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Operating and maintenance cost in seawater reverse osmosis desalination plants. Artificial neural network based model

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ABSTRACT

The implementation of seawater reverse osmosis (SWRO) desalination plants was key to ensure the fresh water supply in arid and coastal regions. The high operating and maintenance (O&M) cost in these plants are an impediment. In this paper,the O&M cost of twelve SWRO desalination plants located in Fuerteventura (Canary Islands) were analyzed. A mathematical model was elaborated to estimate the O&M cost. The inputs were the production capacity of the line, recovery, energy consumption and the price per kWh. The specific cost related to the energy consumption is complex to be evaluated because of its dependence on other factors such as energy recovery system, chemical cleaning frequency and electrical energy tariffs. It was observed that the specific cost of the chemicals, cartridge filters, membrane replacement, staff and maintenance decreased with the production and recovery increase in the studied ranges. The model was verified with the data proving to be a good estimator.

Keywords: Seawater; Reverse osmosis; Operating and maintenance; Costs

1. Introduction

The main impediment for desalination is high costs of constructing and operating desalination facilities [1–3], which directly translates to the cost of desalinated water, paid by consumers. Costs of desalination vary considerably from country to country and from region to region. They are determined by geographical, socio-economic and environmental conditions as well as regulations regarding establishing and operating desalination plants. Usually, in the O&M cost, the relative percentage of power, chemical and membrane replacement costs increase, and percentage of maintenance and staff costs decrease with the increase in source water salinity. Chemical costs are quite variable from one location to another and are mainly dependent on the source water quality, pretreatment processes [4], and the product water quality required.

Some authors have focused their efforts on the study of membranes technology (increasing the membrane active surface, water permeability coefficient or reducing the pressure drop on the membrane surface) to reduce the O&M cost [5–7]. The staff costs of a SWRO desalination plant are closely related to plant size, complexity and number of treatment processes and equipment, and to the overall level of plant automation [8]. The maintenance costs are quite complex to be evaluated, it includes all expenditures associated with routine plant operations and preventive and emergency maintenance of plant equipment, structures, buildings, and piping. Typically, the useful life of most of the key desalination plant equipment is between 25 and 50 years [9]. The energy consumption is the main factor in terms of costs in SWRO [10–14], it is directly related to the source water salinity and temperature, and the associated osmotic pressure that has to be overcome in order to produce fresh water.

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This work aims to evaluate the O&M cost of twelve SWRO desalination plants operating in Fuerteventura (Canary Islands, Spain). An artificial neural network model (ANNM) was designed to estimate the O&M specific cost of SWRO desalination plants knowing the production capacity, recovery and the specific energy consumption (SEC).

2. Material and methods

2.1. Plants data

The data of twelve SWRO desalination plants between 2005 and 2012 were collected; the plants were named with the numbers 1–12 due to the privacy of the information and the inability to make public the status of each desalination plant. The main characteristics are summarized in Table 1.

The chemicals, cartridge filters and membrane replacement, staff and maintenance costs were considered to make the estimating model. The energy consumption of a RO system depends on the pretreatment, arrangement, operating condition, ERS etc. and the electrical market is quite variable depending on the region, so the energy consumption of the RO system was considered as an input as well as the price of the electricity in terms of power and consumption. These average data per cubic meter of produced water are shown in Table 2 and the price of the electricity (averages) in terms of power and consumption in shown in Table 3. Fig. 1 shows the distribution of the O&M specific cost in averages for SWRO desalination plants.

2.2. Artificial neural network based model

Artificial neural networks (ANNs) are based on the architecture of biological nervous system, which consists basically of a large combination of simple nerve cells or neurons that work in parallel to facilitate fast decisions. ANNs are made up of a large number of primitive computational elements that are arranged in a massive parallel set [15]. The ANN is developed in artificial synapses which connect these elements that are characterized by a set of weights, which can typically be adjusted by a learning process. The most important advantage in using this mathematical method is that ANNs do not have to be programmed; instead they use examples to learn how to deal with more complex relationships [15]. ANNs are intensively used in applications such as process control [16], modelling [17], simulation and system identification [18]. Their popularity could be attributed to the fact that ANNs can solve many different types of engineering problems with a relatively simple and flexible structure, in fact,many authors have recently used ANNs to resolve water treatment problems [19–30].

Basically, an ANN sis formed by nets of primitive elements (neurons) that receive signals (inputs) from other neurons or from the outside. These signals are subsequently weighted and summed [15]. The results (also called potentials of the neurons) are then computed by transfer functions, which pass the output to other nodes to the outside environment of the network. The network has a structure consisting of at least an input and an output layer, and possibly one or more hidden layers. Neurons in these layers are connected by means of artificial synapses, each of which is associated with a numerical value or weight. Once the ANN is built, trained, validated and tested, with respect to a different set of inputs, it is able to produce a corresponding set of outputs. Fig. 2 shows how an ANN leads to specifics targets output.

2.3. Artificial neural network architecture and training algorithm

Architecture (or topology) of an ANN refers to the arrangement of neurons in the network. Neurons are organized in layers, so that the neural network can consist of one or more layers of neurons. Each neuron receives a set of inputs multiplied by interconnection (weight), which are added and operated by a transfer function (or activation function) before being transmitted to the next layer or network output.

Each neuron, j, in the i-th layer is fed by a dedicated bias (b_j^i) and is connected with the neurons of the (i–1)-th layer (except the input layer) through the weights (w_{jk}^i). k denotes the neuron of (i–1)-th layer. The total number of neurons in layer i is n_j and the transfer function for layer i and neuron j is f_j^i. In each layer, the value of the neuron a_j^i is calculated with Eq. (1):

$$a_j^i = f_j^i\left(\sum_{k=1}^{n_{i-1}} w_{jk}^i \cdot a_k^{i-1} + b_j^i\right) \tag{1}$$

As a large amount of data was not managed, the Levenberg-Marquardt back propagation training algorithm [31] was used because it got closer to an optimal solution and the memory space required by this algorithm was not a problem in this case. Fig. 3 shows a typical ANN architecture, the number of layers is similar to the ANN used in this study.

In this work, five inputs and one hidden layer with four neurons using a hyperbolic tangent and linear as transfer functions (Fig. 3). The correlations of the ANN were expressed as follows:

$$a_1^1 = \tanh\left(w_{11}^1 \cdot p_1 + w_{12}^1 \cdot p_2 + w_{13}^1 \cdot p_3 + w_{14}^1 \cdot p_4 + w_{15}^1 \cdot p_5 + b_1^1\right) \tag{2}$$

$$a_2^1 = \tanh\left(w_{21}^1 \cdot p_1 + w_{22}^1 \cdot p_2 + w_{23}^1 \cdot p_3 + w_{24}^1 \cdot p_4 + w_{25}^1 \cdot p_5 + b_2^1\right) \tag{3}$$

$$a_3^1 = \tanh\left(w_{31}^1 \cdot p_1 + w_{32}^1 \cdot p_2 + w_{33}^1 \cdot p_3 + w_{34}^1 \cdot p_4 + w_{35}^1 \cdot p_5 + b_3^1\right) \tag{4}$$

$$a_4^1 = \tanh\left(w_{41}^1 \cdot p_1 + w_{42}^1 \cdot p_2 + w_{43}^1 \cdot p_3 + w_{44}^1 \cdot p_4 + w_{45}^1 \cdot p_5 + b_4^1\right) \tag{5}$$

$$C_{O\&M} = a_1^2 = \left(w_{11}^2 \cdot a_1^1 + w_{12}^2 \cdot a_2^1 + w_{13}^2 \cdot a_3^1 + w_{14}^2 \cdot a_4^1 + b_1^2\right) \tag{6}$$

where $C_{O\&M}$ is the specific O&M cost (€/m^3), p_1, p_2, p_3, p_4 and p_5 are the scaled-up inputs, production capacity (m^3/d), water flux recovery (%), SEC of the RO system (kWh/m^3), power and consumption tariffs (€/kWh). The ANN was trained, validated, tested and simulated using the MATLAB® Neural Network toolbox.

Table 1
Characteristics of each SWRO desalination plant

Plants	Intake	Temperature (ºC)	Pretreatment	Production (m^3/d)	Production lines	PV(Elements/ PV) / line	Membranes	Average recovery (%)	Energy recovery system
Plant 1	open intake	23	NaClO,$NaHSO_3$	300	1	5(6)	KOCH 8040-SW-400	42	Isobaric
Plant 2	open intake	24	NaClO,$NaHSO_3$	300	1	5(7)	KOCH 8040-SW-400	42	Pelton turbine
Plant 3	beach well	23	NaClO,$NaHSO_3$, H_2SO_4	600	2	3(6)	TORAY T-400	42	NO
Plant 4	beach well	22	antiscalant	2,500	1	36(7)	SW30HR-400LE	42	ERI
Plant 5	beach well	22	NaClO,$NaHSO_3$	3,000	3	12(7)	SW30HR-380	42	Pelton turbine
Plant 6	open intake	24	NaClO,$NaHSO_3$	4,000	2	25(7),36(7)	SW30HR-320	40	Pelton turbine, ERI
Plant 7	beach well	21	NaClO,$NaHSO_3$, H_2SO_4	4,000	4	14(7)	SW30HR-380	43	DWEER
Plant 8	beach well	22	antiscalant	4,000	2	24(7)	SW30HR-380	43	Pelton turbine
Plant 9	beach well	20	NaClO,$NaHSO_3$	4,800	6	14(6)	TORAY TM820M-440	42	Isobaric
Plant 10	beach well	22	NaClO,$NaHSO_3$	5,000	3	16(6),28(6),31(6)	SW30HR-380(1&2), HYDRANAUTICS SW PLUS 4 (3)	42	Pelton turbine
Plant 11	beach well	22	antiscalant	7,000	3	26(6):14(6)	SW30HR-380:SW30HR-400LE	45	Francis turbine
Plant 12	beach well	22	antiscalant	13,000	2	74(7),80(7)	FLUID SYSTEM 2832SS, FLUID SYSTEM 2822SS	43	Francis turbine

Table 2
Costs (c€/m^3)and energy consumption (kWh/m^3) of the SWRO desalination plants

Plants	Chemicals	Cartridge filters	Membranes	Staff	Maintenance	Energy consumption
Plant 1	3.19	0.25	6.72	137.83	5.20	6.41
Plant 2	3.18	0.26	6.77	137.83	5.20	6.02
Plant 3	3.15	0.24	6.60	68.92	4.50	4.59
Plant 4	2.90	0.22	6.44	16.54	3.70	5.06
Plant 5	3.10	0.23	6.27	13.78	3.50	4.57
Plant 6	3.09	0.23	5.83	10.34	3.10	4.87
Plant 7	2.90	0.23	5.72	10.34	3.10	5.02
Plant 8	3.03	0.23	6.22	10.34	3.30	6.00
Plant 9	3.12	0.23	5.66	8.61	2.90	3.32
Plant 10	3.01	0.23	5.83	8.27	2.90	5.86
Plant 11	2.80	0.22	4.94	5.91	2.80	5.65
Plant 12	2.70	0.21	4.88	3.18	2.70	4.99

Table 3
Electrical energy tariff (€/kWh)

Year	Electrical energy tariff	
	Consumption	Power
2005	0.0693	0.013
2006	0.073	0.024
2007	0.082	0.033
2008	0.086	0.044
2009	0.089	0.054
2010	0.096	0.064
2011	0.103	0.074
2012	0.11	0.084

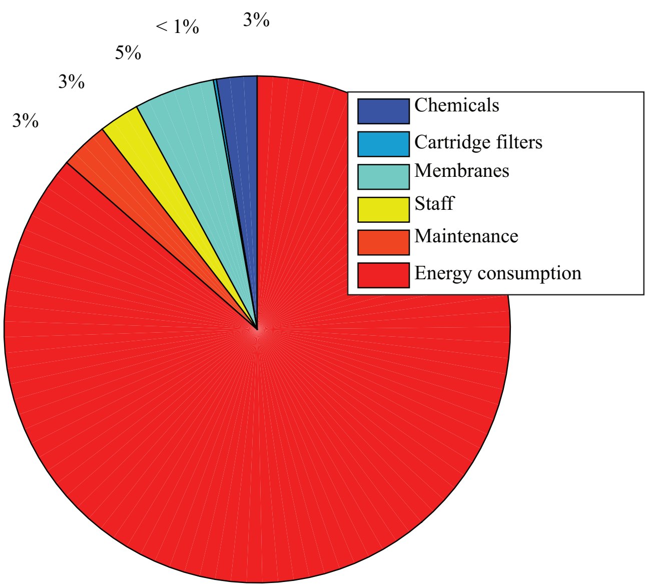

Fig. 1. Distribution of the O&M specific cost.

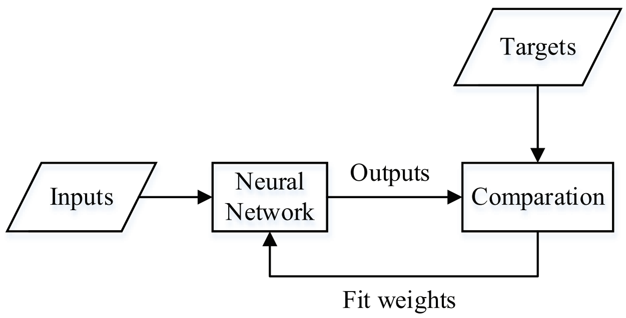

Fig. 2. Building process of ANNs.

2.4. Data processing

The input data for the ANN were the production capacity (m^3/d), water flux recovery (%), energy consumption of the RO system (kWh/m^3) and the price of the electrical tariff of each year (2005–2012) in terms of power and consumption (Table 3). The total input data were divided into three data sets: training (70%), validation (15%) and testing (15%). The testing values were used to fit the ANN using mean square error (MSE). The validation data were used to measure the ANN generalization and to halt training when generalization stop improving. The test data did not have any effect on training process, it provided other measure of the ANN performance during and after the training process. The target was the O&M cost, being the sum of the items included in Table 2 and cost due to the SEC.

3. Results and discussion

In this case 99 iterations were needed to fit the parameters of the ANN. Fig. 4 shows the graphical performance assessment having the best validation in iteration 93. The calculated weights and bias are shown in Table 4.

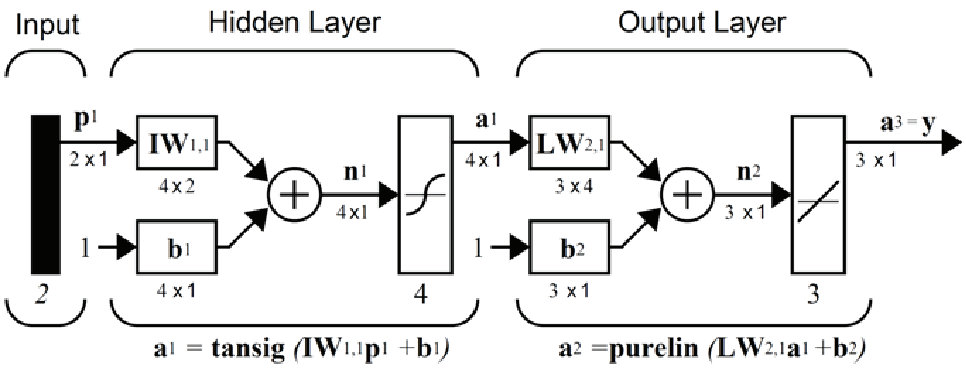

Fig. 3. ANNs architecture [15].

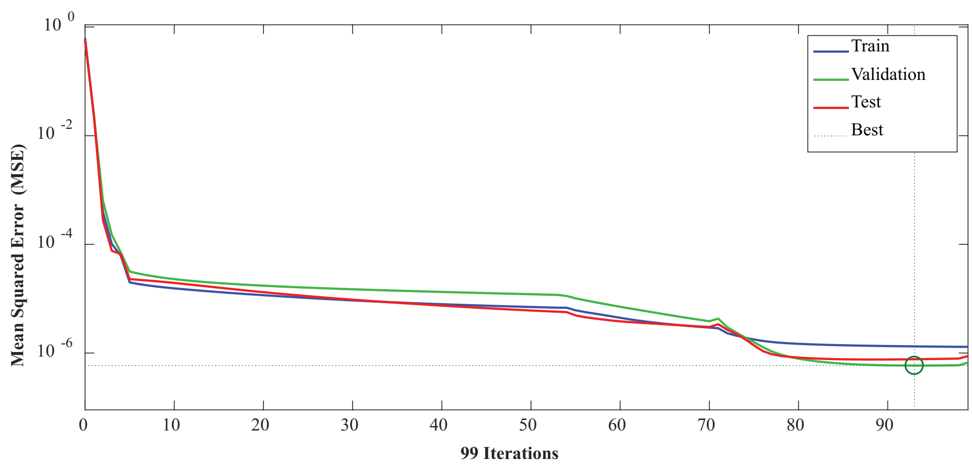

Fig. 4. Graphical performance of the ANN in the fitting process.

Table 4
Calculated parameters of the ANN

Weights					Bias	Transfer function
w^1_{11} =–1.0887	w^1_{12}=–1.8121	w^1_{13}=–0.1187	w^1_{14}=0.2889	w^1_{15}=–0.5673	b^1_1 =1.4945	tanh
w^1_{21} =1.7734	w^1_{22}=1.5891	w^1_{23}=–0.4437	w^1_{24}=–0.2963	w^1_{25}=0.7665	b^1_2 =–0.0052	tanh
w^1_{31} =–4.6819	w^1_{32}=0.2910	w^1_{33}=0.0014	w^1_{34}=–0.1576	w^1_{35}=0.2657	b^1_3 =–5.0726	tanh
w^1_{41} =–2.2939	w^1_{42}=0.1356	w^1_{43}=–0.0105	w^1_{44}=0.1975	w^1_{45}=–0.1945	b^1_4 =–0.9128	tanh
w^2_{11} =–0.0357					b^2_1 =1.1508	1
w^2_{21} =–0.0371						
w^2_{31} =2.0179						
w^2_{41} =0.0865						

The results were reasonable, because the final mean square error is relatively small (~ $5\cdot10^{-7}$), the test set and validation set errors have similar characteristics, and it appears that significant over-fitting has not occurred. The statistical regression between the real O&M cost and the estimated by the ANN is shown in Fig. 5. The regression figures are used to study the influence of the number of layers, neurons and transfer function on the ANN performance. A perfect architecture would result in a regression value (R) of 1.0, which is this case.

The ROSA (Dow®) software was used to simulate the plant 7 operating in a range of water flux recoveries (42–45%), the SEC, which is the most relevant in O&M costs, was between 3.98–3.92 kWh/m³. Fig. 6 shows the O&M cost trend with the increase of the recovery and increasing the production.

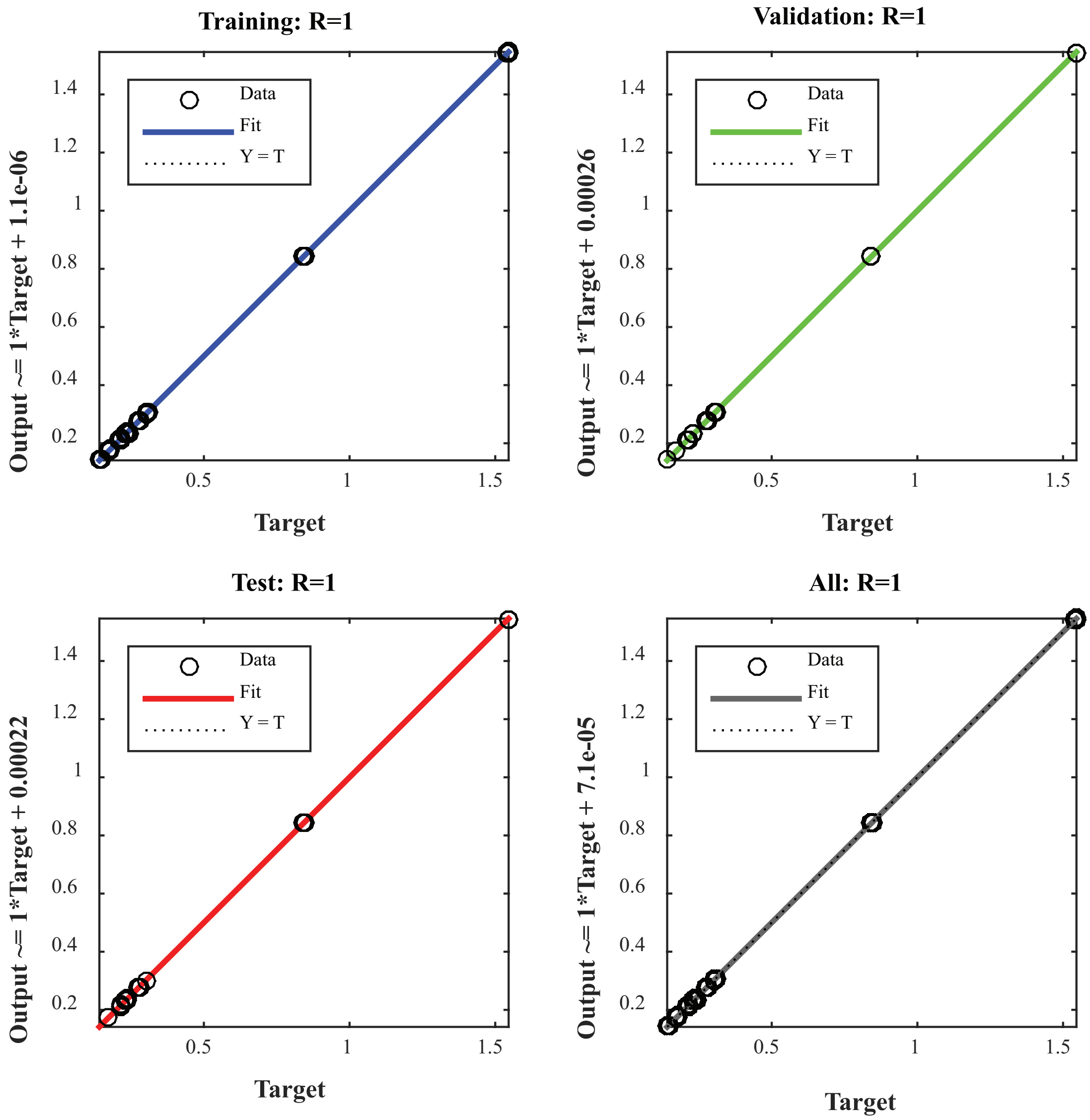

Fig. 5. Statistical regression of the ANN.

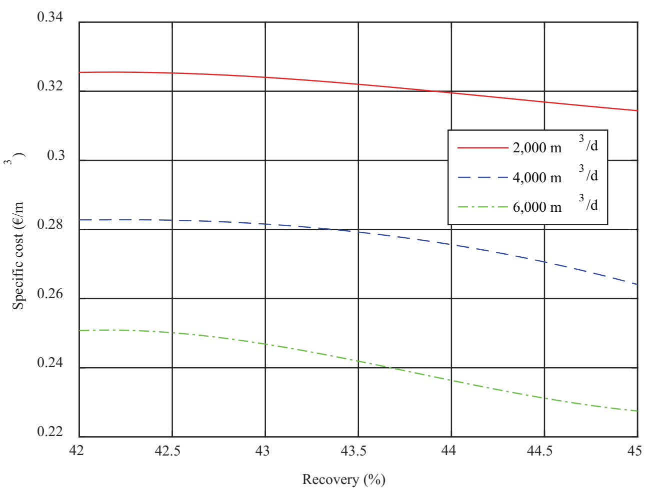

Fig. 6. O&M cos trend for different production capacities.

4. Conclusions

An ANN based model was made from the experimental data of twelve SWRO desalination plants located in Fuerteventura Island (Spain) corresponding to a period of five years of operation. The ANN based model was verified and tested obtaining decent results comparing with the experimental data. A simulation was carried out to study the trends of the O&M cost varying some input parameters.

The estimation of the O&M cost is complex, the energy consumption is the most relevant item in these costs and quite variable in time. The rest of the O&M costs depended strongly on the production capacity due to the economy of scale. Due to the characteristics of the studied SWRO desalination plants it could be said that the model is accurate within the ranges of the plants studied. It would require more experimental data in wider operating ranges in order to improve accuracy and applicability.

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