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Energy analysis of a seawater reverse osmosis desalination system for small marine vessels

G. Nicolás Marichal Plasencia, Jorge Camacho-Espino*, Deivis Ávila Prats, José A. Rodríguez Hernández, Felipe San Luis Gutiérrez

Department of Agricultural, Nautical, Civil and Maritime Engineering, University of La Laguna (ULL), Avda. Francisco Larroche s/n, 38071, Santa Cruz de Tenerife, (Canary Islands), Spain, emails: jcamache@ull.edu.es (J. Camacho-Espino), nicomar@ull.edu.es (G. Nicolás Marichal Plasencia), davilapr@ull.edu.es (D. Ávila Prats), jandas@ull.edu.es (J.A. Rodríguez Hernández), fsanluis@ull.edu.es (F.S. Luis Gutiérrez)

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ABSTRACT

Desalination in the marine world has always been one of the most widely used resources for obtaining fresh water. Its greatest disadvantage is energy consumption, which has led to many studies to investigate how to reduce it. This work presents the results obtained from analysing the energy consumption of a small-scale seawater reverse osmosis desalination plant and its application in small marine vessels. An artificial neural network model was applied to optimise the performance of the plant. For this research, different parameters have been considered, namely, the flow rate, pressure and conductivity of the water demanded in the vessel. In the experimental study, the optimal pressure points applied in the system are estimated to satisfy both the water quality and low energy consumption requirements.

Keywords: Desalination; Reverse osmosis; Artificial neural networks; Small vessels

1. Introduction

For millions of years, desalination has been occurring through the natural process of water evaporating from the sea surface [1]. Eventually, this method was industrialised and widely adapted by mankind to obtain fresh water. Throughout history, different ways have been used to desalinate salt water. Spain has been a pioneer in this area, and more specifically the Canary Islands, where this technology has been developed due to the scarcity of water on the Western Islands (Gran Canaria, Fuerteventura and Lanzarote) [2].

The main drawback of desalination is the large amount of energy consumed throughout the process to produce fresh water, something that has been gradually reduced over the years after numerous studies. When reverse osmosis technology started in the 1970s, the specific energy consumption in plants was over 15 kWh/m^3 of water produced. Currently, plants consume in total between 2.5 and 5 kWh/m^3 [3].

The two major technologies for desalting sea or brackish water are distillation and membrane processes. Within desalination technologies, reverse osmosis (membrane process) is by far the most dominant, producing 69% (65.5 million m^3/d) of the total global desalinated water. This is due to its low energy consumption compared to other water desalination technologies. Multi-effect distillation and multi-stage flash (distillation technologies) produce most of the remaining desalinated water, with market shares of 18% and 7% respectively [4].

* Corresponding author.

1.1. Vessels and the marine world

A bibliographic review shows that there have been many studies and improvements in onshore desalination; however, there are not as many references regarding the marine world. The intention of this research is thus to improve the control and planning of these systems in boats of different sizes.

To obtain drinking water on a ship, there are mainly two methods: storing it on board and refilling it in port once it is used or obtaining it from the sea through a desalination process. Rainwater can also be collected, but it would not be suitable for human consumption. For long trips, saving space on any boat is always an advantage, making desalination an attractive option to meet the water demand.

Desalination systems are widely used nowadays on large ships, such as cruise ships, but not as much on small ones. The vessels to which this study could be applicable include pleasure craft such, as sailboats or yachts, and fishing vessels. A primary concern in boats is calculating the energy consumption of the whole system, which makes it necessary to carry out the best possible planning if a seawater reverse osmosis (SWRO) plant is to be used on the boat.

Most of the energy supplied in ships comes from fossil fuels. Employing these resources to supply energy not only has economic consequences, but their environmental and social cost is very high in terms of damage to human health and the environment. For example, electricity in fishing boats in Spain is produced using generators located in the engine room, sized according to the power of the equipment installed on board. Although a coefficient that considers the simultaneity of equipment should be considered, a lack of knowledge in this regard leads to excessive oversizing of generators [5].

1.2. Artificial Intelligence applied to desalination

Many studies have been carried out over the years since El-Hawary [6] first applied a neural network in 1993 to the field of desalination. Other researchers have applied different Artificial Intelligence techniques to desalination, such as artificial neural networks [7,8], fuzzy logic, genetic programming and model trees [9–11].

In the field of desalination, several approaches based on the development of physical equations have been used. In general, these mathematical models tend to be complex, in the sense that they are high-dimensional models and show a complex interaction between their different variables. Consequently, many researchers have applied new paradigms as an alternative approach from the point of view of identification and control of systems [12,13]. In this article, artificial neural networks have been chosen as this alternative paradigm. Therefore, the main novelty of this work lies in proposing a predictive tool based on neural networks to optimize the operation of a desalination plant based on different relevant criteria within a vessel.

1.3. Aims of the research

Considering the points mentioned above, the need arises to design tools that can be used to adequately plan energy consumption on boats. The main objective of this study is to develop a predictor tool that allows the user or operator to adjust the main actuator of the plant (pressure vessel) to plan the time of use of the equipment considering the needs of the boat and the salinity of the permeate water.

Through the model developed using artificial neural network (ANNs), the system was able to output the pressure at which it is necessary to run the pump and the time the plant takes to desalinate the water demanded. This minimises the energy consumed to produce water on the boat. The parameters used in the neural network are specified below.

For the study, measurements were made onshore; however, in the future, we propose implementing the system in vessels such as the one shown in Fig. 1 (University of La Laguna) to obtain data on the high seas with different feedwater temperatures in the desalination plant.

The paper is structured as follows. Section 2 describes the equipment used, while the model developed is shown in Section 3. Then, Section 4 discusses the results, and the conclusions of the study are presented in Section 5.

2. Description of the equipment

Experiments were carried out with a small-scale seawater reverse osmosis desalination plant (OSMOMAR OM-02-01). It is a single-stage plant (Fig. 2) that consists of a low-pressure pump that transports the salt water to the device after it goes through a pre-filtration system (which includes a disk filter and three cartridge filters). Once the water is filtered, it is transported to the membrane, in which a high-pressure pump (HPP) supplies enough pressure to force the feed flow to pass through one membrane, exceeding the osmotic pressure and leaving behind the salts present in the water.

In this study, the plant was assembled with a single membrane because the objective is to find the optimum working pressure in the simplest scenario possible. However, the device allows up to a maximum of three membranes. Note that our interest is focused on small marine vessels where a simpler configuration is desired. Therefore, as the device used is a pilot plant for research purposes, a single membrane has been assembled.

The main characteristics of the plant are shown in Table 1. The values shown in this table are indicative since they vary depending on different parameters: temperature and conductivity of the feedwater, number of membranes used in the plant, etc.

The entire unit is shown in Fig. 3. This structure makes it possible to transport the plant and to take datasets in different places. In this case, data were taken onshore. The MATLAB software was used to design the tool.

3. Methodology

3.1. Data generation

The experimental data used to feed into the neural networks were obtained in Tenerife (Canary Islands, Spain). The feedwater temperature, pH and conductivity used in the data collection are considered constant. The values

Fig. 1. Sailboat of the Polytechnic School of Engineering (Universidad de La Laguna).

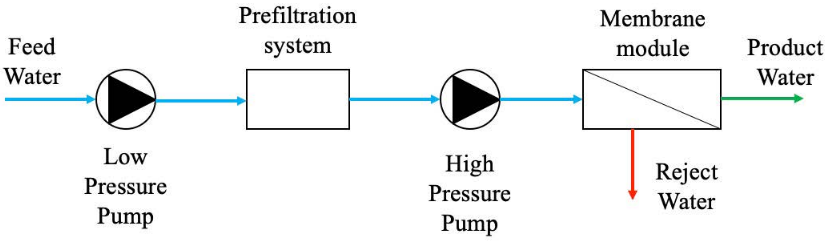

Fig. 2. Layout of the single-stage SWRO plant.

Table 1
Main characteristics of the plant

Parameter	Characteristics
Production capacity, l/d	1,500–2,000
HPP working pressure, bar	55
HPP maximum pressure, bar	65
HPP rpm	1,500
Feed flow rate, l/min	16
Permeate recovery rate, %	35 (3 membranes)
Electrical connection	400 V, 3 ph, 50 Hz
Power consumption, kW	2.75
Membrane type	Cross-lined aromatic polyamide
Element configuration	Spiral wound, tape wrap

shown below are the average feedwater readings during the data collection:

- Temperature: 19.68°C
- pH: 8.06
- Conductivity: 51,623 µS/cm

While the data were collected, the plant was connected to the conventional electricity grid, meaning the feed flow and the power consumed by the lower pump were constant. The pressure applied in the HPP was varied from 0 to 60 bar, which allowed us to observe the behaviour of the system. As mentioned before, the variables of interest in the study are the pressure of the HPP, the power consumed by the plant, the permeate flow rate and the permeate conductivity.

In total, 901 samples of each variable were considered. Table 2 shows an example of the dataset used to feed the artificial neural networks. It is important to remark that a variation from 0 to 60 bar has been done. Only values above 50 bar have provided an adequate amount of water. Because of that, only these values have been considered in Table 2.

3.2. Artificial neural networks structure

As already explained in the introduction, there is a need to achieve the greatest possible energy savings in any marine vessel. The tool developed allows the crew of a small boat to plan the use of the desalination plant in detail. This, therefore, can be used to anticipate the energy consumption of the system and to vary the working pressure depending on the conductivity of the desalinated water.

The plant was operated in different scenarios; that is, different positions of the valve were tested. Different parameters, such as, HPP pressure, permeate flow rate, permeate conductivity and power were obtained for each case. Note that these parameters were obtained in steady state; hence, each scenario corresponds with each experimental run.

Fig. 3. SWRO desalination plant used in the research.

With this in mind, the goal is to find the most efficient scenario for a given permeate conductivity value and adjust the valve pressure to that value. Once that value is chosen, the other parameters can be obtained by using the corresponding values of these parameters for this scenario, since it was already tested previously.

In this paper, an alternative approach for devising a model is shown that relies on experimental scenarios instead of using a model developed from theoretical knowledge. Because of this, the resulting model in this case is less general that one based on equations associated with theoretical knowledge.

In this case, only a specific plant in a particular working environment is considered, which means that only a limited change in the conditions of the plant and their variables is allowed. In order to achieve this prediction model in these restricted working conditions, neural networks were used.

To control several variables of the desalination plant, a strategy based on varying the pressure and keeping constant the input flowrate was chosen from the various alternative control strategies shown by Pohl et al. [14]. Note that, the recovery rate, water amount, and permeate conductivity are values changing in the control process. However, in this paper, the devised control strategy was focused on dealing only as setpoints the water conductivity and a water amount. A diagram representing the open-loop control scheme is shown in Fig. 5. The open-loop controller has been named "predictor tool" in the figure.

The networks used to solve this problem are three two-layer feed-forward networks using the Levenberg-Marquardt optimisation method, which stops the training automatically when the generalisation stops improving. The dataset obtained feeds it. The input to the ANNs is the permeate conductivity rate, while the outputs are the HPP pressure, the permeate flow rate and the power consumed by the plant (Fig. 4).

The optimal number of hidden layers used in neural networks was previously studied [7]. When choosing the number of neurons in the hidden layer, ten neurons were chosen in each of the three neural networks using a trial-error system. The network uses an activation sigmoidal function (1) in the hidden layer and a linear activation function (2) in the output layer.

$$f(x) = \frac{1}{1+e^{-x}} \tag{1}$$

where x is the sum of the weighted inputs to the neuron and $f(x)$ represents the output of the node.

$$f(x) = x \tag{2}$$

Finally, the data were divided into three groups for training, validation, and testing. 70% of the data were used to train the network (it adjusts to its error), 15% to validate it (these samples were used to measure network generalisation and stop the training when this generalisation stops improving) and 15% to test it, which provided an independent measure of the network's performance during and after the training.

The network validation system is the mean square error (MSE), one of the most widely used systems today, and the root mean square error (RMSE). MSE is the average squared difference between outputs and targets and is defined by the following equation:

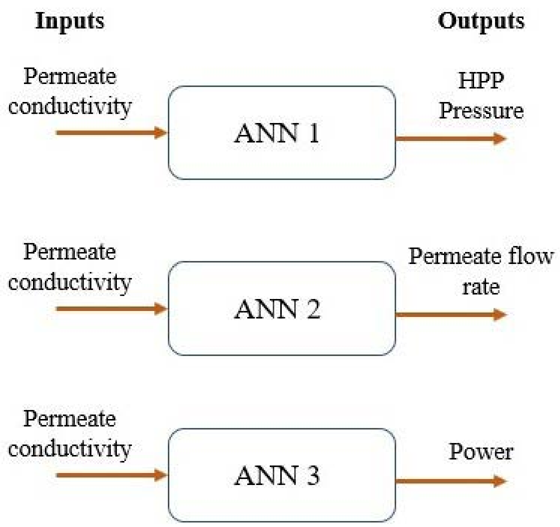

Fig. 4. Diagram of the artificial neural networks.

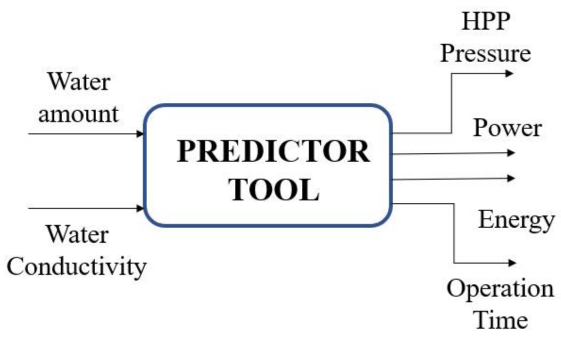

Fig. 5. Layout of the predictor tool developed.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \quad (3)$$

where n is the number of predictions, Y is the vector of observed values and $\hat{Y}$ is the vector of predicted values.

From a certain amount of water and a permeate conductivity as set-points, the following variables are obtained: the pressure at which the HPP has to turn on, the energy consumption and the run time of the unit. Note that the set-points given as inputs in Fig. 5 are achieved by these output variables. The results are discussed in the next section.

4. Results

After training, validation and testing the network, the results were analysed and displayed using different graphs. Figs. 6, 7 and 8 show the correlation coefficients R of the three different ANNs developed. In addition, Table 3 provides the results of the MSE and RMSE used to validate the ANN.

Note that the RMSE values given in Table 3 are the output errors; that is, the RMSE values corresponding to ANN1, ANN2 and ANN3. As we can see, the value obtained was 1.494 bar. This means that the output value only varies by approximately 1.494 bar with respect to the real value. The RMSE values corresponding to ANN2 and ANN3 refer to errors in permeate flow rate units and power units, respectively. Note that the values obtained exhibit a small variation with respect to the real values, so the results are satisfactory.

Figs. 6, 7, and 8 show plots of the network outputs (predicted rates) vs. the targets (actual rates). We see that the correlation coefficients R of the ANNs are not far from 1. The values of ANN1 (R = 0.93062), ANN2 (R = 0.95848) and ANN3 (R = 0.94251) are consistent with good results.

Finally, an example is shown in which the input values of the predictor tool are simulated to validate the method used in the paper.

For example, if the needs of a vessel were to obtain 100 L of water with a conductivity of 500 µS/cm, the outputs of the predictor function would indicate the following:

- HPP pressure: 49.202 bar
- Plant run time: 1.6 h
- Power used: 3.9 kW
- Energy used: 5.711 kWh

Table 3
Validation systems of the ANNs

Artificial neural network	MSE	RMSE
ANN1	2.232	1.494 bar
ANN2	8.4712	2.9105 µS/cm
ANN3	1,267.5	35.6022 W

Table 2
Sample of the recorded dataset

Row number	Permeate flow rate (l/h)	Permeate conductivity (µS/cm)	HPP pressure (bar)	Power (W)
1	50	657	50	2,139
…	…	…	…	…
…	…	…	…	…
450	62.5	475	55	2,394.7
…	…	…	…	…
…	…	…	…	…
900	75	415	60	2,526.5

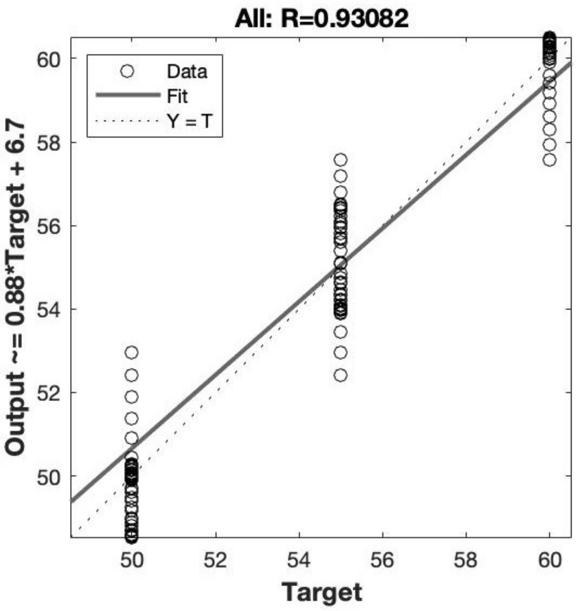

Fig. 6. Regression values of ANN1.

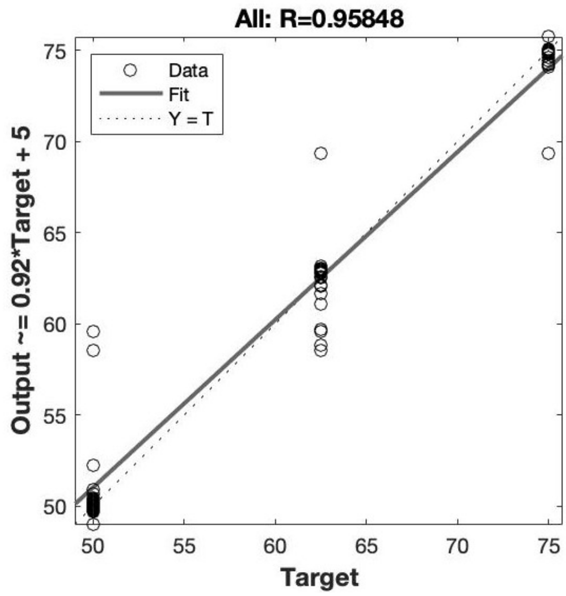

Fig. 7. Regression values of ANN2.

5. Conclusions

In this paper, three artificial neural networks were used to predict the behaviour of an SWRO desalination plant implemented in a small boat. After that, a predictor tool was developed to facilitate the planning of the plant.

The predictor tool provides a good energy planning on small vessels. It is important to remark that this fact is relevant, considering how limitations in the availability of energy is a common characteristic in vessels (especially when renewable energies are used).

As shown in Table 3, good results are obtained in terms of the root mean squared errors for the variables of

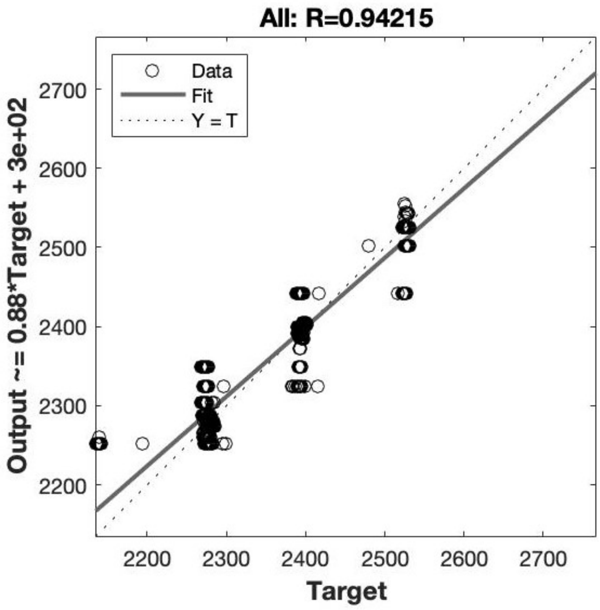

Fig. 8. Regression values of ANN3.

interest. That is, the level of prediction for the variables of interest allows devising a convenient predictor tool for the optimal operation of the desalination plant according to a set of established criteria.

Although the proposed predictor tool is adequate for vessels in general, this paper focused on small vessels where a tool of this kind is essential, given their more restrictive water and energy limitations. Moreover, the small size of the vessel suggests having the desalination plant run for a short period of time in order to avoid excessive noise, and also to avoid concurrent operations with other equipment. The methodology proposed thus provides a convenient tool with which to achieve these objectives.

For the sake of simplicity, only one membrane has been used. However, the proposed methodology could be easily extended to a greater number of membranes. The use of new membranes would allow reducing the working pressure. On the other hand, new studies could be carried out to improve the plant performance including new elements as antiscalants. These new elements could be a significant improvement from the maintenance point of view.

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