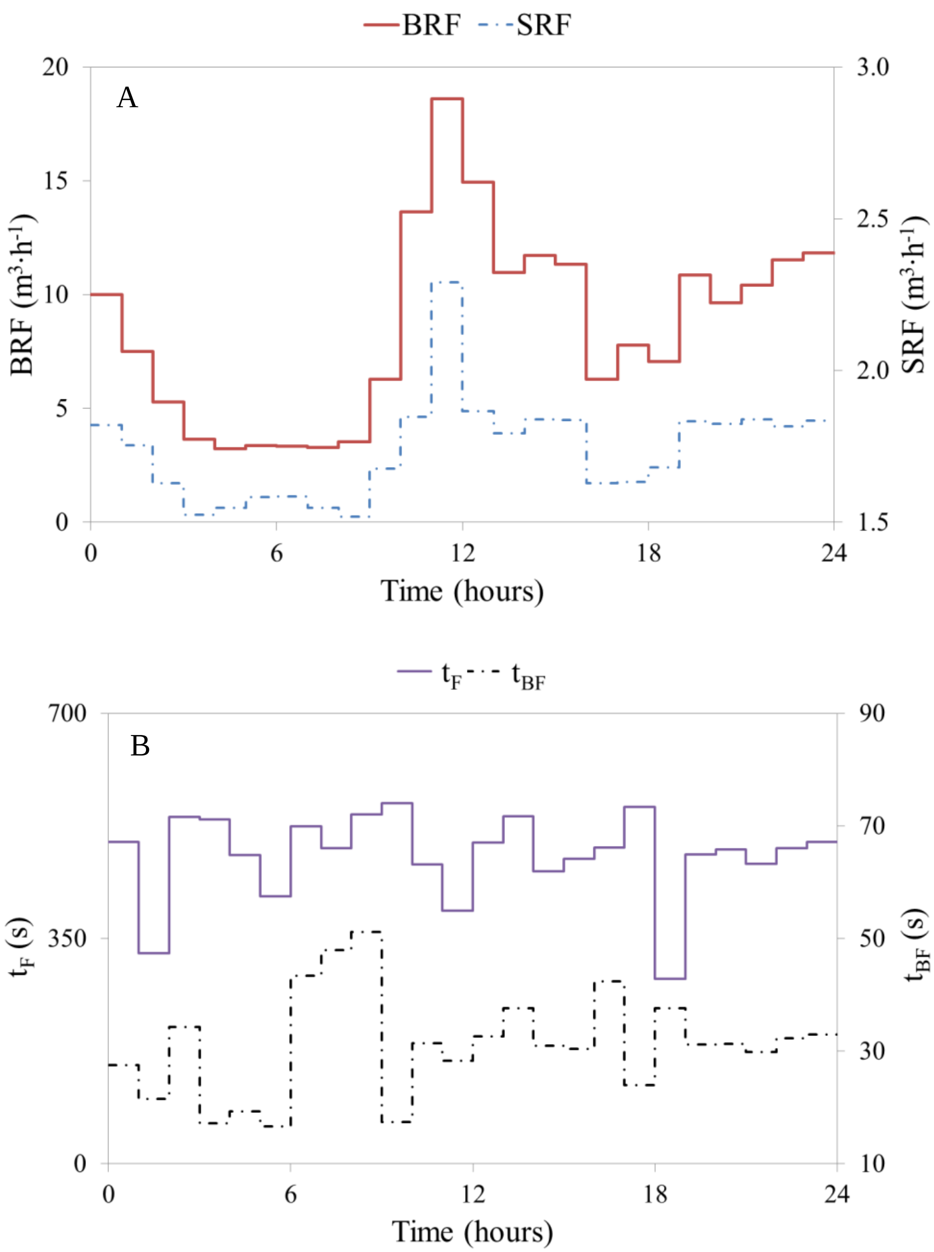

Figure 4. (A) Values of BRF and SRF and (B) t_F and t_{BF} optimized by the model-based controller. The results were obtained by applying the transmembrane flux shown in Figure S1 with a MLTS concentration entering the tanks of 17 $g \cdot l^{-1}$ and using UWW and FW as substrates

Figure 5

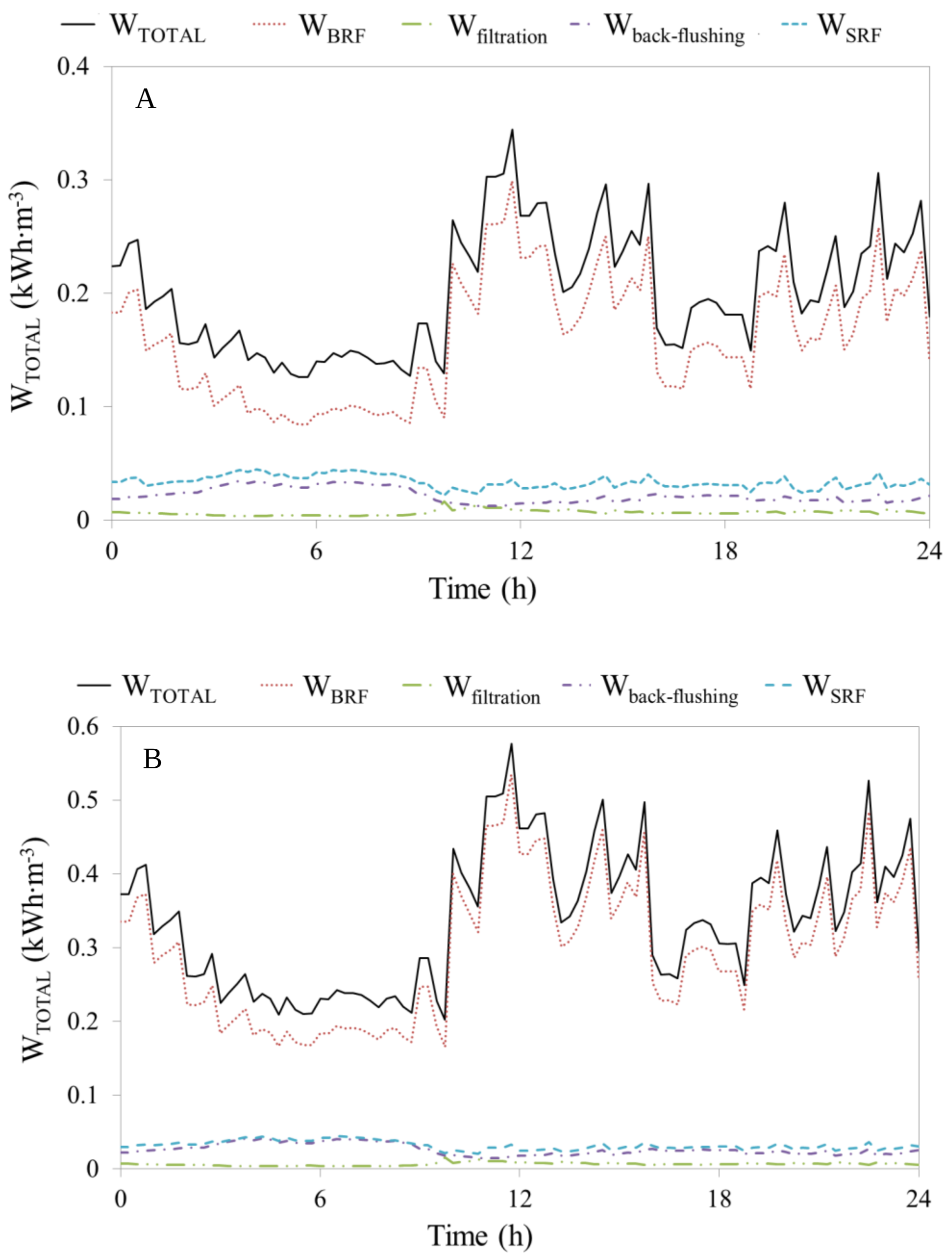

Figure 5. Evolution of the energy requirements of the filtration process with the controller operating at 17 $g \cdot l^{-1}$ MLTS entering the membrane tanks. The results for feeding strategies are shown: (A) UWW and (B) mixture of UWW and FW

Figure 6

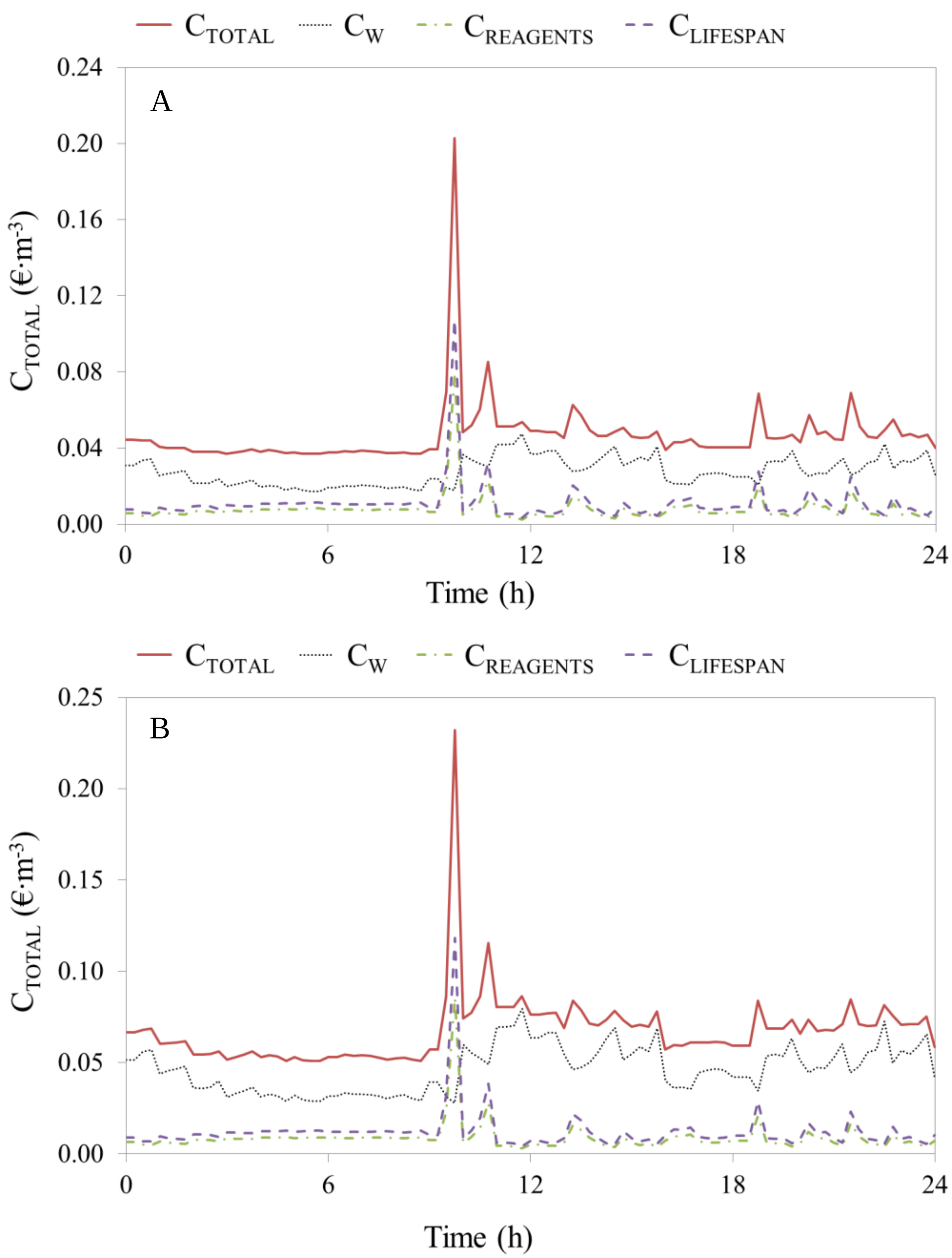

Figure 6. Evolution of the costs of the filtration process with the controller operating at 17 $g \cdot l^{-1}$ MLTS entering the membrane tanks. The results for feeding strategies are shown: (A) UWW and (B) mixture of UWW and FW

Figure S1

Figure S2

Figure S3

Click here to download E-Component: Figure S3.docx

Figure S4

Figure S5

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Table S1
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