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Investigation of the Efficiency of Small-Scale NF/RO Seawater Desalination by Using Artificial Neural Network Modeling

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ABSTRACT

An attempt is conducted in this paper to develop an artificial neural network (ANN) model for predicting the efficiency of small-scale NF/RO seawater desalination, then applied to the simulation of permeate flow rate and water recovery. A feed-forward back-propagation neural network with the Levenberg-Marquardt learning algorithm is considered. The performance of ANN compared to the multiple linear regression (MLR) is based on the calculated value of the coefficient of determination (R^2). For ANN, R^2 permeate flow rate was 0.997, and R^2 permeate water recovery was 0.999, and for MLR, R^2 permeate flow rate was 0.508, and R^2 permeate water recovery was 0.713. It was observed that ANN performed better than the MLR.

1. INTRODUCTION

Nowadays, reverse osmosis membranes are utilized in various applications, such as the treatment of drinking water, wastewater reuse, and seawater desalination [1]. The membrane fouling often causes a limitation of the efficiency of reverse osmosis (RO) membranes in the treatment of water. To reduce or even overcome these limits, several studies have shown that nanofiltration (NF) membrane process is the concurrent technology and can be coupled to reverse osmosis for seawater desalination [2]. Thus, NF is a membrane technology that has positioned between reverse osmosis and ultrafiltration (UF) [3, 4].

Several researchers have tried to increase the water recovery of reverse osmosis systems without reducing the membrane's life [5, 6]. The performance of NF processes cannot meet drinking water standards because of its inability to reduce salinity in seawater [7-10].

A percentage of 92.8% for the water recovery was achieved by Drioli et al. [11, 12] by integrating the MF-NF-RO with membrane distillation/crystallization system. The adopted system allowed a reduction in the energy consumption of the NF-RO-MC process and the water cost to 1.54-1.61 kWh m^{-3} and 0.56 $\$/m^3$, respectively. NF is utilized as a pretreatment step of seawater feed and RO or MSF as final treatment step [13]. AlTaee and Sharif [14] carried out the cost analysis on a dual NF-NF, NF-RO, and single RO systems. Their findings indicated that NF-NF combination was the cheapest, followed by RO, then NF-RO systems. In other study by Kaya et al. [15], applicability of NF membranes prior to SWRO system was also investigated. They reported that SWRO flux increased from 30.1 LMH to 55.1 LMH when NF was utilized as a pretreatment before the seawater SWRO unit. The results showed an excellent rejection concerning all ions.

Many works reported the use of ANN to model the nanofiltration (NF) and reverse osmosis (RO) process of seawater desalination separately [16].

In recent years, the utilization of ANN is increasingly successful in various industrial areas [17-23]. The novelty of the current study is to investigate the use of ANNs to model the operation of small-scale NF/SWRO desalination plants to determine the performance of permeate flow rate and permeate water recovery. Moreover, a comparison with the multiple linear regression method (MLR) was made to test the robustness and performance of the ANN model.

2. METHODS

2.1 Data

In this study, the database was provided by experimental data available in the literature [24]. A pilot plant testing in which the nanofiltration membrane NF product is sent to the RO unit and its brine reject is used as make-up to the MSF plant, the NF unit received pre-treated seawater with a temperature feed between 24°C and 34°C and was operated with operating pressure about 23.54 bar at a recovery of 53-57%. The SWRO unit received the NF product as feed, the operating pressure was maintained at 58.84 bar with temperature ranged from 23 to 34°C, and overall recovery of SWRO system was about 45%. The experimental data is presented in Figure 1.

The selected input parameters included: the feed pressure, temperature, conductivity, flow rate, permeate flow rate, and permeate water recovery. The variation of selected experimental inputs over time is depicted in Figure 2. The values of the standard deviations (STD) are given in Table 1.

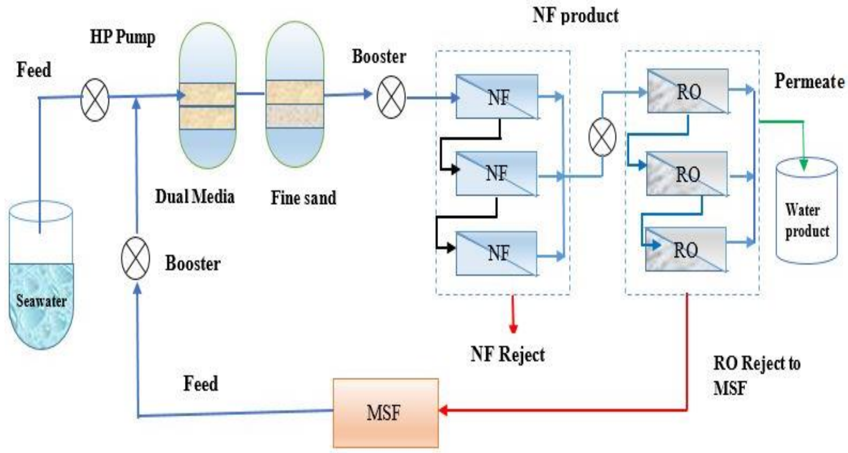


Figure 1. Desalination pilot plant of NF/SWRO

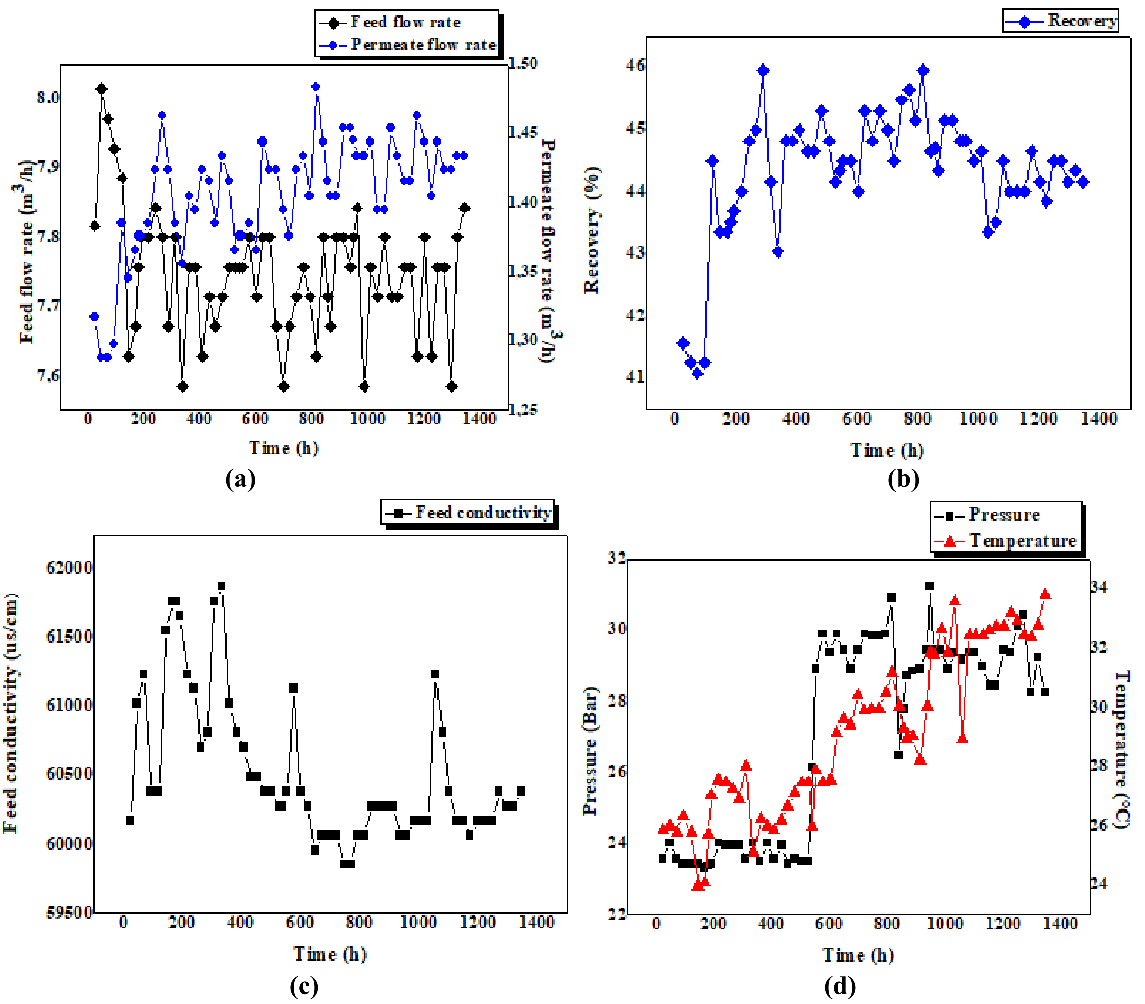


Figure 2. Performance of NF/SWRO

Table 1. Parameters statistics of inputs and outputs

Variable category	Parameters	Symbol	Unit	STD	mean	min	max
inputs	time	*t*	h	385.92	680.317	25.197	1343.830
	pressure	*p*	bar	2.820	27.069	23.505	31.222
	temperature	*T*	°C	2.7422	29.063	23.968	33.789
	feed flow rate	*Qf*	m^3h^{-1}	0.088	7.748	7.586	8.014
	feed conductivity	*δf*	μScm^{-1}	535.01	60519.500	59851.06	61872.34
outputs	permeate water recovery	*y*	%	1.018	44.308	41.093	45.951
	permeate flow rate	*Qp*	m^3h^{-1}	0.042	1.406	1.288	1.483

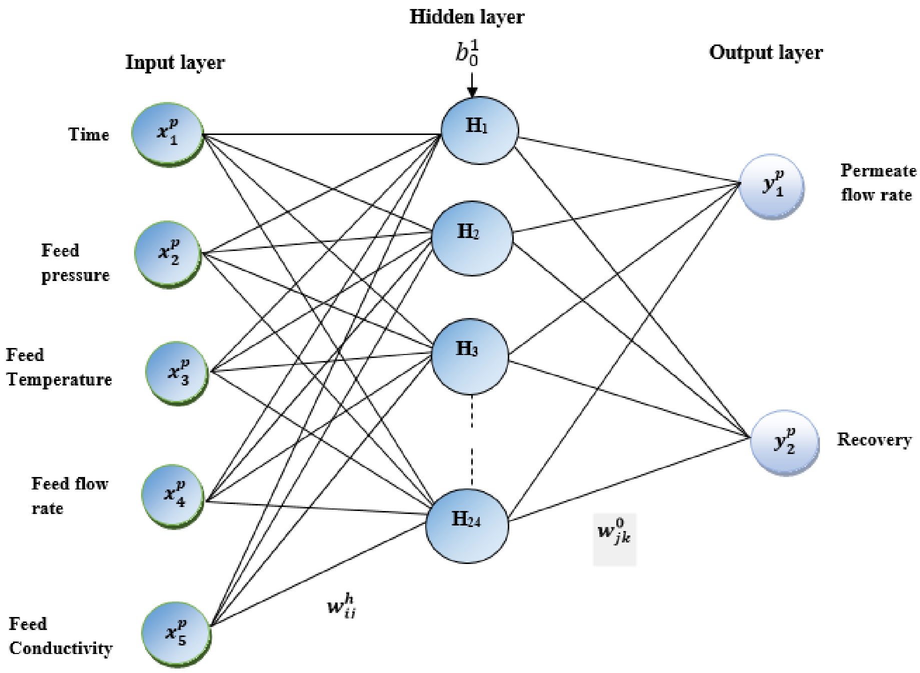


Figure 3. Schematic diagram of an artificial neural network model

2.2 Modeling development

To predict the efficiency of the hybrid NF/SWRO desalination system, two approaches were utilized to develop an adequate model to determine the permeate flow rate and water recovery.

2.2.1 Modeling with multiple linear regression (MLR)

The linear relationship between the explanatory (independent) variables xi and response (dependent) *yi* variables [25] as shown in Eq. (1):

$$y_i = a_0 + \sum_{i=1}^{n} a_i x_i \qquad (1)$$

where, yi represents the response or dependent variable (outputs), x_i represents the explanatory independent (inputs), and a_0 represents the constant (intercept). MLR calculations were performed using STATISTICA v. 8.0 (StatSoft, Inc.) software.

2.2.2 Modeling with neural network

To construct the ANN model, the database was presented in 75 samples divided into training and test subsets. A training subset has some 60 pieces, which is 80% of all available data. For the test subset, 15 samples (20%) have been considered. The neural network-training model was developed by means of a program written in MATLAB software.

The results showed that the optimal fully connected ANN was obtained using 24 neurons in the hidden layer, with high R2 and low RMSE. Different ANN structures with two hidden layers and other neurons in each layer have been tested. It was notable that the ANN with 02 hidden layers can predict the two outputs accurately (Figure 3).

3. FINDINGS AND ANALYSIS

3.1 Validation of the model

In the training and testing stage, the calculation of errors between the experimental values and prediction is a criterion for evaluating the model and optimum network structure determination.

The correlation coefficient R_2, the root means square error RMSE (square root of the average sum of squares), and mean absolute error (MAE) are the statistical parameters commonly used in the literature [26-29] for error calculation. They are calculated according to the following equations:

$$R^2 = \frac{\sum_i (y_{\exp} - y_{\text{cal}})^2}{\sum_i \left(y_{\exp} - \overline{y_{\exp}}\right)^2} \qquad (2)$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y^{\exp} - y^{\text{cal}}\right)^2} \qquad (3)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|\left(Y_{\exp} - \mathrm{Y}_{\mathrm{cal}}\right)\right| \quad (4)$$

where, N is the number of experiments, $y_{\exp}$ is the experimental value for each parameter, y_{cal} is respectively the predicted value of the i^{th} experiment calculated by the model for each parameter. $\overline{y_{\exp}}$ and $\overline{y_{\mathrm{cal}}}$ are the arithmetic mean of experimental and calculated values [30-33].

3.2 Mathematical equations of MLR developed model

The linear models obtained to determine the permeate flow rate (Q_p) and permeate water recovery (y) are:

$$Q_{\mathrm{p}} = 2.607 + 0.661t - 0.04P - 0.07T - 0.19Q_{\mathrm{A}} + 0.15\delta_{\mathrm{A}} \quad (5)$$

$$(F = 14.259,\ P < 0.001)$$

$$y = 101.123 + 0.542t - 0.124P - 0.51T - 0.34Q_{\mathrm{A}} - 0.27\delta_{\mathrm{A}} \quad (6)$$

$$(F = 7.609,\ P < 0.001)$$

3.3 Mathematical equations of ANN developed model

The proposed neural network model successfully predicts the NF/RO performance parameters i.e. permeate flow rate and permeate water recovery. Integrating all the inputs x_i by the mathematical formula is presented as follows. Knowing that f_h is the exponential transfer function used in hidden layer:

$$Z_j = f_h\left[\sum_{i=1}^{5} w_{ji}x_i + b_j^h\right] = \exp(-\sum_{i=1}^{5} w_{ji}x_i + b_j^h) \quad (7)$$

$$j = 1, 2, ...24$$

where, j is the number of neurons in the hidden layer (j=24), i is the number of neurons in the input layer (i=24), w^I ($w^H_{(j,i)}$) and b_1^H are weights and bias between input and hidden layer, w^H ($w^0_{(l,j)}$) and b_2^0 are weights and bias between hidden and output layer, and l *is* the number of neurons in output layer (l = 2). The output H, where f_0 is the exponential transfer function used in output layer is presented as Eq. (8):

$$\mathrm{H} = f_0\left[\sum_{i=1}^{24} w_{ji}^H Z_i + b_2^0\right] \quad (8)$$

Combining Eqns. (7) and (8) to obtain the relation formula of the output parameters of the ANN as follows:

$$Q_{\mathrm{p}}, y = \sum_{i=1}^{24} w_{ji}^H \exp(-\sum_{i=1}^{24} w_{ji}x_i + b_j^h) + b_2^0 \quad (9)$$

The equation of the predicted permeate flow rate (Q_{p}) and permeate water recovery (y) is given by the Eq. (9).

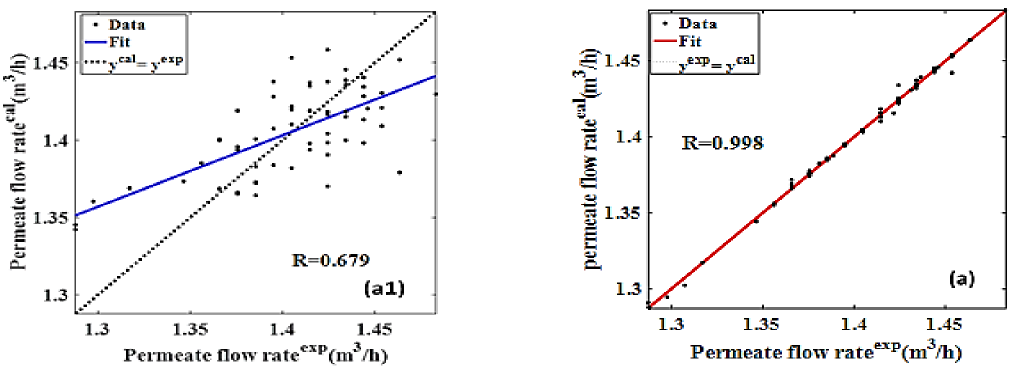
4. COMPARISON

The results of the ANN model and MLR model were evaluated based on the comparison between the model values predicted and the experimental data using the different statistical parameters as shown in Table 2. The models statistical parameters for the prediction results obtained using MATLAB function “postreg”.

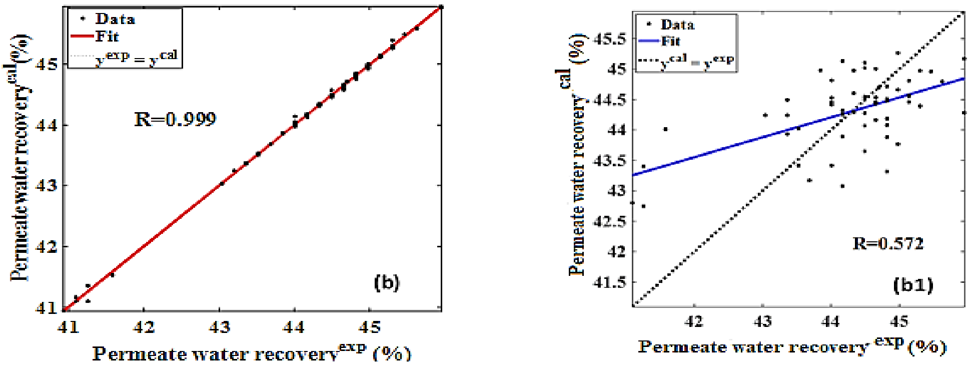
In fact, ANN showed a higher regression coefficient value than MLR, as presented in Figure 4. However, for the permeate flow rate and permeate water recovery, the error (MAE and RMSE) of the ANN model is lower than the MLR model. It appears that ANN is more appropriate than MLR. As shown in Figure 5, the result of ANN is a logic that can relatively quickly be reflected on the operating system for NF/RO process and the existence of a non-linear correlation between the outputs of the network (Q_p and y) and the experimental variables. On the other hand, the result of MLR cannot be used by the NF/RO operating systems.

Table 2. Comparison of statistical parameters for ANN and MLR model

		α	β	R^2	RMSE	MAE
permeate flow rate/m^{3}h^{-1}	ANN	0.9988	0.0017	0.997	0.00256	0.0014
	MLR	1	2.33×10^{-6}	0.461	0.021	0.0246
permeate water recover/%	ANN	1.0005	-0.0212	0.999	0.0401	0.0257
	MLR	1	-7.56×10^{-5}	0.327	0.482	0.6463



(a)



(b)

Figure 4. Results from ANN model of (a) permeate flow rate (b) permeate water recovery

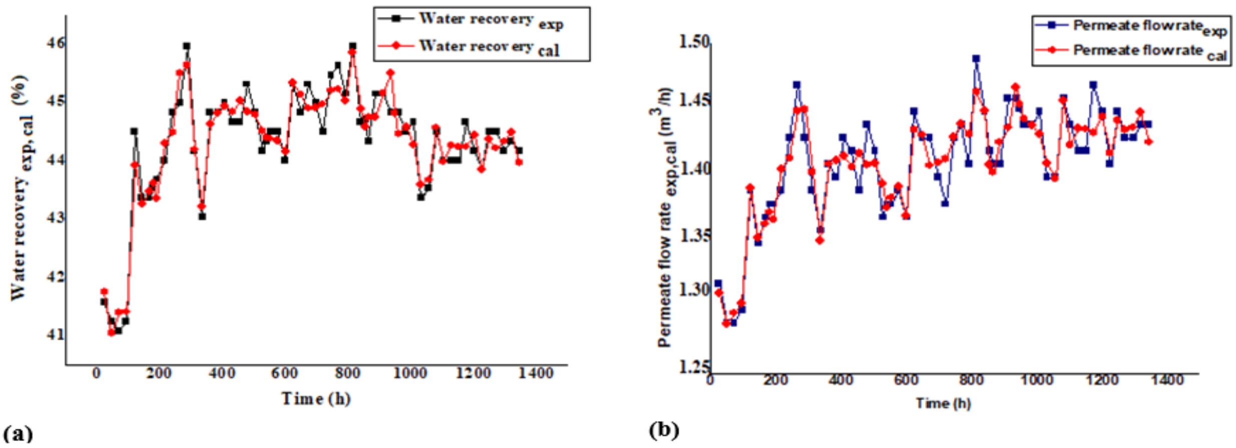


Figure 5. Validation of the predicted values of (a) permeate flow rate (b) permeate water recovery for NN structure 5-24-2

4.1 Sensitivity analysis

To explore the sensitivity of the performance of hybrid NF/RO desalination pilot plant to the inputs and to find the most dominant parameters, the weights method was employed in this study.

The relative importance (%) was calculated based on the Garson equation [34-36] (see Eq. (10)).

$$R_{Ij} = \frac{\sum_{m=1}^{N_h}\left(\left(\frac{\left|W_{jm}^{ih}\right|}{\sum_{k=1}^{N_i}\left|W_{km}^{ih}\right|}\right)\times\left|W_{mn}^{h0}\right|\right)}{\sum_{k=1}^{N_i}\left\{\sum_{m=1}^{N_h}\left(\frac{\left|W_{km}^{ih}\right|}{\sum_{k=1}^{N_i}\left|W_{km}^{ih}\right|}\right)\times\left|W_{mn}^{h0}\right|\right\}} \qquad (10)$$

where, I_j is the relative importance of the j_{th} input variable on the output variable.

According to each input that exceeds 6% [28, 34], all the information has a considerable impact on the output (permeate flow rate and permeate water recovery). In the present study, the time has an effect of about 19% on both outcomes. The feed pressure (31.3%) strongly affects the permeate flow, whereas the feed pressure (26.6%) and feed flow rate (21.7%) significantly affect the permeate water recovery (Figure 6), which explains that the selected inputs parameters have a substantial effect on the outputs and a great significance in the performance of NF/RO desalination plant.

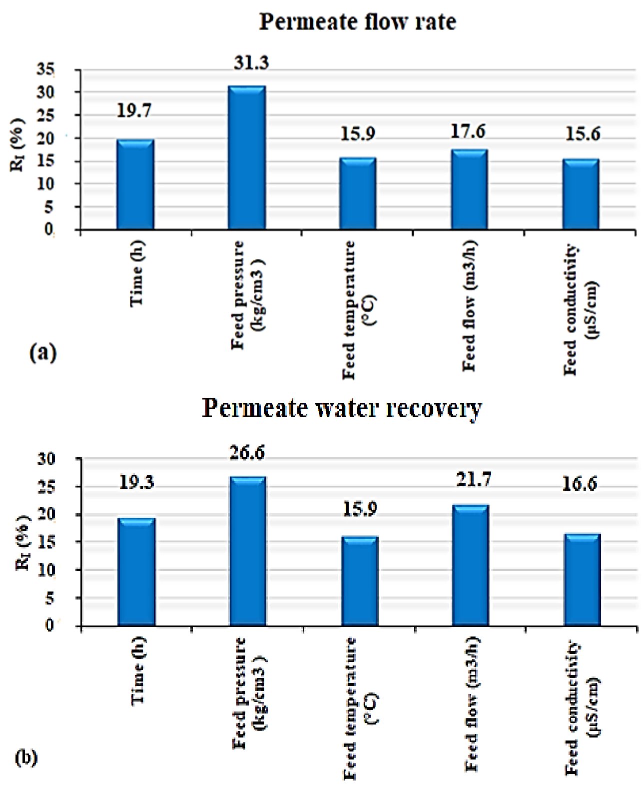


Figure 6. The importance percentage distribution of each inputs variable on: (a) Permeate flow rate and (b) Permeate water recovery

5. CONCLUSION

To predict the efficiency of small-scale NF/SWRO desalination plants, an ANN model was developed for simulation of the permeate flow rate and permeate water recovery. The efficiency of ANN models and MLR models was determined. The inspection of the results from the ANN models with the MLR models revealed that ANN models were good at predicting permeate flow rate and permeate water recovery with high R_2 values and low RMSE and MAE values, which implied the robustness of the neural model. Finally, the ANN models can be considered as a powerful tool in predicting the efficiency of the seawater desalination hybrid process NF/RO.

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NOMENCLATURE

ANN	artificial neural network
b	bias factor
H	output function
MAE	mean absolute error
MLR	multiple linear regression
MSF	multi-stage flash
NF	nanofiltration membrane
P	pressure, bar
Q	flow rate, $m^3 h^{-1}$
R^2	regression coefficient
R_I	relative importance, %
RMSE	root mean square error
t	time, h
T	temperature, °C
w	weight factor
x	sigmoid function
y	permeate water recovery, %
Z	transfer function in the hidden layer

Greek symbols

δ	conductivity, $\mu S\ cm^{-1}$
α	intercept
β	slope

Subscripts

exp	exponential
f	feed
i	number of neurons in the input layer
h	number of neurons in the hidden layer
p	permeate