Fuzzy C-Means Clustering Identification of Desalination Plant Model

Pablo G. Camacho[1[0009−0008−6717−5469]], William D. Chicaiza[1[0000−0001−5473−9538]], Juan M. Escaño[1[0000−0003−1274−566X]], Juliana S. Barros[2[0009−0002−8965−5099]], Bismark C. Torrico[2[0000−0001−8972−3974]], and Fabrício G. Nogueira[2[0000−0003−1935−8937]]

[1] Departamento de Ingeniería de Sistemas y Automática, Universidad de Sevilla, Camino de los Descubrimientos s/n., 41092 Sevilla, Spain
{pgonzalez7,wchicaiza,jescano}@us.es

[2] Departamento de Engenharia Elétrica, Universidade Federal do Ceará (UFC), Fortaleza, CE, Brasil
julianasobral@alu.ufc.br, {brismark,fnogueira}@dee.ufc.br

Abstract. This paper presents the identification of a desalination plant model using fuzzy inference techniques, as well as their comparison with the Linear Parameter Variation (LPV) experimental identification. Identification of the plant model has been carried out using the fuzzy C-means clustering (FCM) technique. The identified model was then validated, and the estimated output was compared with the measured output. Both models were obtained with experimental data by running the plant in three different scenarios, with the only variation in the operating point of the waste reuse valve, although the differences are minimal. The results obtained show that the FCM presents the lowest variability in the estimates, the lowest discrepancy between the predicted and observed values.

1 Introduction

Desalination is used to address the scarcity of water resources by eliminating salt from the water. Among the various methods available, reverse osmosis (RO) is one of the most widely used worldwide. This process involves applying pressure higher than the natural osmotic pressure to induce a reverse flow, directing water from the more concentrated medium to the less concentrated. This results in one stream with a high total dissolved solids (TDS) value and another with permeated water of high purity, depending on the membrane's rejection rate.

Due to its complex and nonlinear nature with variable parameters, developing mathematical models based on a phenomenological approach is challenging. Furthermore, there are parametric uncertainties and variations in the components over time in RO desalination plants. However, modelling and control of desalination systems are crucial for safe and efficient operation. Numerous strategies have been used, ranging from the application of dynamic matrix control to regulate pH and nominal pressure to nonlinear control methods using open- and closed-loop algorithms [1].

The linear parameter variation (LPV) strategy represents a robust control approach designed to handle real-time variations in system parameters effectively. This control methodology typically comprises three main stages: system model identification, controller synthesis, and performance analysis. Numerous studies are in the literature that focus on LPV control. Application to systems with time delays [3] or in hydroelectric power plants [9] are some of those works.

Nonlinear dynamic systems often necessitate the use of complex mathematical equations, notably differential equations. However, while mathematical tools support modelling, they may not always adequately address the uncertainties inherent in systems. Developing optimal control and optimisation strategies for nonlinear models presents a significant computational challenge, particularly when time constraints and sampling intervals must be considered. Consequently, the need for fast models becomes imperative to overcome this obstacle efficiently.

Fuzzy modelings as a valuable technique for modelling and controlling nonlinear systems. It effectively captures the essence of the original non-linear model [12] while offering advantages such as rapid update and execution capabilities. Among the different methods of obtaining fuzzy models, the Fuzzy C-Means (FCM) have been used, similar to other reference works ([5], [4] and [7]). Clusters have been created with FCM from the input and output data to obtain the different membership functions and fuzzy rules.

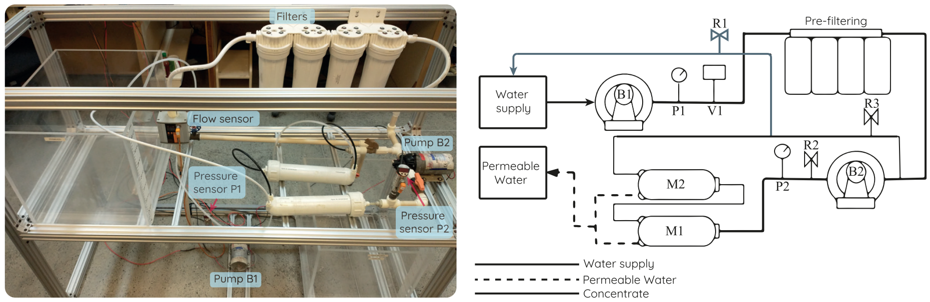
In this paper, we propose to show the identification of the desalination plant model using fuzzy inference techniques, as well as their comparison with the LPV experimental identification. The rest of the article is structured as follows. Section 2 describes the desalination plant under study, Section 3 presents the methodology for preparing the data to model the system. Section 4 describes the two models developed for comparison. Section 5 shows the validation results, and Section 6 presents the conclusions.

2 Case study: Desalination pilot system

This work was carried out using a bench scale reverse osmosis desalination system shown in Fig. 1a. This plant is located in the laboratory of the Federal University of Ceará, in Fortaleza, Brazil.

Fig. 1b illustrates the block diagram of the system. The system comprises a brackish water reservoir (feed water), a permeate reservoir (resulting liquid), two water pumps (B1 and B2), a prefiltration system (10 micron, 5 micron, activated carbon and deionised resin), two RO desalination membranes (M1 and M2), one reverse osmosis desalination membrane (M1 and M2), a flow sensor (V1), two pressure sensors (P1 and P2) and registers along the circuR2, (R1, R2 and R3).

The membranes were arranged in series to optimise the concentrate for disposal or reuse in another test. The two tanks are consistently interconnected, either by pipe or equipment. Consequently, the opening level of the valve in



(a) Pilot desalination plant. (b) Simplified system schematic.

Fig. 1: Reverse osmosis desalination facility.

the pipelines directly affects the pressure and flow rate of the concentrate and, therefore, the operational efficiency.

To acquire the necessary input and output data of the system for various models, three experimental tests were conducted. The pressure was maintained at a constant operating point of approximately 50 psi, while the waste reuse valve (R3) was opened incrementally. The operating conditions adopted were closed valve (0% opening), half-open valve (50% opening),) and fully open valve (100% opening).

The input signals consisted of square wave pulses generated to operate the two pumps of the desalination system. However, for the output signal, the pressure values of pump 2, located just downstream of the filters, were used. These data were collected through the pressure sensor (P2) located immediately after the water flow outlet of this pump, as shown in Figure 1a.

With these data and their subsequent preparation, explained in the following section, the three models of the plant have been carried out, depending on the degree of opening of the aforementioned valve.

3 Data preparation

During the data acquisition process, as explained above, a square wave excitation was applied, the system operating at about 50 psi, which is equivalent to approximately 3.5 bar. The voltage applied to the pressurisation pump of the RO membranes was taken to be the input of the model, while the pressure measurement of the sensors at the inlet of the membranes was used for the output. The sampling period used was Ts = 0.01 s.

Fig. 2 shows the behaviour of the variation in system pressure at the diaphragm inlets as a function of the valve opening. As a consequence of the progressive opening of the valve, the pressure at the pump outlet decreases until it reaches a significant reduction when the valve is 100% open, as can be seen in the figure below.

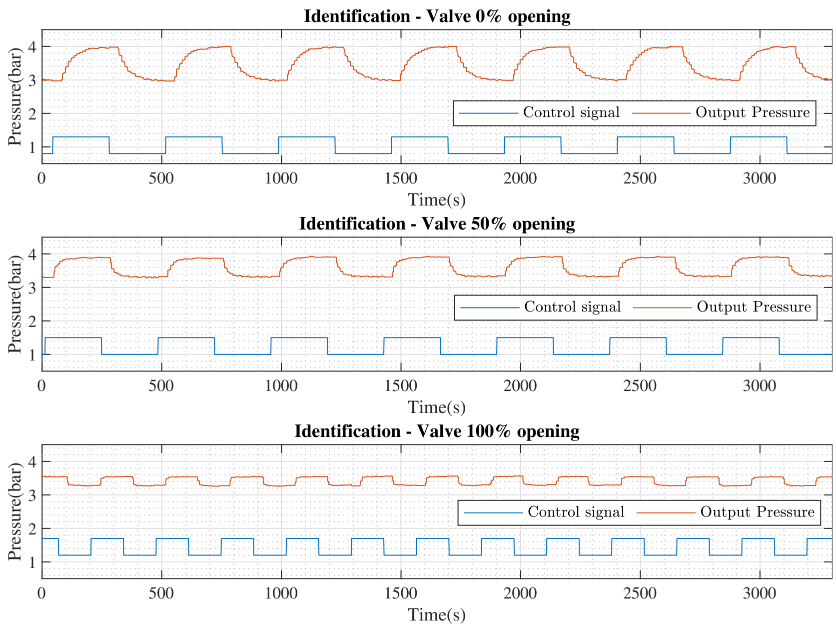


Fig. 2: Data of the system

For LPV experimental identification, the collected data shown above were processed, removing the mean and trend, and then normalised to obtain models with well-conditioned parameters. The base value of the input signal is 12 Vdc and the output signals are pressure variations with a base value of 20 psi.

For the identification of the model using fuzzy techniques, the original data have been normalised in the range [0 1] using the following:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1a}$$

4 Modelling

This section details the modelling of the system following the LPV method first and then using a fuzzy inference method. The first of the models is taken from [10].

4.1 LPV model of the plant

The LVP model of the plant is shown below, which has an ARX-LPV structure:

$$y(k) = \frac{B(z, \theta(k)}{A(z, \theta(k)} z^{-d} u(k) + e(k) \tag{2a}$$

where y(k) and u(k) are the output and input of the system, respectively, and θ is the level of valve opening.

The terms nb and na are respectively the orders of the polynomials $B(z,\theta)$ and $A(z,\theta)$, which can be described by:

$$B(z,\theta(k) = b_1(\theta)z^{-1} + b_2(\theta)z^{-2} + b_3(\theta)z^{-3} \tag{3a}$$

$$A(z,\theta(k) = 1 + a_1(\theta)z^{-1} + a_2(\theta)z^{-2} + a_3(\theta)z^{-3} \tag{3b}$$

Among the possible choices for parameter-dependent functions, we chose functions with polynomial dependence in the form dependence:

$$b_i(\theta) = b_{i1} + b_{i2}\theta + ... + b_{iN}\theta^N, i = 1, ..., n_b \tag{4a}$$

$$a_j(\theta) = a_{j1} + a_{j2}\theta + ... + a_{jN}\theta^N, j = 1, ..., n_a \tag{4b}$$

where N is the degree of the polynomial functions.

The parameter identification method used was the LPVLMS (Parallel Least Mean Squares) (F. G. Nogueira, 2018), which is grounded on the local LPV approach. As mentioned above, operating points were selected for the scheduling variable (feedback valve). The recursive P-LMS algorithm aims to minimise the estimation error $\epsilon(k) = y(k) - \hat{y}(k)$ simultaneously for m datasets acquired under various operating conditions of the system, where *y(k)* represents the measured output signal and $\hat{y}(k)$ signifies the estimated output.

The normalised data obtained previously were divided into two sets for model identification and validation purposes. Following an analysis of the performance of various identified models, it was determined to employ a third-order ARX-LPV model (with Na = Nb = 3) with a second-degree dependence (N = 2).

The polynomial values of the identified ARX-LPV model are shown below:

$$a1(\theta) = -0,5700 - 0,08570\theta - 0,07380\theta^2$$
$$a2(\theta) = -0,2602 + 0,03030\theta + 0,01890\theta^2$$
$$a3(\theta) = -0,1583 + 0,06910\theta + 0,04980\theta^2$$
$$b1(\theta) = 0,0011 - 0,00140\theta + 0,00390\theta^2$$
$$b2(\theta) = 0,0080 - 0,00930\theta - 0,00210\theta^2$$
$$b3(\theta) = 0,0269 - 0,00980\theta - 0,00300\theta^2$$

The identified model was validated by simulating it over time, where the estimated output is compared with the measured output. This procedure was carried out under the same three operating conditions that were considered during the data acquisition process.

4.2 Fuzzy model of the plant

With the data obtained from Section 3, a three-input, one-output fuzzy model has been created as shown in Fig. 3. The output of the model is the pressure in the current state, which feeds back into the model, giving as one of the input the pressure in the previous state. Likewise, the other two inputs are the current control signal and the valve opening.

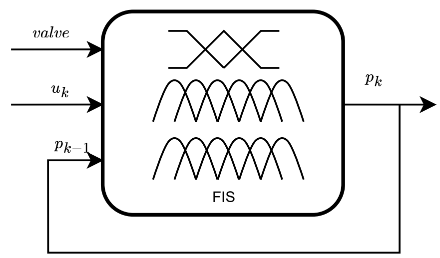


Fig. 3: FIS

The type of inference in the fuzzy model is Takagi-Sugeno (TS) [11]:

$$\begin{aligned}
&Rule\ j:\\
&\qquad \texttt{IF}\ valve\ \texttt{is}\ F_{1v}\ \texttt{and}\ u_k\ \texttt{is}\ F_{2j}\ \texttt{and}\ p_{k-1}\ \texttt{is}\ F_{3j}\quad ,\\
&\qquad \texttt{THEN}: \hat{p}_j(x) = g_{0j} + g_{1j}\cdot valve + g_{2j}\cdot u_k + g_{3j}\cdot p_{k-1}
\end{aligned}$$

This type presents rules with parameters on the antecedents and on the consequents. For the antecedents, these parameters are the means or centre (c_{ij}) and deviations (σ_{ij}) of the Gaussians that make up each fuzzy set (F_{ij}) (in the case of valve input, there are just three fuzzy sets, $v = 1, 2, 3$, one for each state of the valve), while the consequents consist of coefficients (g_{ij}) of each of the first-order polynomial functions, multiplying each input, plus an independent term (g_{0j}). The final output of the system will be the weighting of each of these polynomial functions based on the degree of weight obtained from each of the membership functions of the inputs.

To obtain these antecedent and consequent parameters, three Takagi-Sugeno fuzzy models have been created, one for each valve position, using the membership function and the rules derived from the clusters obtained from the input and output data. The clustering method used was Fuzzy C-Means Clustering (FCM), in which the clusters are obtained using an iterative approach, with satisfactory results. The iterative process involves the progressive update of the cluster centroids and the degrees of membership of the data points. Iterations occur until a convergence condition is reached, which may be manifested by the stabilisation of the centroids or the minimisation of an objective function that evaluates the discrepancy between the data and the centroids.

Thus, with the input and output data of the model and the clustering method used, a fuzzy inference system (FIS) is generated that captures the behaviour of the data. The FCM approach determines the number of rules, the Gaussian membership functions for the antecedents, and the first-order polynomial functions for the consequents of the FIS. These parameters are shown in the following tables throughout the text. In addition, the parameters of the antecedents and consequents could be further improved with fuzzy neural networks based on an adaptive neuro-fuzzy inference system (ANFIS). Finally, in the antecedent parameters, each input variable has a Gaussian input membership function for each fuzzy cluster, while in the consequent parameters, each output variable has a linear output membership function for each fuzzy cluster. In terms of fuzzy rules, each model has a rule for each fuzzy cluster.

The valve has only three membership functions, with three different shapes (linear z-shaped, triangular, and linear s-shaped), as shown in Fig. 3 corresponding to the three states of the valve: closed, half-opened, or opened. The other inputs have a different number of membership functions depending on the state of the valve. The control signal and pressure both have six membership functions when the valve is closed, as shown in Table 1, but in the rest of the states, the number of membership functions is four. All are Gaussian, with the parameters shown in Tables 2 and 3. The parameters of the membership functions of the valve input have not been shown because they are always the same depending on the case: a downward ramp between 0 and 0.5 for the closed valve case, a triangle between 0, 0.5 and 1 for the half-opened valve case, and an upward ramp between 0.5 and 1 for the opened valve case.

Table 1: Obtained parameters during the learning process: valve 0%

Antecedent Parameters MFs				
Inputs (x)	u_k		p_{k-1}	
	A_{1j}		B_{2j}	
j	σ_{1j}	c_{1j}	σ_{2j}	c_{2j}
1	0.0913	0.0085	0.1255	0.4245
2	0.0872	0.0010	0.1748	0.0769
3	0.0913	0.0017	0.1543	0.9610
4	0.0866	0.5546	0.1752	0.9252
5	0.0919	0.5534	0.1542	0.0348
6	0.0912	0.5487	0.1267	0.6027
Consequent Parameters $\hat{p}_{k,j}$				
j	g_{2j}	g_{3j}	g_{0j}	
1	0.01887	0.9927	-0.0016	
2	0.01887	0.9927	-0.0016	
3	0.01887	0.9927	-0.0016	
4	0.01887	0.9927	-0.0016	
5	0.01887	0.9927	-0.0016	
6	0.01887	0.9927	-0.0016	

Table 2: Obtained parameters during the learning process: valve 50%

Antecedent Parameters MFs				
Inputs (x)	u_k		p_{k-1}	
	A_{1j}		B_{2j}	
j	σ_{1j}	c_{1j}	σ_{2j}	c_{2j}
1	0.0877	0.2228	0.1255	0.3656
2	0.0882	0.7746	0.0946	0.3676
3	0.0835	0.7772	0.1519	0.8680
4	0.0898	0.2255	0.0971	0.8771
Consequent Parameters $\hat{p}_{k,j}$				
j	g_{2j}	g_{3j}	g_{0j}	
1	0.01488	0.9881	-0.0016	
2	0.01488	0.9881	-0.0016	
3	0.01488	0.9881	-0.0016	
4	0.01488	0.9881	-0.0016	

Table 3: Obtained parameters during the learning process: valve 100%

Antecedent Parameters MFs				
Inputs (x)	u_k		p_{k-1}	
	A_{1j}		B_{2j}	
j	σ_{1j}	c_{1j}	σ_{2j}	c_{2j}
1	0.0726	0.9999	0.0511	0.3126
2	0.0708	0.4445	0.0501	0.5548
3	0.0722	0.9999	0.0758	0.5473
4	0.0702	0.4444	0.0770	0.3081
Consequent Parameters $\hat{p}_{k,j}$				
j	g_{2j}	g_{3j}	g_{0j}	
1	0.00903	0.9850	-0.00009	
2	0.00903	0.9850	-0.00009	
3	0.00903	0.9850	-0.00009	
4	0.00903	0.9850	-0.00009	

Within the different clustering methods, Fuzzy C-Means Clustering (FCM) [2] is a technique in which the data set is divided into a determined number of clusters with every data point in the dataset belonging to every cluster to a certain degree. The objective of this method is to minimise the following objective function:

$$J_m = \sum_{i=1}^{C} \sum_{j=1}^{N} \mu_{ik}^m D_{ik}^2 \tag{6}$$

where m represents the exponent of the fuzzy partition matrix, controlling the extent of fuzzy overlap, where m is greater than 1, D_{ij} denotes the distance from the j_{th} data point to the i_{th} cluster, and μ_{ij} signifies the degree of membership of the j_{th} data point in the i_{th} cluster.

The FCM clustering process initially involves setting the initial cluster centres, which are by default randomly chosen, so the optimum number of clusters could be chosen. Subsequently, the membership values of the cluster μ_{ij} are randomly initialised. Then, the updated cluster centres are calculated iteratively based on current membership values, using (7). These steps are repeated until convergence criteria are met, such as the objective function J_m improves by less than a specific value, has been established previously, or has reached a maximum number of iterations. To recalculate the values of the membership functions, equation (8) is used. As can be seen, in this formula, the metric distance from each point to the cluster centre has to be calculated. There are several algorithms to obtain it, but the one used is Gath-Geva (GG).

$$c_i = \frac{\sum_{j=1}^{N} \mu_{ij}^m x_i}{\sum_{j=1}^{N} \mu_{ij}^m}, 1 \leq i \leq C \tag{7}$$

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{N} (\frac{D_{ij}}{D_{ik}})^{\frac{2}{m-1}})}, 1 \leq i \leq C, 1 \leq j \leq N \tag{8}$$

In the Gath-Geva (GG) FCM algorithm [6], the process begins by computing the covariance matrices $\mathbf{F}_i$ for each cluster centre. Subsequently, it determines the prior probability P_i to select each cluster. Finally, it calculates the distance from each data point to each cluster using an exponential distance measure with the following formula:

$$D_{ij} = A_i \cdot exp\left(0.5 \sum_{j=1}^{N} (x_j - c_i)^T F_i^{-1} (x_j - c_i)\right), 1 \leq i \leq C, 1 \leq j \leq N \tag{9}$$

where A_i is calculated with (10) using the covariance matrices and the previously calculated probability.

$$A_i = \frac{det(\mathbf{F}_i)}{P_i} \tag{10}$$

5 Results

The results obtained from the neurofuzzy modelling of the plant, as well as the comparison with the system identified by LPV, are now presented. Both models have been validated with part of the total data set obtained experimentally. For the neurofuzzy model, it has been necessary to normalise the data beforehand, as was done for the modelling, as explained above, and in the figure 4, the two models adequately reflect the dynamics of the system.

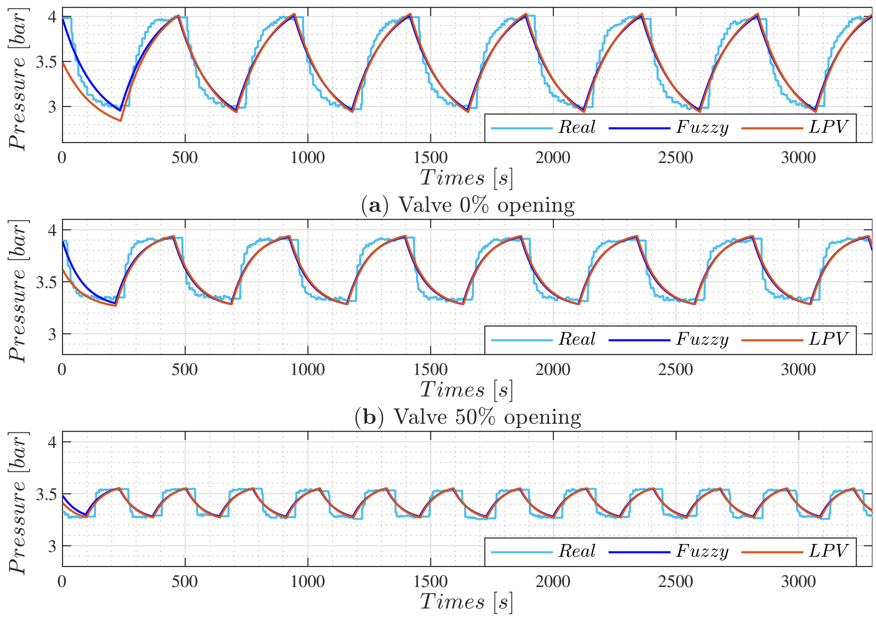
In order to make a comparison of the two models, four different metrics have been used: the error mean ($\bar{E}$), the standard deviation of the error (σ_E), the Root Mean Squared Error (RMSE) and the R^2, which are consistently used to compare the model outputs with a new dataset of real data validation data, as pointed out in [8].

$$\bar{E} = \frac{\sum_{i=1}^{N} (x_i - \hat{x}_i)}{N} \tag{11a}$$

$$\sigma_E = \sqrt{\frac{\sum_{i=1}^{N} (E_i - \bar{E})^2}{N}} \tag{11b}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \hat{x}_i)^2}{N}} \tag{11c}$$

$$R^2 = 1 - \frac{x_i - \hat{x}_i}{x_i - \bar{x}_i} \tag{11d}$$



(**a**) Valve 0% opening

(**b**) Valve 50% opening

(**c**) Valve 100% opening

Fig. 4: Validation results. Real data (cyan line), fuzzy model (blue line) and LPV model (orange line), outputs.

The validation of the three models obtained with each of the applied techniques (LPV and FCM) is shown in Fig. 4. Fig. 4a shows the comparison of the models when the valve is closed. On the other hand, the comparison of the models when the valve is at 50% is shown in Fig 4b, while Fig. 4c shows the comparison of the two models when the valve is fully open. Furthermore, the error indices of all models are shown in Table 4.

Table 4: Overall performance indices

Validation index						
Model output	Close		Semi-open		Open	
	Fuzzy	LPV	Fuzzy	LPV	Fuzzy	LPV
$\bar{E}$ [bar]	0.0023	0.0229	0.0052	0.0088	-0.0108	-0.0063
σ_E [bar]	0.1210	0.1363	0.0845	0.0865	0.0592	0.0554
RMSE [bar]	0.1210	0.1382	0.0847	0.0869	0.0602	0.0558
R^2	0.9372	0.8951	0.9055	0.8961	0.8205	0.8381

Based on the indices provided in Table 4, we compare the different models obtained for each valve state. When the process is with the valve closed, the FCM model presents the lowest mean with 0.0023; $[bar]$, while the LPV model is around the hundredths. Taking into account the variability of the estimations, measured by the standard deviation of the error (σ_E), it is observed that the LPV model shows the highest deviation, with a value of 0.1363 [bar]. Regarding the precision of the estimates, measured by RMSE, the FCM model shows the lowest value with 0.1210, while the LPV model has the highest RMSE with 0.1382 [bar], indicating a larger discrepancy between predicted and observed values. Finally, both models exhibit relatively high R^2 values, suggesting a good fit to the observed data. However, the FCM exhibits the best error rates.

On the other hand, when the valve state is at 50%, the metrics obtained show that the FCM presents the lowest variability in the estimates, the lowest discrepancy between the predicted and observed values. In the case where the valve state is 0.50 the mean error indicates that both models, FCM and LPV, respectively, overestimate the outlet pressure, as they present a positive value in both cases.

Finally, when the valve is at 100%, fully open, the mean error indicates that both techniques underestimate the outlet pressure, as it has a negative value. However, the lowest value of -0.0063 [bar] is found in the LPV model. Furthermore, the variability of the estimates measured by σ_E, the discrepancies in $RMSE$ between the predicted and observed values, together with the R^2 of the LPV, have relatively low values compared to the FCM.

In general, both techniques show good results, with the FCM fitting best when the valve is closed and semi-open, and the LPV fitting best when the valve is fully open, although the differences are minimal.

6 Conclusion

This article compares two different models of a reverse osmosis desalination plant. Both models were obtained with experimental data by running the plant in three different scenarios, with the only variation in the operating point of the waste reuse valve. A detailed description of the fuzzy C-Means modelling of the system has been shown, and this has been validated with some data, obtaining results similar to the LPV model, even better in certain scenarios. However, the greatest advantage lies in the computational speed of the fuzzy method, since with only a few rules and a few seconds of simulation, it achieves a dynamic almost identical to the real system and with less computational cost than the LPV model. The ease of modelling the fuzzy system can also be mentioned.

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