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Operation of desalination plants using renewable energies and hybrid control

Luis G. Palacin[a*], Fernando Tadeo[b], Cesar de Prada[b], Johanna Salazar[b]

[a]*Sugar Technology Centre,* [b]*Department of Systems Engineering and Automatic Control, University of Valladolid, 47011 Valladolid, Spain*
Tel. +34 (983) 423162; Fax +34 (983) 423161; email: palacin@cta.uva.es

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ABSTRACT

This paper presents a control system for the operation of desalination plants powered by locally generated renewable energy. To cope with the variability of the water demands and the available energy, the amount of water produced must be manipulated optimally. This is carried out by regulating a variable speed pump, using hybrid predictive control, which takes into account the operational limits of both the pump and the process. The operation is complex because the scheduling of the cleaning operations and the optimization of the energy consumption must be performed simultaneously to the control of the plant, fulfilling a set of additional constraints. The paper uses a continuous reformulation of the problem in order to simplify the optimization process. Simulations of a specific plant show that an optimal operation reduces the extra energy consumption, and makes it possible to supply the variable water demand.

Keywords: Reverse osmosis; Desalination plants; Hybrid control; Dynamic optimization; Model predictive control; Balance of energy supply and demand

1. Introduction

Reverse osmosis (RO) is known to be an effective means to produce drinkable water from brackish wells or sea water [1]. This is thanks to the fact that RO plants need less energy, investment cost, space and maintenance than other alternative desalination processes [2]; hence, they are the preferred desalination technique worldwide [3,4]. In particular, water supply to villages in remote areas is provided by small to medium size RO plants. In this case, advanced control techniques are needed to facilitate its autonomous functioning by reducing the human maintenance, breakage of plant elements, plant stops, etc. On the other hand, an optimal design of the operation and a good integrated design of the plant can help to reduce the size and price of the elements, decrease the energy consumption, increase the life of the plant elements, and fulfil the changing water demands of the population [5–9].

Model predictive control (MPC) is one of the most powerful tools of advanced control, and it is the technique used in this paper. Basically, a predictive controller calculates the system inputs by an optimization of the evolution of the different variables. This evolution is estimated by the use of an adequate model of the system. The difficulty of resolving the optimization problem increases when non linear models are considered and restrictions taken into account. An overview of the state-of-the-art of predictive control can be consulted in [10] and [11]. Some interesting and advantageous applications of predictive control in desalination plants can be seen in [12–16]. RO plants are typically designed to operate at a constant operation point. However, water demand var-

* Corresponding author.

ies strongly over time (over a day or a year). Commonly, these variations are eliminated by big storage tanks at the end of the production line, but there are better ways to do it. For example, a variable operation point, adjusted to the water demand variability, will decrease the size of the storage tanks, reducing the cost of equipment, the water evaporation, and the growth of microorganisms. On the other hand, the energy cost varies during a day. With a variable operation point, it is possible to decrease the costs of the operation, producing more potable water when energy is cheaper.

This paper focuses on the development of control strategies for the optimal operation of these RO plants while fulfilling the water demand. As the operation of the RO plants mixes continuous decisions on the flow of water with discrete ones, such as the cleaning operations or the loading pump, the resulting problem is hybrid in nature. At the same time, the control and operation design of the plant are considered simultaneously. An overview of non-linear and mixed-integer optimization can be consulted in [17]. The method that is proposed here within the MPC framework avoids the use of mixed-integer optimization, so that it can be implemented in real time [18]. In this task, hourly predictions of energy and water demand are used, estimated from previous measurements. The MPC applied in this paper uses a dynamic RO plant simulation tool, presented elsewhere [9], which is based on using first-principles and correlations from the literature: mass balances, energy balances, and physic-chemical equations are in the model core.
This paper is organized as follows: Section 2 presents a brief description of a typical reverse osmosis plant, the osmosis process and the energy generation. Section 3 presents the control problem, while the proposed operation strategy is shown in section 4. Finally, some results are given in section 5.

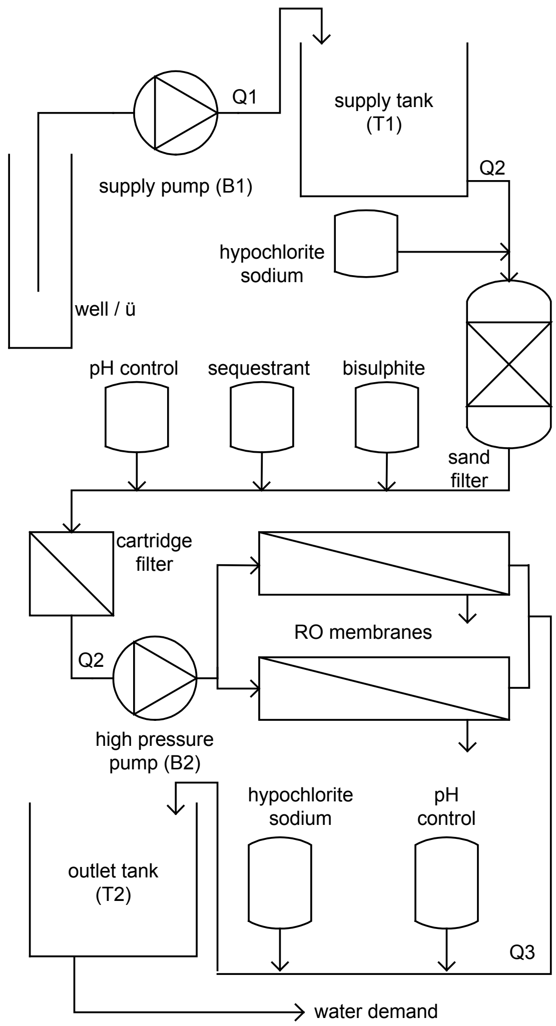

Fig. 1. Typical reverse osmosis plant.

2. Reverse osmosis plants

A typical reverse osmosis plant is shown in Fig. 1. First, a pump (B1) pumps brackish water (Q1) from a well to a supply tank (T1). From this tank, water (Q2) is pumped through a high pressure pump (B2) that increases its pressure to a value above the osmotic pressure. Next, the pressurized water goes to the RO membrane rack. The difference in pressure between each side of the membranes produces a flow of clean water through the membranes. Finally, this clean water (Q3) is stored in another tank (T2) that supplies water to the consumers. An in-depth description of the components of an RO plant can be consulted in [19].

2.1. Reverse osmosis process

Reverse osmosis is a separation process that uses high pressure to force a solvent (water) through a semi-permeable membrane that retains the solute (salt) on one side. The clean water flow is called "permeate" and needs a remineralization before being consumed. The rejected water flow is called "retentate". Typical values of permeate flow are 45% of the inlet flow for sea water, and 75% for brackish water.

A central problem during operation is the decrease in performance of the membranes, due to deposits (silt, scale, organic components, etc). Thus, in order to prevent precipitation and eliminate microorganisms, a pre-treatment is needed. It consists of filtration and the addition of chemical products. In addition, periodic cleanings are scheduled to reduce the amount of deposits. The final part of the process is a post-treatment, to make the water potable by the addition of chlorine and a remineralization.

2.2 Energy generation in RO plants

The RO process requires a high pressure on the feed side of the membrane: up to 80 bar for very salty seawater. This pressure is generated by a high pressure pump (B2) that consumes most of the electrical energy needed by the plant.

The problem at hand deals with RO plants in which the main sources of energy are renewable energies (solar, wind, etc.). These energy sources are strongly variable during the day, so good energy evolution estimation is needed in order to design an adequate control strategy.

Backup systems, to provide auxiliary energy, consisting of a diesel generator and batteries are usually needed for the correct operation of RO plants in remote areas: these involve extra cost and their use must be minimized.

3. The control problem

The main objective of the control problem is to fulfil the water demand during a given time horizon, while taking into account several constraints. In this case, the time horizon selected is 48 h and the feed water comes from a source of brackish water.

3.1 Water demand

The water demand, which varies during the day, is roughly a periodic curve that is repeated every 24 h [20]. The forecasting of the characteristic water demand curve is fundamental in a good design of a water desalination plant. This is normally carried out from historical measurements of water demand.

Fig. 2 shows a typical water demand curve of a population of 250 inhabitants over two days. It can be seen that during the night, the water consumption reaches its minimum value. It is important to note that water demand curves are slightly different for each day of the week, and especially, for each month of the year.

3.2. Control objective

Energy consumption comes from the operation of the pumps of the plant and the cleaning of the membranes. As has been mentioned, the available renewable energy (usually, solar photovoltaic panels and wind generators) can change drastically in the course of a day, so part of the energy needed is provided from (auxiliary) non-renewable energy sources (diesel generator). The control strategy must take into account the fact that auxiliary energy is needed only when the energy consumption of the plant is greater than the available renewable energy. For the optimization of the energy consumption, renewable energy predictions are required. There are good models available for solar energy prediction [21], but short-term predictions of wind energy production are more difficult [22].

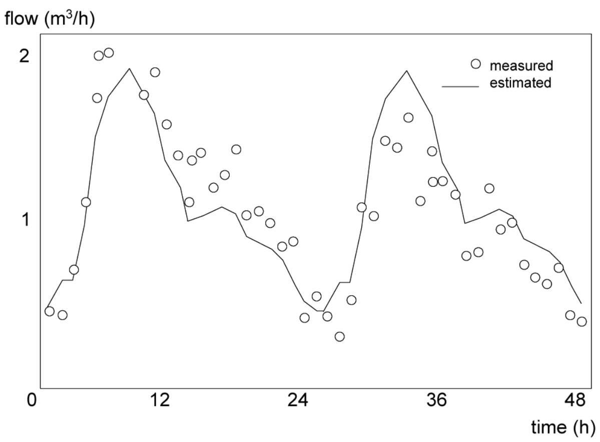

Fig. 2. Typical water demand curve: water consumption (m^3/h) vs. time (h).

The control objective is formulated jointly with an economic aim: to fulfil the potable water demand while minimizing the energy consumed using smooth control signals. Notice that as renewable energies are used the most important aspect is the minimization of the auxiliary energy consumption.

3.3. Control variables

In order to fulfil the water demand, the manipulated variables that can be modified in the control problem are:

- flow through the supply pump (B1),
- flow through the high pressure pump (B2),
- membrane cleaning.

Water recovery is another important control variable that can be taken into account, mainly if the retentate stream must be disposed of. Due to particular circumstances of the studied plant, this variable could not be considered and the water recovery was kept at around 60%.

In the case study of this paper, which represents a typical situation, the supply pump (B1) is an on/off centrifugal pump, which can pump a water flow several times higher than the maximum water flow of the high pressure pump. Thus, the pump B1 will be switched off most of the time. In order to formulate the optimization problem in practical terms, a vector input parameterization has been used that, instead of the classical formulation attaching a value (in this case 0 or 1) to every sampling period, uses a continuous parameterization, choosing decision variables than can be modified in the pump B1 whenever it switches on, as well as the duration of these switches (Fig. 3).

The high pressure pump (B2), in the case study considered in this paper, is a variable speed positive displacement pump. The nominal water flow of the pump is 1.5 m^3/h, although the pump speed can be modified by approximately 30% around this value. Thus, the manipulated variables than can be modified in the pump B2 are the n different values of pump speed in the control horizon, where n is fixed by the user (Fig. 4).

The required pressure of the retentate flow, which is

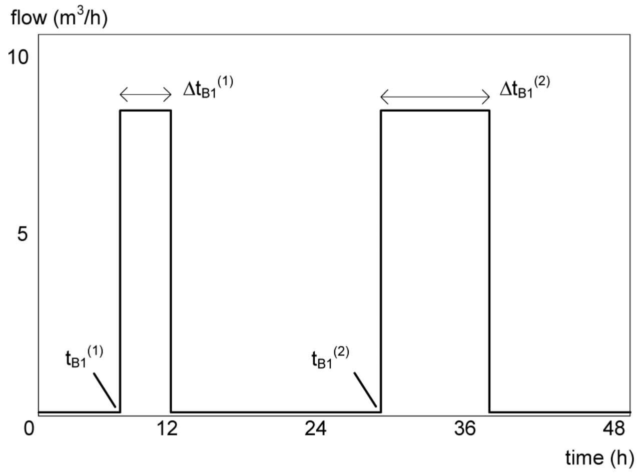

Fig. 3. Pump B1 parameterization: water flow (m^3/h) vs. time (h).

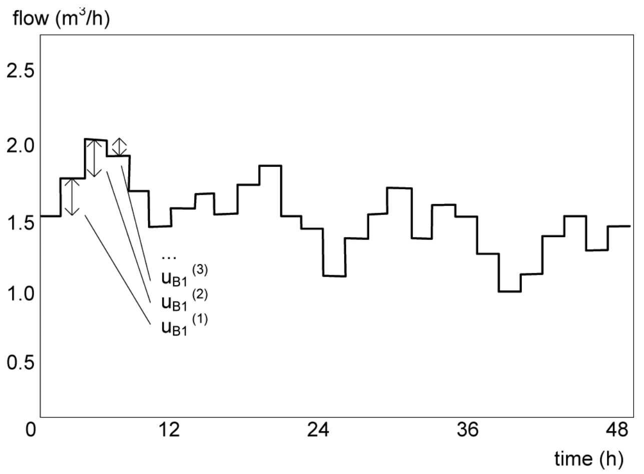

Fig. 4. Pump B2 parameterization: Water flow (m^3/h) vs. time (h).

supplied by the high pressure pump (B2), depends on the salinity of the feed water, which can also vary on a daily basis. In the considered case, a certain feed water quality (15.2 g/L of salinity) was assumed.

In order to increase the life of the membranes, it is important to perform an adequate pre-treatment and periodic cleanings of the membranes. There are several types of cleaning, but the ones studied in this paper are the half-hour long cleanings normally carried out once a day, as they are the most relevant from a control point of view. In the same way as in the case of pump B1, a special parameterization has been considered for the cleaning operation, taking advantage of its special shapes and choosing the times of the cleanings as decision variables (Fig. 5).

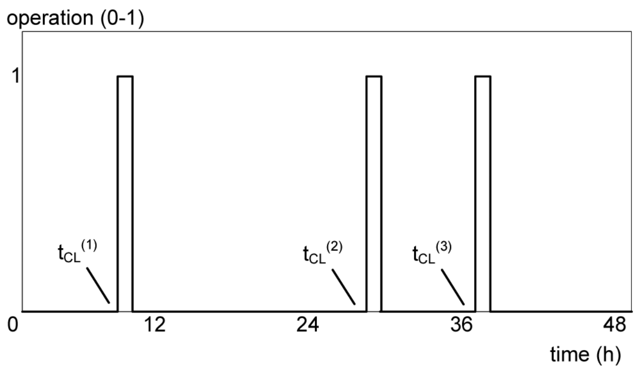

Fig. 5. Membrane cleaning parameterization.

3.4. Constraints

Following the previous discussions, there are several constraints on the control problem that have to be taken into account. The main one is keeping the water level of both tanks (T1 and T2) between a certain minimum and maximum levels. Moreover, several constraints are attached to the manipulated variables:

- After a switch on of the supply pump (B1), the following switch off cannot be done until a minimum period. In the same way, there is a minimum time between a switch off and the next switch on.
- In the high pressure pump (B2), the difference between two consecutive changes of pump speed is limited by a maximum value in order to get a smooth operation of the membranes.
- The feed water flow is limited between a minimum and a maximum value, depending on the high pressure pump (B2).
- Membranes require the permeate flux to be located between a certain minimum and maximum value.
- Finally, one membrane cleaning has to be done at least each 24 h. This means that the time between two cleanings is limited to 24 h.

4. Predictive control

The problem can be formulated in the framework of predictive control taking into account two important elements:

- First, the previous parameterization of the control problem allows a re-formulation of the hybrid control problem in terms of continuous variables only (the values of the flow pump B2 and the times of operation of the pump B1 and the cleanings).
- Second, both the economic optimization of the RO plant operation and the control problem are formulated in a single problem, avoiding the typical two layer structures (real time optimization plus model predictive control).

4.1. Mathematical formulation

Mathematically, the problem can be formulated as a minimization at each sampling time through the following equation (which takes into account the consumption of auxiliary energy and the control efforts):

$$J = \beta_1 \int_0^{24\text{h}} E_{\text{auxiliary}} \, d\tau + \frac{\beta_2}{n_{\text{B2}}} \sum^{n\text{B2}} \Delta u_{\text{B2}}^2 \tag{1}$$

where β1 and β2 are weighting factors, $E_{\text{auxiliary}}$ is the auxiliary energy (kJ), and nB2 is linked to the number of values of the parameterization of the flow of the high pressure pump (B2). Δu_{B2} are the changes between two consecutive values of the flow of the high pressure pump (B2).

As for the following manipulated variables:

$$t_{\text{B1}}^{(1)}, t_{\text{B1}}^{(2)}, t_{\text{B1}}^{(3)} \ldots t_{\text{B1}}^{(n\text{B1})}$$
$$\Delta t_{\text{B1}}^{(1)}, \Delta t_{\text{B1}}^{(2)}, \Delta t_{\text{B1}}^{(3)} \ldots \Delta t_{\text{B1}}^{(n\text{B1})}$$
$$u_{\text{B2}}^{(1)}, u_{\text{B2}}^{(2)}, u_{\text{B2}}^{(3)} \ldots u_{\text{B2}}^{(n\text{B2})}$$
$$t_{\text{CL}}^{(1)}, t_{\text{CL}}^{(2)}, t_{\text{CL}}^{(3)} \ldots t_{\text{CL}}^{(n\text{CL})}$$

t_{B1} are the time instants when the pump switches on; Δt_{B1} values are the duration of the supply pump B1's operation; u_{B2} are the different values of the high pressure pump speed; t_{CL} are the time instants when the membrane cleaning starts; nB1 are the number of allowed supply pump switchings; nB2 are the parameterization of different speeds of the high pressure pump (B2): nCL are the number of membrane cleanings and the super index i means the element of each discretization.

The following constraints must be taken into account:

$$t_{\text{B1}}^{(i)} - t_{\text{B1}}^{(i-1)} + \Delta t_{\text{B1}}^{(i-1)} \geq \varepsilon_1$$
$$\Delta t_{\text{B1}}^{(i-1)} \geq \varepsilon_2$$
$$\varepsilon_3 \leq \Delta u_{\text{B2}}^{(i)} \leq \varepsilon_4$$
$$t_{\text{CL}}^{(i)} - t_{\text{CL}}^{(i-1)} \leq \varepsilon_5$$

where ε_1, ε_2, ε_3, ε_4 and ε_5 are constants.

The process model must also be included. Notice that, for the particular use of the MPC optimization, a reduced RO plant model can be considered that takes into account only the mass balances in the two supply and output tanks of Fig. 2 and the associated flow of B1, B2, as well as the cleaning operations. The model is formulated in continuous time and solved using the simulation software EcosimPro©, when needed by the optimizer. The hybrid dynamic optimization has been reformulated in continuous terms using the above-mentioned parameterization of the pump B1 and the cleaning operation, so it can be solved with a sequential approach combining an SQP algorithm and the process simulation [18].

The optimization is repeated each sample time, and the differences between estimated variables and measurement values are incorporated as corrections, as is the usual practice in MPC. Notice that the hybrid controller will use the water demand predictions (Fig. 8), as well as estimations of the available renewable energy (Fig. 11), that would be supplied by an energy management system in charge of the wind turbines, solar panels, diesel generators and batteries of the energy subsystem. How to generate these predictions is beyond the scope and length of this paper.

5. Simulation results

A complete tool for the dynamic simulation of RO plants has been developed and presented elsewhere [9]. This software is a dynamic and modular library, which is developed in EcosimPro© simulation environment, and it is based on using first-principles and correlations from the literature and requires the typical system parameters in an RO plant (quality of feed water, salinity, scale concentration, pH, temperature, pump characteristic curves, type of filter, membrane characteristics , etc.). A detailed simulation of an existing RO pilot plant was developed and tested [23]. This simulation is being used for testing the proposed hybrid control system. Some preliminary results are now presented.

Control of the RO plant during two days was simulated, using a prediction horizon for the MPC controller of one day. Results of the closed loop operation are given in Figs. 6–11. Fig. 6 displays the inlet flow (Q1) and outlet flow (Q2) of the supply tank (T1) and Fig. 9 the corresponding level in the tank. This level is kept within the desired limits of 10% and 90%.

The flow of water to be cleaned (Q2) and the changing water demand (Q3) are given in Fig. 7, while the difference between the real water demand (Q3) and the estimated water demand appears in Fig. 8. Next, Fig. 9 shows the evolution of the tank. The optimized system

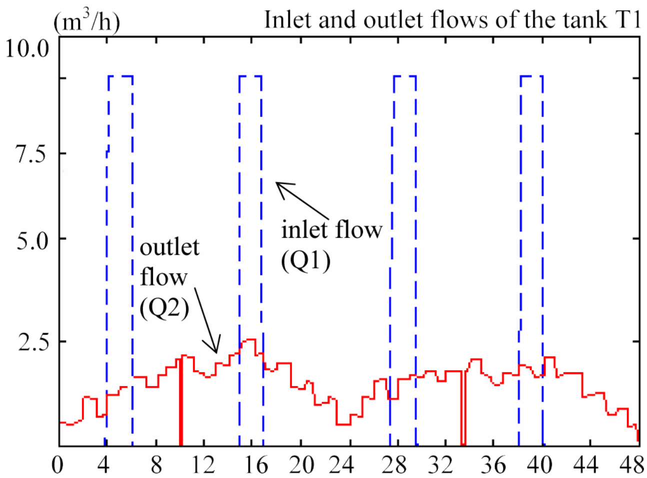

Fig. 6. Inlet flow (Q1) and outlet flow (Q2) of the tank T1, during 48 h. Notice the time instants when the membrane cleaning starts (time = 10 and 33 h).

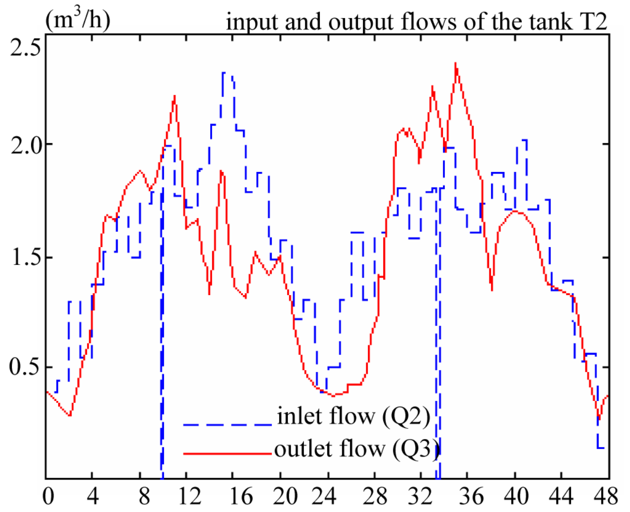

Fig. 7. Input and output flow of the tank T2, during 48 h. Notice the time instants when the membrane cleaning starts (time = 10 and 33 h).

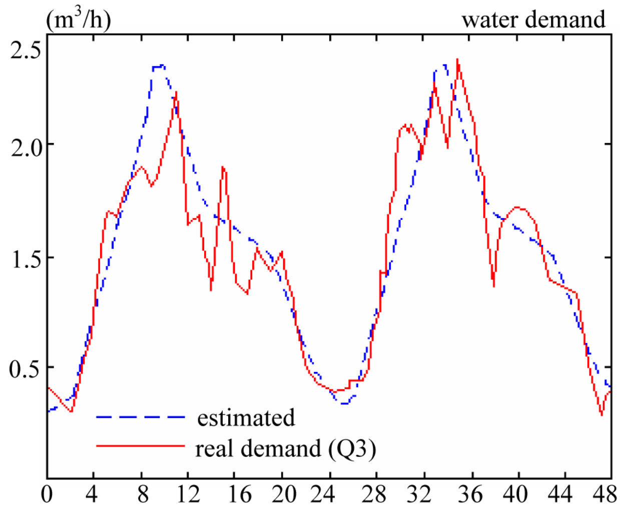

Fig. 8: Water demand during 48 h.

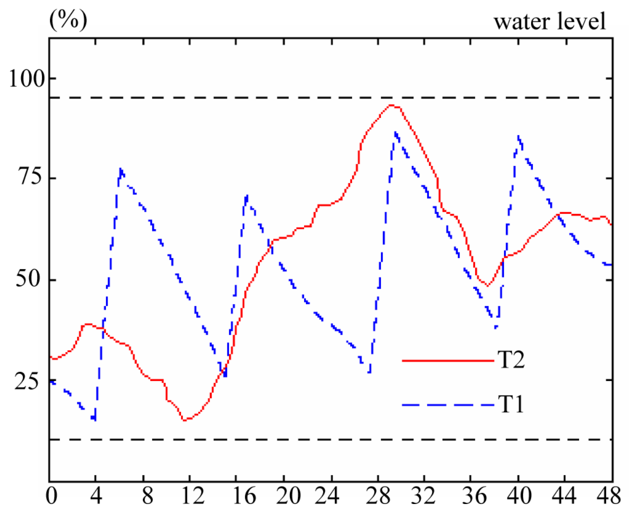

Fig. 9. Water level of both tanks during 48 h.

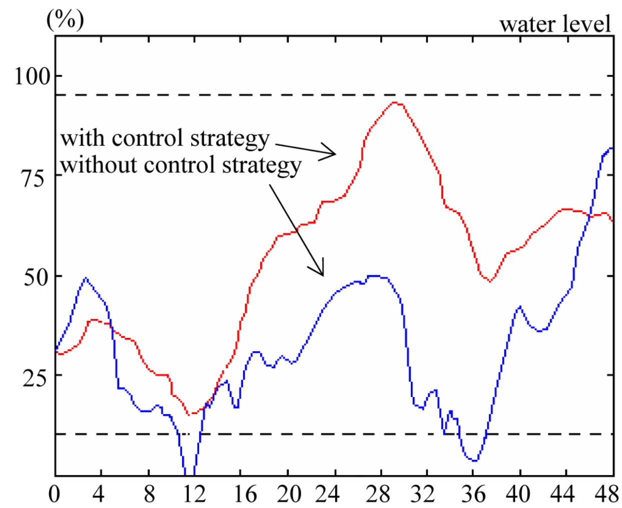

Fig. 10. Water level of the outlet tank during 48 h.

uses the temporal excess of renewable energy to produce more drinking water and store it (in tank T2) for the off-peak energy hours and fulfil the demand. Fig. 10 shows the produced water level of the outlet tank (T2) with and without control strategy. Notice that only with the proposed strategy is the water demand fulfilled, maintaining the level within the range of 10–90%. Without a correct control strategy, the water demand is not fulfilled and the tank T2 gets empty. More benefits of the proposed hybrid control strategy can be seen in [24].

The optimal energy consumption is represented in Fig. 11, where the renewable energy that is available and the energy consumed by the RO plant are shown. The controller minimizes the grey areas where non renewable energy has to be used, favouring the processing of a higher flow of water when more renewable energy is available, as can be seen from Fig. 7.

5. Conclusions

This paper presents a hybrid control algorithm for the automation and optimal operation of reverse osmosis plants, coupled with autonomous energy sources. The proposed approach is devised to improve efficiency, extend the life of the components and reduce installation and operation costs. The developed algorithms are based

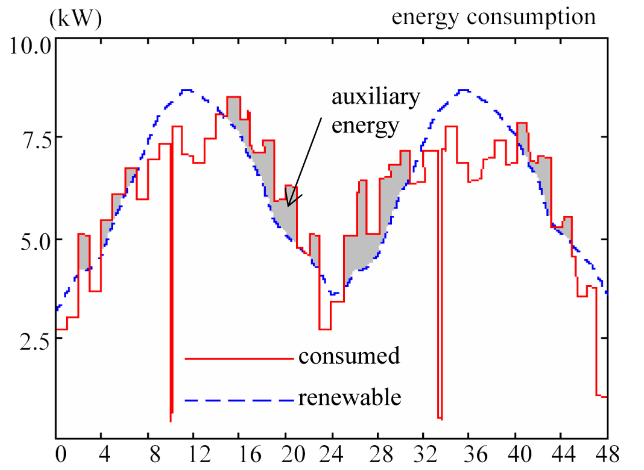

Fig. 11. Energy consumption by the RO plant and available renewable energy during 48 h. Notice the time instants when the membrane cleaning starts (time = 10 and 33 h).

on a reformulation of the control problem in terms of continuous variables that avoids mixed-integer optimization and integrates the economic operation of the process. It uses hourly predictions of water demands to adequately schedule the cleaning times and the operation of the pumps, taking into account the different restrictions of the components of the plant. Preliminary results, based on the application to a model of a specific pilot plant powered by renewable energies, are promising, in the sense that an adequate control of the system is achieved, fulfilling the control objectives and without excessive use of auxiliary energy.

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Symbols

E — Energy consumption, kW
J — Objective function for the optimization, kWh
nB1 — Number of allowed pump B1 switchings during the simulation time
nB2 — Number of different speeds of the high pressure pump B2 during the simulated time
nCL — Number of membrane cleanings during the simulated time
t_{B1} — Time instants when the pump B1 switches on, h
t_{CL} — Time instants when the membrane cleaning starts, h
u_{B2} — Different values of the high pressure pump speed, Hz
β — Weighting factor in the objective function
ε — Value of restrictions, h for i = 1,2,5, Hz for i = 3,4
Δt_{B1} — Duration of the pump B1 switched on, h

References

[1] C. Fritzmann, J. Löwenberg, T. Wintgens and T. Melin, State-of-the-art of reverse osmosis desalination, Desalination, 216 (2007) 1–76.
[2] A. Gambier, A. Krasnik and E. Badreddin, Dynamic modeling of a simple reverse osmosis desalination plant for advanced control purposes, Proc. of the American Control Conference, New York, USA, 2007.
[3] R. Baker, Membrane Technology and Applications, Wiley, 2004.
[4] M. Wilf, The Guidebook to Membrane Desalination Technology, Balaban Desalination Publication, L'Aquila, Italy, 2007.
[5] A. Mindler and A. Epstein, System identification and control of reverse osmosis desalination, Desalination, 59 (1986) 343–379.
[6] I. Alatiqi, H. Ettouney and H. El-Dessouky, Process control in water desalination industry: an overview, Desalination, 126 (1999) 15–32.
[7] A. Gambier and E. Badreddin, Dynamic modelling of MSF plants for automatic control and simulation purposes: a survey, Desalination, 166 (2004) 191–204
[8] U. Seibert, G. Vogt, C. Brennig, R. Gebhard and F. Holz, Autonomous, desalination system concepts for seawater and brackish water in rural areas with renewable energies, Desalination, 168 (2004) 29–37.
[9] L. Palacin, C. de Prada, S. Syafiie and F. Tadeo, Library for dynamic simulation of reverse osmosis plants, Proc. 20th European Modeling and Simulation Symposium, Briatico, Italy, 2008.
[10] S.J. Qin and TA. Badgwell, An overview of industrial model predictive control technology, Houston, TX USA, 93 (1997) 232–256.
[11] S.J. Qin and TA. Badgwell. A survey of industrial model predictive control technology, Control Eng. Practice, 11 (2003) 733–764.
[12] A. Bartman, P. D. Christofides and Y. Cohen, Nonlinear model-based control of an experimental reverse osmosis water desalination system, Ind. Eng. Chem. Res., 48 (2009) 6126–6136.
[13] A. Bartman, C. McFall, P. D. Christofides and Y. Cohen, Model predictive control of feed flow reversal in a reverse osmosis desalination process, J. Proc. Contr., 19 (2009) 433–442.
[14] C. McFall, A. Bartman, P.D. Christofides and Y. Cohen, Control and monitoring of a high-recovery reverse-osmosis desalination process, Ind. Eng. Chem. Res., 47 (2008) 6698–6710.
[15] G. Bacelli, JC. Gilloteaux and J. Ringwood, A predictive controller for a heaving buoy producing potable water, Proceedings of the European Control Conference, Budapest, Hungary, 2009.
[16] A. Zafra-Cabeza, M.A Ridao and E.F. Camacho, Optimization in reverse osmosis plants through risk mitigation, Proc/ European Control Conference, Budapest, Hungary, 2009.
[17] C.A. Floudas, Nonlinear and mixed-integer optimization. Fundamentals and applications, Journal of global optimization, Springer Netherlands, 12 (1998) 108–110.
[18] D. Sarabia, F. Capraro, L.F.S. Larsen and C. de Prada, Hybrid NMPC of supermarket display cases, Control Eng. Practice, 17 (2009) 428–441.
[19] N.M. Al-Bastaki and A. Abbas, Modeling an industrial reverse osmosis unit, Desalination, 126 (1999) 33–39.
[20] F. Tadeo, R. Val, L. Palacin, C. de Prada and J. Salazar, Control

of reverse osmosis plants using renewable energies, control and applications, July, Cambridge, UK, 2009.

[21] S. Alvisi, M. Franchini and A. Marinelli, A short-term, pattern-based model for water-demand forecasting, Hydroinformatics, 9 (2007) 39–50.

[22] G. Giebel, The State-of-the-art in short-term prediction of wind power. Project ANEMOS ENK5-CT-2002-00665, 2003.

[23] S. Syafiie, L. Palacin, C. de Prada and F. Tadeo, Membrane modeling for simulation and control of reverse osmosis in desalination plants, Proc. Control 2008, September, Manchester, UK, 2008.

[24] L. Palacin, F. Tadeo and C. de Prada, Integrated design using dynamic simulation of reverse osmosis plants, Proc. Conference on Industrial Eng. and Management, IEEE 2009, Hong Kong, China, 2009.