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Advanced control system for reverse osmosis optimization in water reuse systems

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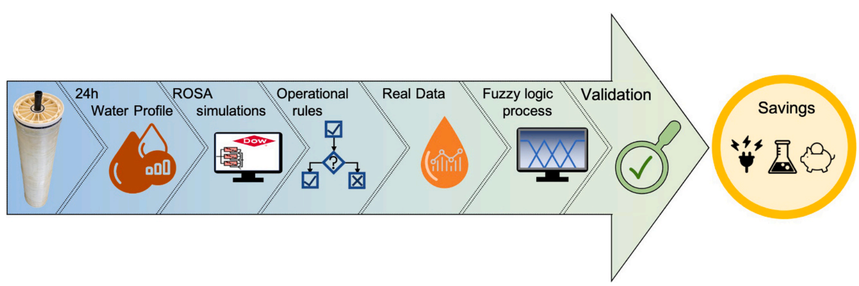
HIGHLIGHTS

- The control system for RO optimization uses fuzzy inference system.
- The Temperature and EC of feedwater determine the optimal recovery set-point.
- The control system proposes the maximum water RO recovery at a lower cost.
- The control system minimises inorganic membrane fouling potential through the use of the $Ca_3(PO_4)_2$ stability index.

GRAPHICAL ABSTRACT



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ABSTRACT

A main reverse osmosis (RO) limitation is the operational costs (including energy filtration costs), which are significantly affected by energy costs and the expense of membrane maintenance. Both costs are affected by influent characteristics, including feedwater temperatures (T), electrical conductivity (EC), and recovery set points. A fuzzy logic advanced control system optimizes the RO operational costs considering feedwater EC and T as input values, and the RO recovery setpoint as a control action. Verification results show that, once calibrated, the simulation of the control system can save more than one million euros per year in large RO facilities (>30.000m^{3}·day^{-1}). Which represents a reduction of 0.11€·m^{-3} of influent treated water.

1. Introduction

Reverse osmosis (RO) is a well-established membrane technology used to produce high quality water from a variety of waters with a saline nature. Since the 1980s, this technology has been successfully implemented to produce potable water from seawater or brackish waters. More recently, it has also been integrated in reclaimed water production trains [3,27], mainly for direct or indirect potable reuse or industrial applications. In such process, pre-treatment by a first membrane process such as microfiltration (MF) or ultrafiltration (UF) is frequently used before RO to protect the RO membrane. This combination of two membrane processes in series is typically referred to as an Integrated

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Membrane System (IMS).

A main limitation for pressured based membrane technologies, including RO, is the operational cost resulting from the chemicals consumption and the specific energy consumption (SEC) ($kW\cdot h^{-1}$) [21,29,33] required to pressurise the water to drive the water through the membrane. For RO, SEC is affected by (1) the characteristics of the influent, i.e. the feedwater temperature (T) and the electrical conductivity (EC) (as a surrogate for salinity), and (2) the operational conditions like the water recovery set point (i.e., the amount of water produced per unit of influent treated water) which is a balance in-between optimised water production and process limitations such membrane fouling [47]. Fouling can be due to microbiological growth (biofouling), precipitation of sparingly soluble inorganic salts (scaling), particulate and colloidal organic matter (organic fouling). Biofouling can be inhibited by intermittent or continuous addition of chlorine-based disinfectants such as chloramine, while organic colloidal and particulate fouling is mitigated by MF or UF pre-treatment. On the other hand, scaling can be controlled through scaling indicators like Langelier Saturationi Index (LSI) or Calcium phosphate stability index (SI_p) [13]. In water reclamation schemes involving IMS, scaling due to inorganic salts is a major limitation for high water recovery; strategies to overcome scaling mitigation involve lowering the pH by dosing hydrochloric or sulfuric acid, antiscalant, or operation at lower recovery [13]. Antiscalant and acid dosages are assessed based on the feedwater composition and the calculation of the saturation indexes for inorganic salts at the design recovery rate [5,13]. Raffin et al. [33] and Greenberg et al. [19] showed a significant reduction in operating costs by utilising an effective antiscalant to control inorganic scaling at neutral pH. That said, although antiscalant supplier software shows that it is possible to control the inorganic salts precipitation lowering the pH, these strategies are costly and injection of those compounds should be automatically controlled.

A review of various RO-based water reclamation full-scale plants located around the world reveals high heterogeneity of EC and total dissolved salts (TDS) feedwaters. EC and TDS concentration increase the filtration resistance on RO membranes and can lead the process to a non-optimal operational condition. However operational conditions (i.e., recovery set points) are not regulated in any of the reviewed studies except for that of the Torreele facility [41] which operated with a system recovery between 75 and 80% (Table 1).

Van Houtte and Verbauwhede [41] reported a real-time optimisation strategy of Torreele facility (Belgium) that allowed for significant operational cost savings. The strategy was made up of two components: (1) the automatic control of the recovery set point by setting up a relationship between the feedwater conductivity and the RO recovery and (2) the discontinuous use of chloramination according to the T of the feedwater. Such control strategy allowed the system recovery to be increased, based on the conductivity monitoring and did not require any additional chemicals, thus allowing a net decrease of energy consumption per cubic meter of produced water without increasing the risk of fouling. Although details of the recovery control strategy are not given in the paper, it is assumed that an empirical relationship between EC and recovery was used to minimise energy requirements.

Raffin et al. [35] sought to optimise the operational conditions of IMS used in wastewater reclamation. A Box-Behnken approach was used to optimise MF flux backwash frequency, chloramine dose and dosing point, together with RO flux, recovery, pH and antiscalant dose, using an experimental plan combined with statistical analysis to define the optimal operating conditions required to minimise membrane fouling. While the study was comprehensive in how it looked at the effect of combining membrane fouling parameters, the work did not focus on how these process conditions were affected by fluctuating influent water quality and how data can be used in real time.

Daigger et al. [11] reported data of first years of operation of the MBR/RO water reclamation train at Gippsland Water in South Eastern Australia. The implemented an online conductivity and TOC removal monitoring system, supplemented by periodic confirmation of effluent quality through laboratory analysis. Robustness and resilience of the process and high-quality reclaimed water with occasional deviations from the 90th percentile values were achieved. The need to continuously monitor analytical systems was raised; However, this study recommended not monitoring all the constituents because it would imply excessive analytical costs.

For this reason, even though this can represent an increased water monitoring cost, the most common operational strategies for RO plants are to reduce the SEC by adjusting the recovery set point according to the characteristics of the influent water. Nevertheless, the SEC is not the only limiting factor for RO, preventive actions such as pH regulation or scaling prevention in order to maintain RO membranes in good condition and increase membrane lifetimes, also increase the overall cost of this technology. In a similar context, Ahmed et al. [1] analysed developments in the optimization of RO configurations from the perspective of energy consumption for desalination processes. The authors remark on the importance of the system's configuration and the optimization of the pre- and post-treatments, integrating RO with other processes.

Therefore, control of fouling and energy optimisation are directly related each other and crucial parameters for operational cost optimisation. As can be seen, online monitoring of EC and feedwater parameters can reduce RO operational costs and likewise fouling control can increase membrane lifetimes which equates to lower maintenance costs. However, literature reviewed has showed that no studies have been considered chemicals dosage, recovery percentage, energy cost and membrane life time all together for RO optimisation.

Regarding optimisation strategies, fuzzy logic is an evolution from binary logic and was presented by Zadeh [49] for the first time and has been well described in a number of books [37]. Fuzzy logic systems consider the entire range of responses between true and false generating a gradual response. Moreover, the variable categories can be codified and combined using linguistic levels (low, medium, high, etc.). Each category has a numerical interval. These characteristics make fuzzy logic systems suitable for application in many different contexts [7,9,15,39]. RO is a complex, but quite well-known, system. Thus, an advanced control system based on fuzzy logic appears to be a simple and robust way to generate operational rules for RO optimization.

The main objective of this work is to develop an advanced fuzzy control system for RO optimization and to illustrate its usefulness in reducing operational costs in water reclamation facilities. Taking into account the EC and T of the feedwater, together with operational costs, including energy and chemicals, the aim is to propose the maximum water recovery at a lower cost and minimise inorganic membrane fouling potential through the use of the $Ca_3(PO_4)_2$ stability index. The

Table 1
RO plants.

Name and location	EC ($\mu S\cdot cm^{-2}$)			TDS ($mg\cdot L^{-1}$)			T (°C)			Recovery	References
	$\bar{X}$	Min	Max	$\bar{X}$	Min	Max	$\bar{X}$	Min	Max		
Torreele (Belgium)	1161	442	1442	581	216	723	15.3	9.8	22.3	75–80%	[41]
Sulaibiya (Kuwait)	2550	–	5700	1280	–	3014	–	–	–	Fixed	[17]
Ulu Pandan (Singapore)	–	800	2000	–	500	1200	–	–	–	Fixed	[45]
León (Spain)	2338	2065	2542	–	–	–	–	–	–	Fixed	[29]

control system rules are first developed using the historical water quality data from industrial pilot plant (3.5 $m^3 \cdot day^{-1}$) operating with real urban wastewater. Then, tested and verified with a different data set profile.

2. Materials and methods

To develop the advanced control system, typical urban wastewater quality profiles were used to determine the feedwater EC and T variations. Then, DOW Filmtec's reverse osmosis system analysis (ROSA) software (from [13]) was used to simulate the RO performance under different operational conditions of feedwater EC and T. The RO operational conditions were then converted to RO operational rules for process optimization. These rules were subsequently codified using fuzzy logic to develop a control system to adjust the RO recovery. Finally, operational rules were verified using long-term EC and T data profiles. A comparison of the process recovery, total water cost and fouling potential (in this case with the $Ca_3(PO_4)_2$ stability index) was carried out by the advanced control system and the current practice open loop control (at constant water recovery).

2.1. Case study

Part of this study was carried out in an industrial-scale pilot plant treating real urban wastewater. The plant features a bioreactor (2.43 m^3) designed to eliminate organic matter and nutrients (nitrogen and phosphorus) using a submerged membrane bioreactor (MBR) system followed by RO treatment (Fig. 1). The plant is located at the Quart waste water treatment plant (WWTP) (Girona, NE Spain) to treat real domestic wastewater. Further details about the pilot plant can be found in [31]. The plant was operated for 6 months period in order to obtain the data for this study.

2.2. Water characterization

The wastewater quality, characterized by parameters like EC and T, fluctuates due to daily and seasonal variations. Thus, to identify the range of EC and T values, two different data sets were considered.

The first data set used was a 24 h profile where hourly samples were taken with an autosampler from the primary effluent of the industrial pilot plant. The sampling campaign was carried out during dry weather flow to avoid the dilution of the influent with rainwater due to a combined sewage system. Samples were filtered through a 1.2 μm microfiber filter and a 0.45 μm nylon membrane filter before analysis. Samples were then analysed for EC, dissolved organic carbon (TOC; Shimadzu TOC-VCSH analyzer), ammonium (BÚCHI B-324 distiller, Titrino 719S Methrohm), total Kjeldahl nitrogen (BÚCHI B-324 distiller, Titrino 719S Methrohm), nitrite (NO_2^- - N) and nitrate (NO_3^- - N). Major cations (Ca^{2+}, $Mg2^+$, Na^+, K^+) and anions (Cl^-, SO_4^{2-}, P – PO_4^{3-}) were analysed using ion chromatography (Metrohm 761-Compact; APHA standard method 4110B).

As EC is based on the presence of ions, it is commonly used as a surrogate parameter for the concentration for dissolved minerals in water, commonly termed as total dissolved salts (TDS) [43]. In this work, a correlation in-between EC and total ions, cations and alkalinity (HCO_3^-) was set. Also, feedwater EC measured in the first dataset was divided into three ranges: low, medium and high EC. Medium EC was defined as the arithmetic average ($\bar{x}$) of the results from hourly analysis over the 24-hour period. The low and high feedwater EC profiles were defined as the $\bar{x}$ EC +/- the SD over the 24-hour period, respectively (Table 2). These EC ranges were used in the ROSA software to find by simulation the most adequate operational conditions.

The second data set corresponds to a one year of daily EC and T values (one value per day), based on real EC and T values from the pilot plant operation and the typical variability of EC and T considering the effects of the local meteorology. This second data set was created to test

Table 2
EC ranges for the first data set used in the ROSA simulations.

Parameter	Low EC EC < 1198 ($\mu S \cdot cm^{-2}$)	Average EC 1198 < EC < 1344 ($\mu S \cdot cm^{-2}$)	High EC EC > 1344 ($\mu S \cdot cm^{-2}$)	Units
EC	978	1343	1674	$\mu S \cdot cm^{-2}$
pH	7.4	7	8	–
Ca_2^+	59	69.5	86	$mg \cdot L^{-1}$
Mg_2^+	7.8	16.5	16.3	$mg \cdot L^{-1}$
Na^+	115.8	159	169	$mg \cdot L^{-1}$
K^+	13.5	20	33.3	$mg \cdot L^{-1}$
NH_4^+	32	–	57	$mg \cdot L^{-1}$
Alk	240	182	583	$mg \cdot L^{-1}$
Cl^-	192.4	254.6	228.2	$mg \cdot L^{-1}$
NO_3^- - N	1	28	–	$mg \cdot L^{-1}$
SO_4^{2-}	18	18	18	$mg \cdot L^{-1}$
PO_4^{3-} - P	1	7.4	9.5	$mg \cdot L^{-1}$

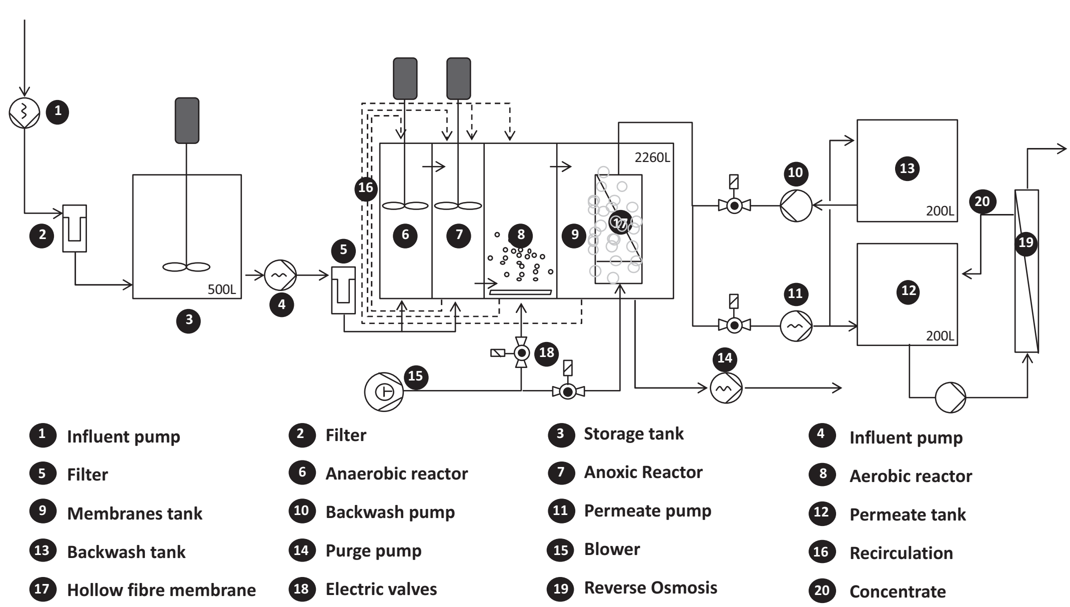

Fig. 1. Industrial-scale pilot plant process diagram.

and verify the advanced control system under all different possible scenarios and seasonal variations, i.e., from low EC with low T (due to the dilution effect during wet period) to high EC with high T (dry period). The complete first and second data set are provided in the supplementary information (SI).

2.3. Reverse osmosis simulation analysis

ROSA (from [13]) is one of the typical softwares used by process engineers to design RO plants and predict performance under changing conditions to operate sustainably at the lowest water costs. ROSA software was used to simulate the effect of EC and T feedwater variations, both of which directly impact energy demand and chemical pretreatment dosage.

For the simulation, the 24-h profile (first data set) was chosen to obtain an indication of the daily variability of the ionic constituents rather than an average concentration over a 24-h period. Simulations were performed under different conditions, i.e. covering the three different EC ranges (low, medium and high) with two ranges of temperature (low and high) at three different recovery rates 75%, 77.5% and 80% (low, medium and high).

To understand the behaviour that can be expected in real facilities, a virtual RO plant with a two-stage design was assumed to be operating with a recovery range between 75% and 80%, with a train producing 5000 $m^3 \cdot day^{-1}$. The configuration consisted of 28 pressure vessels (PVs) in the first stage, followed by 12 PVs in the second stage, each with seven Filmtec BW 30-400 membrane elements. The system was designed to operate at an average permeate flux of 20 $L \cdot m^{-2} \cdot h^{-1}$ (LMH) and average pH of 7.3 for the simulations. Moreover, inorganic fouling was controlled using the calcium carbonate scale and through the Langelier Saturation Index (LSI) (LSI $<$ 1) and the calcium phosphate ($Ca_3(PO_4)_2$) stability index (SI_p) ($SI_p < 0$)(Kubo et al. [25].

The LSI control was done adjusting the pH considering the water temperature. At higher water T more chemical volume need to be added to lower the pH. Also, water pH has a direct impact on the SI_p which can be regulated adding more chemicals or limiting the recovery (calculations in SI).

These indices provide an indication of the potential for scaling considering the concentrations of calcium and phosphate along with feedwater pH and T. The ionic constituents, which are typically affected by the secondary treatment process, namely NH_4^+, HCO_3^- and PO_4^{3-}, were obtained from samples following the MBR treatment process from the pilot plant.

Output data obtained from the software simulations for each of the process conditions enabled to compose a matrix with the operational cost for each combination of EC, T and recovery.

2.4. Operational cost estimation

The total water cost ($Cost_{total}$) is considered in this work as the sum of the cost of electrical energy ($Cost_{energy}$) for pumping the feed and for the high-pressure pump, together with the cost of the RO pre-treatment chemicals to control inorganic fouling ($Cost_{pt}$). The cost of the biofouling control, which is typically carried out using chloramines, was not included, nor was the cost of concentrate disposal.

The $Cost_{energy}$ (Eq. (1)) is estimated as the SEC of the pump (SEC_{pump}) (Eq. (2)) multiplied by the cost of the energy during the studied period. In this case, the cost of the energy was fixed at 0.10€$\cdot KWh^{-1}$ as a mean value between the off-peak and peak periods.

$$Cost_{energ} = SEC_{pump} * cost\ of\ the\ energy \tag{1}$$

$$SEC_{pump} = SEC_f + SEC_{HP} \tag{2}$$

where the SEC_{pump} (in €$\cdot m^{-3}$) is a specific value for each system and can be calculated as the sum of the feed pump SEC (SEC_f) (Eq. (3)) and the high-pressure pump SEC (SEC_{HP}) (Eq. (4)), both in €$\cdot m^{-3}$.

$$SEC_f = \frac{Q_f * 1000 * 9.81 * P_f * 10.197}{3600000 * Eff_f * Q_p} \tag{3}$$

$$SEC_{HP} = \frac{Q_f * 1000 * 9.81 * (P_{HP} - P_f) * 10.197}{3600000 * Eff_{HP} * Q_p} \tag{4}$$

Were:

Q_f = Feed flow ($Q_p \cdot Y^{-1}$)
Y = Recovery as a decimal
Q_p = Permeate flow [$m^3 \cdot h^{-1}$]
P_f = Feed water pressure (2.1 bar)
Eff_f = Feed pump efficiency (80%)
P_{HP} = Membrane feed pressure [bar] (determinate from ROSA)
Eff_{HP} = High-pressure pump efficiency (80%)

The pre-treatment cost ($Cost_{pt}$) (Eq. (5)) (in €$\cdot m^{-3}$) includes the cost of dosing the acid ($Cost_{acid}$) and the cost of the antiscalant ($Cost_{as}$).

$$Cost_{pt} = Cost_{acid} + Cost_{as} \tag{5}$$

$Cost_{acid}$ (Eq. (6)) (in €$\cdot m^{-3}$) includes the volume of acid required for a specific recovery and the acid costs, which can vary depending on the acid. Like the $Cost_{acid}$, the $Cost_{as}$ (Eq. (7)) (in €$\cdot m^{-3}$) includes the volume needed for a specific recovery and the cost of the product.

$$Cost_{acid} = \frac{1000}{\gamma} * \frac{Dose_{acid}}{1000} * Cost\ of\ the\ acid \tag{6}$$

$$Cost_{as} = \frac{1000}{\gamma} * \frac{Dose_{as}}{1000} * Cost\ of\ the\ antiscalant \tag{7}$$

Were:

γ = Recovery [decimal]
$Dose_{acid}$ = [$mg \cdot L^{-1}$]
Acid Cost = [€$\cdot L^{-1}$]
$Dose_{as}$ = [$mg \cdot L^{-1}$]
Antiscalant Cost = [€$\cdot g^{-1}$]

$Dose_{acid}$ is determined by the ROSA software and, the cost of the acid corresponds to sulfuric acid cost for influent water litter, which in this case was 0.00019 €$\cdot L^{-1}$. The $Dose_{as}$ is typically obtained from the antiscalant supplier software and the cost of the antiscalant was considered to be 0.00388 €$\cdot g^{-1}$.

Finally, the $Cost_{total}$ (in €$\cdot m^{-3}$) of the RO was calculated using the $Cost_{energy}$ and the $Cost_{pt}$ (Eq. (8)).

$$Cost_{total} = Cost_{energ} + Cost_{pt} \tag{8}$$

Note that the cost of chemicals required to control the inorganic fouling was estimated from the cost of sulfuric acid (H_2SO_4, 98% concentration) required to obtain an LSI just below 1 (0.85-1), i.e., to control calcium carbonate precipitation and continuously antiscalant dosage at 2 $mg \cdot L^{-1}$. The estimation of pre-treatment chemicals in the considered cost was thus based on acidification since the use of proprietary antiscalants is very specific to the chemical manufacturer. Basing the scaling fouling control on acidification allows the generalization of the contributing cost of pre-treatment under different operating conditions. Costs associated with routine clean-in-place (CIP) operations or membrane replacement were not included as these are very case specific in terms of feedwater quality and process conditions. Cost associated to brine disposal were not considered since changes in recovery will not change the mass of contaminants discharged into the natural environment.

2.5. Advanced fuzzy logic control system

The advanced fuzzy logic control system for RO optimisation was developed based on feedforward (FF) control loop. The system describes the relations between the feedwater EC and T to propose the maximum recovery keeping $SI_p < 0$ and $LSI < 1$ while utilising the minimum energy and chemical cost. These relations were obtained from the ROSA simulations and posterior cost estimations (Fig. 2).

The operational rules for the fuzzy control system were developed by using the Matlab® Fuzzy Logic Designer Tool. In this case, two input variables (EC and T) were inferred through a Mamdani inference to generate one output variable (water recovery). Both input variables had three categories each (Low, Medium, High). The output variable was divided in five categories (Very Low, Low, Medium, High, Very High). The operational rules were inferred based on the ROSA simulation results, which used the first data set as input data.

The second data set (one-year profile of EC and T) was used to test and verify the advanced fuzzy logic control system, since the proposed water recovery (on a daily basis) was compared with the current practice open loop (i.e., a constant water recovery) and the corresponding water savings obtained.

2.6. Implementation requirements

Based on the pilot plant operation, some challenges have to be faced for a real facility before the control system implementation. First of all, a preliminary study from influent water needs to be done in order to adjust the range of the operational rules. Afterwards, the control system requires an online T and EC sensor at the inlet as measured variables. In order to modify the recovery set-point, different possibilities are available, a variable frequency drive pump could be an option or a set of electric valves (usually installed in this systems).

EC sensor is a very common measure in RO facilities usually used to monitor the membrane status. On the other hand, temperature sensor is less common because the water T is not always monitored. The control algorithm must be installed in the local server of the facility aiming to have access to the data required for optimization.

3. Results

This section first illustrates the simulations carried out to analyse different operational conditions with the ROSA and the operational rules obtained for RO optimization. Furthermore, the simulation results of the fuzzy logic control system using one-year EC and T profile data are presented and, finally, the total operational cost comparison between the constant vs control system recoveries is provided.

The simulations performed with ROSA covered a number of different operational conditions consistent with the water profiles including three different EC and recovery scenarios with 18 different T (Table 3).

The resulting 162 simulations show the behaviour of the SI_P, providing a clear relation between this index and EC, T and recovery, in order to detect in which situation, the calcium phosphate would precipitate on the membrane ($SI_P > 0$).

Depending on the RO system recovery, at Low EC, the $Ca_3(PO_4)_2$ precipitates between 24 and 26 °C (Fig. 3a); at Medium EC, $Ca_3(PO_4)_2$ between 23.5 and 25.5 °C (Fig. 3b), while at High EC, $Ca_3(PO_4)_2$ precipitates between 24.5 and 27 °C (Fig. 3c).

The control of the SI_P has an impact on the water cost since the precipitation of $Ca_3(PO_4)_2$ onto the membrane surface reduces its efficiency, thus a higher pressure is needed to produce the same amount of water. This precipitation can be controlled by adding chemicals or adjusting the membrane recovery. Chemicals addition to keep the $SI_p < 0$ increases the cost of chemicals and water production.

Table 3
Operational conditions simulated.

	Low	Medium	High
EC ($\mu S{\cdot}cm^{-2}$)	<1198	[1198, 1344]	>1344
T (°C)	[13,17]*	–	[23,27]*
Recovery (%)	75	77.5	80

* 0.5 °C intervals.

The simulations outputs for each of the process conditions enabled to compose a matrix with the relations among the SI_p and the operational cost (related to SI_p) for each combination of EC, T and recovery. Additionally, these relations are the basis for the advanced fuzzy logic control system and the optimization rules for RO optimization.

3.1. Design of the advanced fuzzy logic control system

This section presents the advanced fuzzy logic control system for the optimization of any RO system, based on EC and T, and proposes the maximum recovery at minimum cost avoiding the $Ca_3(PO_4)_2$ precipitation.

The advanced fuzzy logic control system regulates the RO water recovery as a function of the feedwater EC and T as input variables. These input variables were divided into three qualitative categories for membership functions: two trapezoidal (including the Low and High range of values) and one triangular category (Medium range of values) each (Fig. 4a, Fig. 4b). The output variable has five different categories for membership functions: two trapezoidal (Very Low and Very High) and three triangular (Low, Medium, High) (Fig. 4c). All categories are created considering the minimum and maximum values of each variable and divided according expert knowledge. The limits of the categories were based on the analysis of the simulation results (Table 4), providing a 50% overlap between the two consecutive qualitative ranges for all input and output variables.

The operational rules for RO optimization are obtained based on the simulations and the expert knowledge. The rules combine the qualitative categories for EC, T with RO recovery categories to propose new recovery set point. The Mamdani inference process [23] determines the category or combination of categories for input values and enables a proper recovery response to be generated according to the operational rules. As an example, in the "Low EC" and "Low Temperature" scenario, the system proposes a "Very High Recovery" value (Table 5).

When applying these rules, it is apparent that there is a gradient between the best (Low EC and T) and the worst scenarios (High EC and T). According to this, the algorithm can propose a range of RO recoveries from the lowest to the highest value (Fig. 5).

3.2. Verification of the advanced fuzzy logic control system

The advanced fuzzy logic control system was tested and verified by

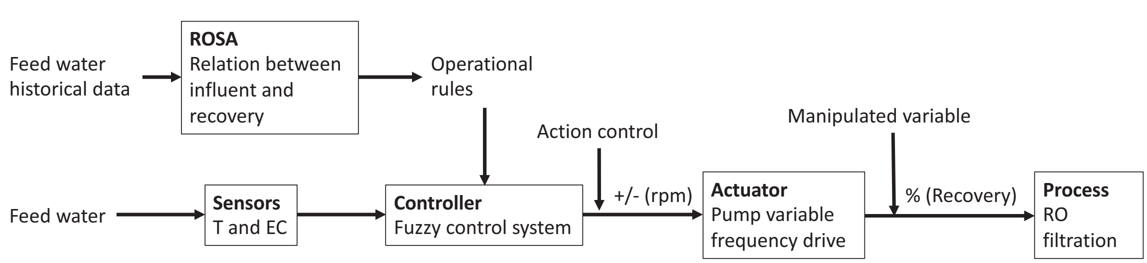

Fig. 2. Control system loop scheme.

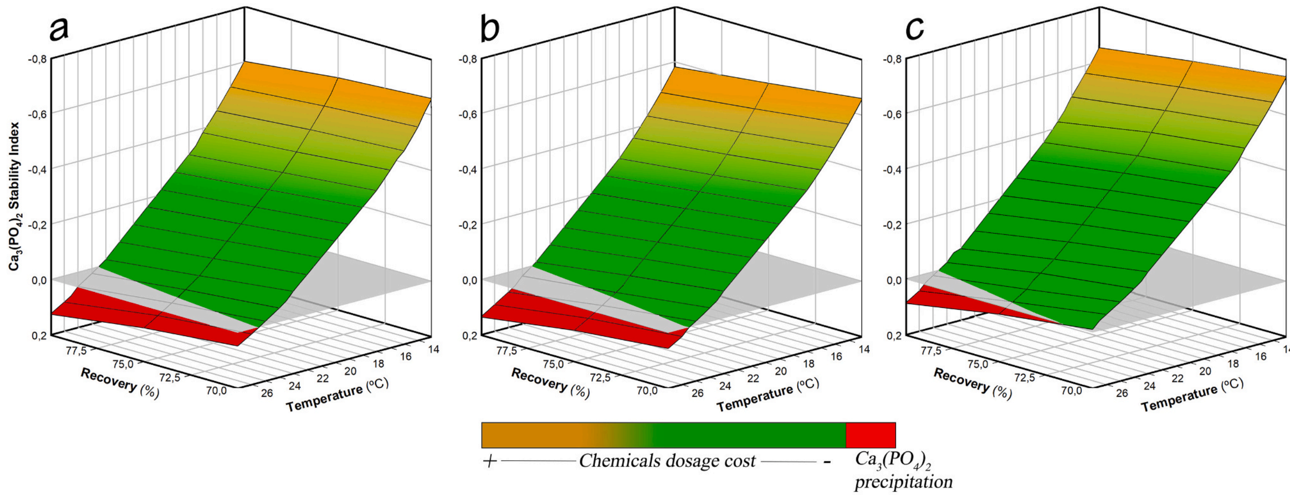

Fig. 3. Calcium phosphate stability index (SI_p): **a)** Low EC scenario; **b)** Medium EC scenario; **c)** High EC scenario.

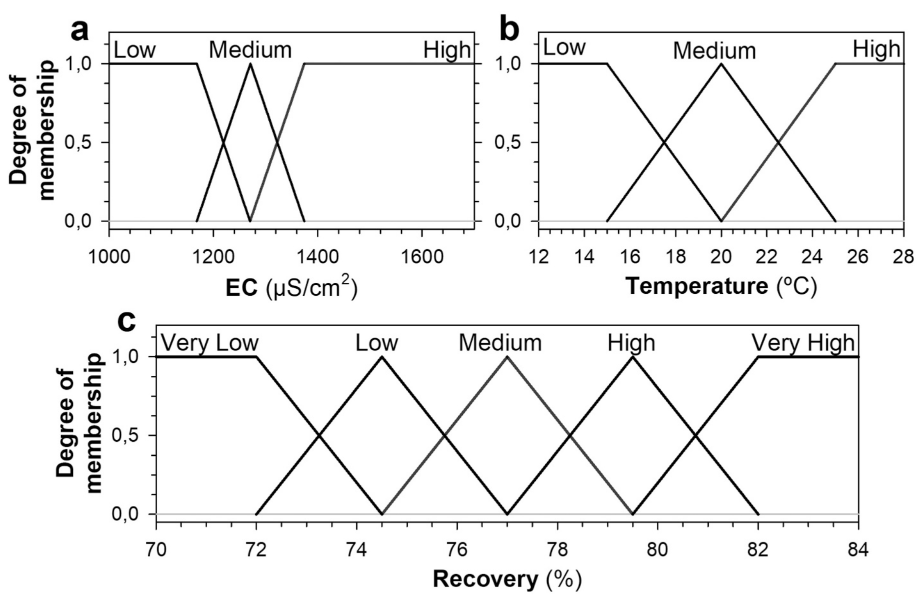

Fig. 4. Fuzzy categories for the input variables: **a)** Electrical Conductivity (EC) and **b)** Temperature; and fuzzy categories for the output variable: **c)** RO Recovery.

Table 4
Limits of membership fuzzy categories.

	Very Low	Low	Medium	High	Very High
EC ($\mu S \cdot cm^{-2}$)	–	< 1270	[1168, 1374]	> 1270	–
Temperature (°C)	–	< 20	[14,26]	> 20	–
Recovery (%)	[70,74.5]	[72,77]	[74.5,79.5]	[77,82]	[79.5,85]

Table 5
Relation between EC, T and Recovery.

		Temperature (°C)		
	Categories	Low < 20	Medium [14,26]	High > 20
EC ($\mu S \cdot cm^{-2}$)	Low < 1270	Very High	High	Medium
	Medium [1168,1374]	High	Medium	Low
	High > 1270	Medium	Low	Very Low

using the one-year T and EC water profiles to observe the response of the system in all operational conditions. Fig. 6a illustrates the T profile, with low T in winter season and high T in summer, while Fig. 6b shows the EC variability between wet or dry periods.

The advanced control system applied over this T and EC water profile proposes a recovery rate varying between 71% and 83%. The results of the control system are compared to the results of an open loop control system, with a constant recovery rate of 80%. For a large part of the year (days 1 to 40 and 130 to 365) the proposed recovery by the advanced control system is lower than 80% because T or EC fluctuate between medium and high categories (Fig. 6a, Fig. 6b). On the other hand, the proposed recovery rate can be higher than 80% (day 45-120) (Fig. 6c). Besides, since the operational rules seek to maintain $SI_p < 0$, it is important to highlight the differences on this index between working at variable or constant recovery rates. At a constant recovery rate, SI_p reaches values over 0 during summer (high T and high EC), while at a variable recovery rate this value is always under 0 (Fig. 6d), thus avoiding $Ca_3(PO_4)_2$ membrane precipitation risk.

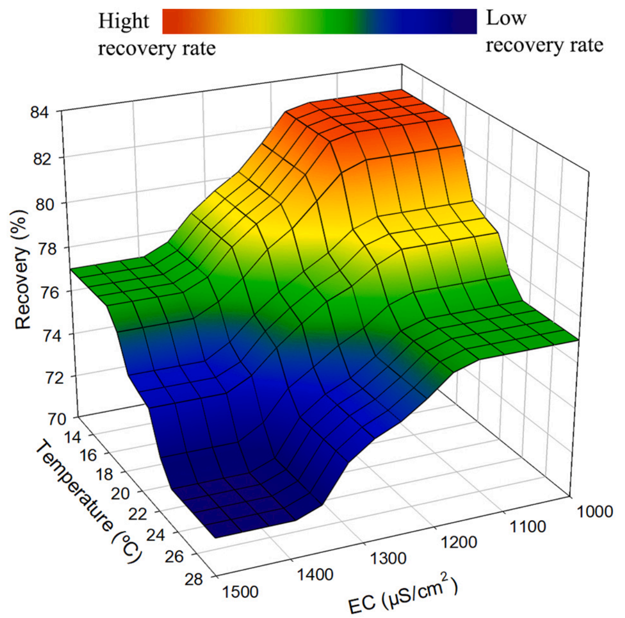

Fig. 5. Recovery response according to EC and T.

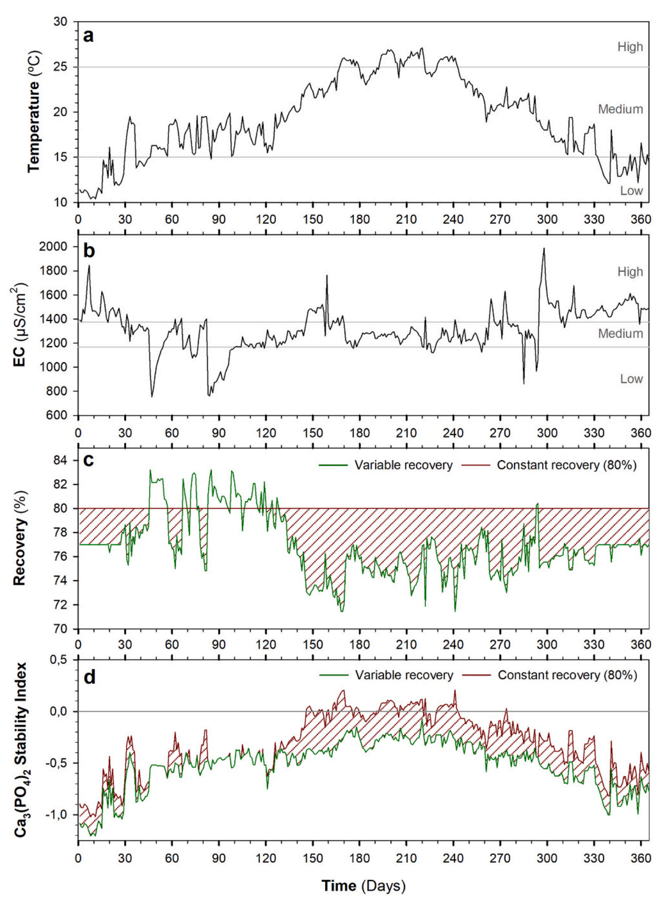

Fig. 6. One-year water profile: **a)** Water T profile; **b)** Water EC profile; **c)** Variable and constant recovery; **d)** SI_p evolution for variable and constant recovery.

3.3. Total water cost comparisons

The cost of the chemicals is linked to the SI_p value obtained from the ROSA software. When SI_p increases, usually at high recovery rate, ROSA proposes a chemical dosage increase to minimise potential inorganic fouling. This cost is therefore directly related to the EC and T of influent. To avoid membrane fouling, higher EC and T values require more chemicals for the same recovery set point. When working at a variable recovery rate, the total chemical cost can be reduced by decreasing the recovery maintaining $SI_p < 0$ (Fig. 7a).

The energy costs fluctuate based on the feedwater EC, T and the recovery applied. Higher costs can be seen during dry periods with higher T and EC (days 150-160 Fig. 7b). On the other hand, periods with low T and EC values with higher recovery proposals coincide with lower energy costs (days 90-120 Fig. 7b).

When comparing the energy cost for the regulated and constant recovery rate alternatives (Fig. 7b), a different behaviour, compared with the chemical costs, becomes apparent. The energy cost is related more to the demand of pumping energy and the amount of influent treated water. If the proposed variable recovery rate is lower than the constant recovery for almost 75% of the year, then the cost of treated water at a variable recovery rate is equal or very slightly higher compared to the energy cost at the constant recovery rate (Fig. 7b).

In terms of the total water cost (chemicals cost plus energy cost), the variable recovery operation presents a lower total cost for a large part of the summer (day 120-210) and winter (day 0-30 and 300-360). In autumn (day 210-300), the total cost of operating at a variable recovery rate is only slightly higher than at the constant recovery rate, while in spring (day 30-120) the variable recovery operational costs are equal to or higher than constant recovery (Fig. 7**c**). Moreover, the differences for daily costs and accumulated savings demonstrate that, globally, the total costs of working at the variable recovery rate are slightly lower than at fixed recovery. In fact, when working at variable recovery, 0.11€$\cdot m^{-3}$ can be saved by the end of a year (Fig. 7d).

The control system simulations were done according to the studied plant's characteristics, but it can easily be adjusted for other plants. Using historical data, new ranges of influent EC and T can be defined and recovery ranges can also be modified according to the requirements of the facility in question.

The input EC and T were used for the control system to produce the highest recovery rate at the lowest cost. This combination seems to be more robust than just adjusting the recovery according to the influent EC (i.e., the Torreele facility) due to consider the effect of T on the water solubility. Furthermore, other parameters can be easily incorporated into the model based on expert rules, like biofouling that can also affect the membrane filtration.

On the other hand, the results of the verification should be done in a real facility for a long-term period to assess the savings in practice. Furthermore, if, for example, the control system was applied to the RO plant in Ulu Pandan (Singapore), which treats 30,000 $m^3\cdot day^{-1}$, the potential cost reduction could result in a savings of 1,095,000€ per year. In another instance, if this control strategy was employed in the RO plant in León (Spain) which treats 50.000 $m^3\cdot day^{-1}$, this could potentially represent a savings of 1,898,000€ in one year.

4. Conclusions

The production of high-quality water through RO process entails high operational costs related to energy demand and chemical consumption. An advanced fuzzy logic control system based on easy-to-measure control parameters like T and EC can optimise the process. Combining ROSA simulations with expert knowledge enabled to develop operational rules which, when integrated in an advanced fuzzy control system, enable to minimise energy and chemicals cost while increasing membrane life time.

Continued daily savings are not always possible due to the risk of

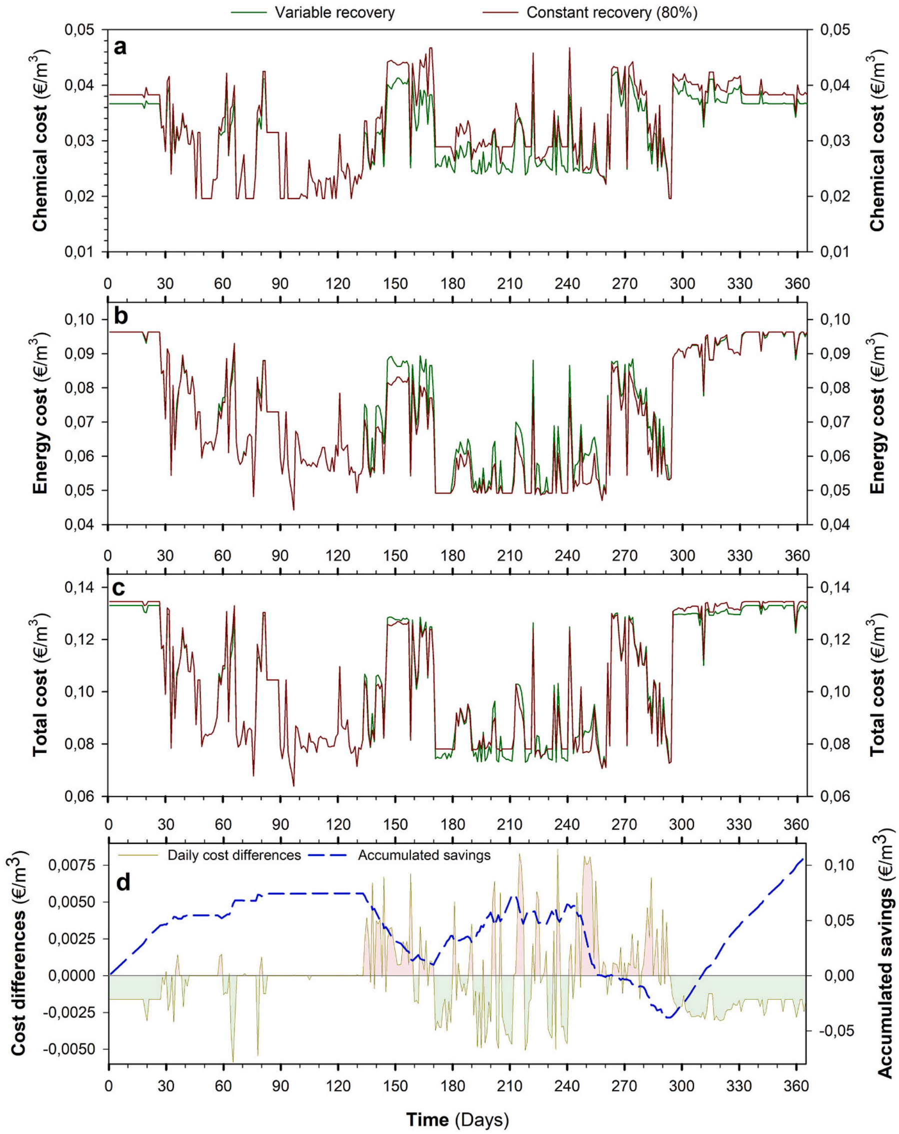

Fig. 7. Cost comparisons: **a)** Chemical cost; **b)** Energy cost; **c)** Total cost; **d)** Differences for daily costs and accumulated savings when working at variable recovery.

membrane fouling. However, the total cost for water reclamation can be reduced by more than 0.1€/m^3 in a long-term (one year) operation. Considering influent water volume by large facilities (more than 30,000 m$_3$ day^{-1}) savings can be more than 1 milion euros per year. Moreover, the ranges of recovery rates, EC, and T, are easily customized to each plant under study, which makes this control system very adaptable to other facilities.

CRediT authorship contribution statement

Albert Galizia: Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Julian Mamo:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Writing – original draft. **Gaetan Blandin:** Writing – review & editing, Visualization. **Marta Verdaguer:** Conceptualization, Methodology, Writing – original draft. **Joaquim Comas:** Conceptualization, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Ignasi Rodríguez-Roda:** Writing – review & editing, Visualization. **Hèctor Monclús:** Conceptualization, Methodology, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

Hector Monclus reports financial support was provided by Ministero de Ciencia, Innovacion y Universidades. Albert Galizia reports financial support was provided by AGAUR. Generalitat de Catalunya. Joaquim Comas, Ignasi Rodriguez-Roda, Manel Poch, Marta Verdaguer reports financial support was provided by Agency for Business Competitiveness (ACCIO). Gaetan Blandin reports financial support was provided by Agency for Business Competitiveness (ACCIO).

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.desal.2021.115284.

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