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Fuzzy demand forecasting in a predictive control strategy for a renewable-energy based microgrid

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***Abstract*— In model based control approaches for the dynamic operation of renewable-energy based microgrid, an accurate demand forecast is crucial. However, the high level of uncertainties in the system and non-linearities make the task of prediction not easy. In this context, we propose the use of a stable Takagi & Sugeno (T&S) fuzzy model to perform the demand forecasting in a real-life microgrid located in Huatacondo, Chile. Based on real-data from the microgrid, located in northern Chile, the T&S fuzzy model was identified and compared with an adaptive neural network, showing the T&S fuzzy model better open-loop prediction capabilities. To increase the prediction capability, an analysis of the amount of historical data needed, and the frequency required for training purposes was also done. For the case study, it is suggested to use a large amount of data rather than increasing the training frequency.**

I. Introduction

MICROGRID is a concept that nowadays involves the operation and interactions between a cluster of loads or demand for energy, and a set of different micro-sources that provides both power and heat to a local area [1]. Given the small-size of the microgrid, any change in the use of the appliances in a house, or any change in the demand patterns for energy, can have a significant effect in the load of the microgrid, and thus, in its normal operation. A proper load forecast serves as a guideline for a safe scheduling, planning and management of the microgrid. For monitoring or for model based predictive control purposes, different methods for doing the load forecasting have been reported in the literature [2-5]. All those methods were designed to deal with the complexity and uncertainties inherent of the load behavior, being fuzzy models used because they permit to capture in a systematic way, the non-linear behavior of the process. Identification of fuzzy models is a complex problem which has been divided in different steps, including clustering and the identification of the model in each rule. Variations in the way the clusters are conceived, the input selection, and different identification methods have been presented in the literature [6], [7]. In this paper we use a standard method for the identification of a Takagi & Sugeno model, to perform demand forecasting in the short term at the microgrid level, and its applicability in the model predictive control used by the energy management system of the real-life operating Huatacondo microgrid located in northern Chile. In addition to the conventional identification procedure, the stability of the model is analyzed and used as a validation criterion, by applying a method based on the Lyapunov theorem. Also, the analysis performed for online training is presented, in which the model was trained with different frequencies and with different amount of data, with the aim of identifying the adequate number of samples and training frequency that make the model more reliable. Other contributions of this paper are 1) to present a nice real-life problem where the application of new control methods is crucial, 2) to show how fuzzy identification for predictive control works in a real-life microgrid.

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The paper is organized as follows: in Section II, the Takagi & Sugeno models are described, and the identification methodology and stability theorems applied for the respective analyses are summarized. The existing microgrid and its corresponding energy management system are described in Section III, together with a description of the behavior of the prediction model, and a comparison with a previous model based on neural networks. Online training results are also included. Finally, in Section IV conclusions and future work directions are presented.

II. Stable fuzzy modeling

A. Takagi & Sugeno modeling

The Takagi & Sugeno (T&S) fuzzy models are based on a fuzzy partition of the input space. In each fuzzy subspace a linear input-output relation is generated. The output of the fuzzy model is given by the aggregation of the values inferred in each fuzzy rule, by implications of the inputs. Fuzzy models can be used to model dynamic systems as they are universal approximations of any nonlinear function [8].

For representing the dynamic non-linear systems, the T&S models can be written as:

$$
\begin{aligned}
R_i : & \; if \;\; y(t-1) \; is \; A_{i,1} \; and \; .... \; and \; y(t-n) \; is \; A_{i,n} \\
& and \; u(t-1) \; is \; B_{i,1} \; and \; .... \; and \; u(t-m) \; is \; B_{i,m} \\
& then \; y_i(t) = a_{i,1} y(t-1) + ... + a_{i,n} y(t-n) \\
& \qquad + b_{i,1} u(t-1) + ... + b_{i,m} u(t-m) + c_i
\end{aligned}
$$

where y_i is the consequence output of rule i, and $A_{i,1}, \dots, A_{i,n}, B_{i,1}, \dots, B_{i,m}$ the fuzzy sets with membership functions representing the fuzzy subspace associated with rule i. The final output y inferrerd from n consequences is given by:

$$Y(t) = \frac{\sum_{i=1}^{R} (W_i y_i)}{\sum_{i=1}^{R} W_i} \qquad (1)$$

with W_i the degree of activation for rule i.

For this study, the next fuzzy dynamic model is considered:

$$R_i: If\, x_1(t)\ is\ A_1^i\ and \dots and x_n(t)\ is\ A_n^i$$
$$then\ x^i(t+1) = a_1^i x_1(t) + \dots + a_n^i x_n(t)$$

The linear subsystem in the consequent of rule i can be written in the matrix form:

$$x^i(t+1) = A_i x(t) \tag{2}$$

where $x(k) \in R^n$, $A_i \in R^{nxn}$. Then the output of the corresponding fuzzy model is:

$$x(t+1) = \sum_{i=1}^{R} w_i A_i x(t) \tag{3}$$

with $w_i = \frac{W_i}{\sum_{i=1}^{R} W_i}$ the normalized degree of activation of rule i.

B. *Identification method*

Next, the main steps for the fuzzy identification methodology are described (see Figure 1).

1) *Data selection*

Necessary data sets for non-linear fuzzy modeling are:

Training set: From these data, the fuzzy model structure and model parameters are obtained.

Test set: An additional test set is defined. This set is not directly used in the training algorithm; however, it allows evaluating the model generalization capacity given by the fuzzy model behavior under a new data set.

Validation set: Necessary new data for evaluating the appropriate behavior of the adjusted model.

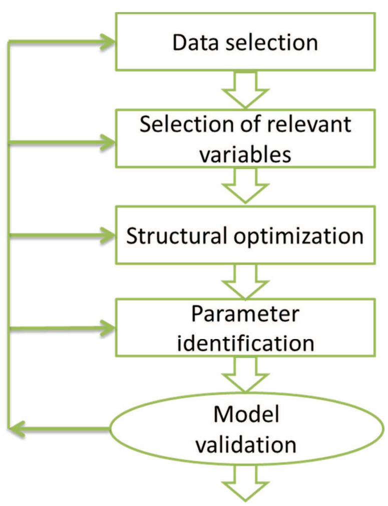

Fig 1: Fuzzy model identification procedure.

The different data set should contain enough information about the non-linear system to be modeled, with information coming from different operational regions, with the proper excitation signals.

2) *Selection of relevant input variables*

For any process modeling, one of the most important points is the appropriate selection of the relevant input variables that must be included in the model. An easy method to solve this problem is by performing a sensibility analysis, as considered in [9]. This methodology consists of adjusting an initial model with the maximum possible input variables, looking for limiting the problem complexity by reducing one by one the less relevant inputs. Then, the influences or sensibilities for each input variable are determined and an optimum set of input variables with the biggest associated sensitivities is obtained.

3) *Structural optimization*

In general, the structural optimization of a non-linear multivariable model is a searching procedure consisting of proposing different architectures, with increasing complexity. This problem is essentially combinational, very difficult to be solved explicitly for all the possible combinations of models (depending on the number of relevant input variables).

For each proposed structure, the idea is to find the one that minimizes the root mean square error (RMSE) and has a good RMSE with the test set. This process is concluded when the test error reach a reasonable value. The RMSE is given by:

$$RMSE = \sqrt{\frac{\sum_{h=1}^{N}(y_h - \hat{y}_h)^2}{N}} \tag{4}$$

where y_h is the sampled datum, $\hat{y}_h$ is the estimated output by the fuzzy model and N is the number of sampled data.

4) *Parameters identification*

In this identification stage, the fuzzy clustering for determining the premise parameters is performed. Clustering is the partitioning of data into groups based on similarities among the data. In fuzzy clustering, the data is assigned to each cluster with a degree of membership between 0 and 1. Fuzzy C-means clustering is one of the most frequently used fuzzy clustering algorithms and allows one piece of data to belong to multiple clusters. Once the premises are determined according to the clustering method, the consequence parameters are obtained based on using the Takagi & Sugeno [10] method which is based on least squares. There are two methods defined by:

Method 1: For each cluster, the square error is minimized between the output $y_i(t)$ linear consequence model of rule i and the corresponding output data in this subspace. Then, the following cost function associated with the i-th fuzzy cluster is minimized:

$$J_j = \sum_{i=1}^{M} u_{ij}^2 \left(y^i - (\hat{x}^i)^T \tilde{a}_j\right)^2 \tag{5}$$

where u_{ij} is the membership degree for the i-th datum to the j-th cluster, y^i is the output of the i-th data pair and $(\hat{x}^i)^T \tilde{a}_j$is the output associated with the j-th rule for the i-th data point. The solution $\tilde{a}_j$ for $j = 1, \dots, r$ is given by:

$$\tilde{a}_j = \left(\hat{X}^T D_j^2 \hat{X}\right)^{-1} \hat{X}^T D_j^2 Z \tag{6}$$

where

$$\hat{X} = \begin{bmatrix} 1 & \dots & 1 \\ x^1 & \dots & x^M \end{bmatrix}^T,$$
$$Z = [y^1, \quad \dots \quad, y^M]^T$$
$$D_j^2 = \left(diag([u_{1j}, \dots, u_{Mj}])\right)^2 \tag{7}$$

Method 2: An alternative is to use the least square method over the whole system, rather than solving a least square problem for each rule. To do this, the fuzzy system is parameterized in such a form that it is linear in the consequent parameters and of the form:

$$f(x|\theta) = \theta^T \xi(x) \tag{8}$$

The output can be written as:

$$Y = \frac{\sum_{i=1}^{R} a_{i0} W_i}{\sum_{i=1}^{R} W_i} + \frac{\sum_{i=1}^{R} a_{i1} x_1 W_i}{\sum_{i=1}^{R} W_i} + \dots + \frac{\sum_{i=1}^{R} a_{in} x_n W_i}{\sum_{i=1}^{R} W_i}$$
$$\xi_i = \frac{W_i}{\sum_{i=1}^{R} W_i} \tag{9}$$

where $\xi = [\xi_1, \dots, \xi_R, \xi_1 x_1, \dots, \xi_R x_1, \dots, \xi_1 x_n, \dots, \xi_R x_n]^T$, $\theta = [a_{10}, a_{20}, \dots, a_{R0}, a_{11}, a_{21}, \dots, a_{R1}, \dots, a_{1n}, a_{2n}, \dots, a_{Rn}]$

So the fuzzy system is $Y = f(x|\theta) = \theta^T \xi(x)$, being linear in the consequent parameters and the recursive least square method can be used to find θ.

5) Model validation

Stability of fuzzy control systems has been difficult to analyze because fuzzy systems are essentially nonlinear systems. The Lyapunov stability theory is one of the main approaches for dealing with the stability analysis of Takagi & Sugeno systems [11], [12].

Theorem 1 [13]: The equilibrium of a fuzzy system with r rules is globally asymptotically stable if there is a common definite-positive matrix P for all the subsystems such that

$$A_i^T P A_i - P < 0 \tag{10}$$

Theorem 2 [13]: Assume that A_i is a stable and nonsingular matrix for $i = 1,2,\dots,r$. The matrix $A_j A_i$ is stable for $i,j = 1,\dots,r$ if there is a common definite-positive matrix such that

$$A_i^T P A_i - P < 0 \tag{11}$$

Proof [13]: From theorem 2, using $(A_i^{-1})^T = (A_i^T)^{-1}$ is it obtained $P - (A_i^{-1}) P A_i^{-1} < 0$. Then, $P < (A_i^{-1})^T P (A_i^{-1})$ for $i = 1,\dots,r$.

As $A_i^T P A_i < P$ the following inequality holds for $i,j = 1,\dots,r$:

$$A_i^T P A_i < (A_j^{-1}) P (A_j^{-1}) \tag{12}$$

From the inequality, $A_j^T A_i^T P A_i A_j - P < 0$. Therefore, $A_i A_j$ must be a stable matrix for $i,j = 1,\dots,r$. If one of the $A_i A_j$'s is not a stable matrix, then there is not a common P.

Using this theorem, we will check if the T&S are stable as a condition for the model validation, together with the evaluation of the RMS for the test data set, so to obtain T&S models suitable for model predictive control applications.

As another criterion to be included in the model validation, the proper real time training frequency and the right amount of data will be considered. Those characteristics are necessary to obtain the best model in terms of prediction capacities. To do this, the same data set is used for forecasting at different horizon predictions (e.g. one-hour ahead, one-day ahead and two-days ahead) and then, their corresponding errors are evaluated. Also, the models are trained with different amounts of data. Considering both aspects (prediction errors and the amount of data needed) the best model is selected for the real-time control.

III. Load Forecasting using stable fuzzy models for a real Renewable Energy Based Microgrid

A. Microgrid description

The microgrid on which this work is based is located in an isolated village in the Atacama Desert, in northern Chile, called Huatacondo (20°55'36.37''S 69°3'8.71''W). The village's electric network was isolated from the interconnected system and energy had been supplied for only 10 hours a day by a diesel generator. The installed microgrid takes advantage of the distributed renewable resources in the area, providing 24-hour electricity service.

The system is composed of a photovoltaic system, a wind turbine, the existing diesel generator unit of the village, an energy storage system (ESS) composed of a lead-acid battery bank (LABB) connected to the microgrid through a bidirectional inverter, a water pump, and a DSM (loads). Figure 2 presents a diagram of the electrical and water flows of this microgrid.

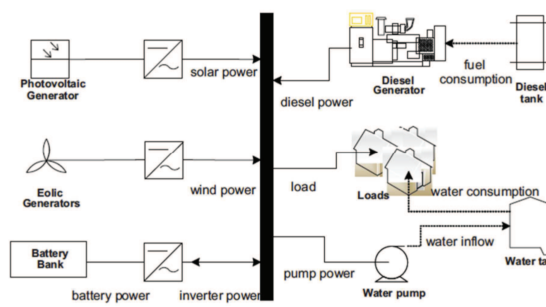

Fig 2: Renewable-based microgrid diagram

B. EMS based on predictive control strategy

The EMS, proposed in [14] minimizes the operational costs while supplying the water and load demands, considering a two-day-ahead forecasting of the weather conditions, water consumption, and electrical load. Fig. 3 shows the EMS that provides the power references for the diesel (P_D) generator, the ESS inverter power (P_I), the binary signals for the water supply system (B_P), the desired solar power (P_S) and the signals for loads (S_L). The EMS inputs are the predicted maximum and minimum attainable solar power (P_{Smax}, P_{Smin}), wind power (P_E), expected load (P_L), water consumption (w_c), initial conditions for the battery charge (E_{SOC_i}), battery bank voltage (V_i) and current (I_i), water tank level (V_{Ti}) and diesel on/off state (B_{gi}). In this work, the electrical load forecasting P_L is performed.

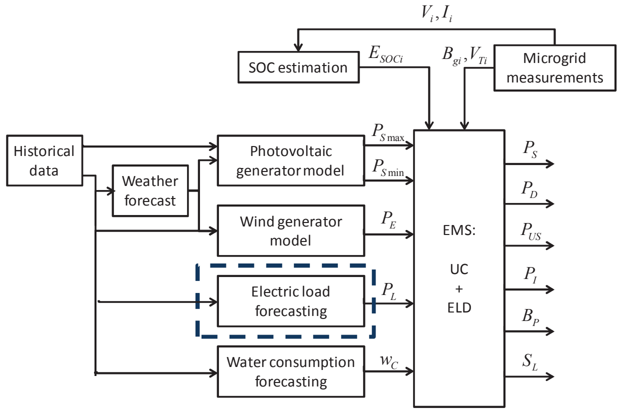

Fig 3. Blocks diagram of the proposed energy management system.

The EMS minimizes the operational costs of the microgrid in a given horizon T, using a discrete time-step δ_t, i.e. $t_{i+1} = t_i + \delta_t$. With this, the objective function is formulated as:

$$J = \delta_t \sum_{t=t_o}^{T} C(t) + \sum_{t=t_o}^{T} C_S(t) + C_{US}\delta_t \sum_{t=t_o}^{T} P_{US}(t) + C_{Tf} \sum_{t=t_o}^{T} V_{Tf}(t) + C_H(T) \quad (13)$$

where $C(t)$ and $C_S(t)$ are the operational cost function and the start-up cost function of the diesel generator respectively, $C_{US}(t)$ is the price for unserved energy, $V_{Tf}(t)$ is the unserved water, $C_{Tf}(t)$ is the cost of unserved water, and $C_H(T)$ is the cost of using the LABB. The first two terms of the objective function represents the operational and start-up costs of the diesel generator respectively; the next two terms penalize the unsupplied electric energy and the unserved water supply respectively and the last term represents the penalty cost of using the LABB and affecting its lifetime.

The problem of the EMS is solved at supervisory level every time-step, using a unit commitment with a predictive control strategy. The rolling horizon of the predictive control scheme is considered for reducing the effect of the uncertainties of the input variable forecasting.

Within this MPC context, short-term load forecasting is an important input to the microgrid energy management system for optimal utilization of available resources. In the next sections, we will focus on the load prediction steps.

C. Evaluation basis

The data used to train and validate the model extends from December, 2010 to May, 2011. This data is divided into three sets: training, set, and validation, with the distribution shown in Table 1. To evaluate the model, the RMSE and mean absolute percentage error (MAPE) are considered as performance indices.

$$MAPE = \frac{100}{N} \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (14)$$

where y_i is the real load, $\hat{y}_i$ is the predicted load, and N is the number of data points.

TABLE I
Data distribution

Set	Start	End
Training	12-December-2010	8-February-2011
Test	8-February-2011	10-April-2011
Validation	10-April-2011	9-May-2011

The model is compared with the one developed in [15], which is based on the same microgrid and uses neural networks to predict load. The comparison is made using the same data and forecast horizon. As the EMS is based on a rolling horizon strategy, the model is evaluated using that strategy, using different forecast horizon and training data set lengths.

D. Fuzzy models

In this section, development of the electric load prediction module for the EMS is detailed. The load forecast is important for the EMS to have a good dispatch.

1) Data selection

To train and validate the model, the data is divided into three sets. The first set, corresponding to 40% of the data, is used to train the model; the next 40% is used as the test set; and the final 20% of the data is used to validate the model.

2) Selection of relevant input variables

The most relevant variables are detected. The variables were chosen based on a correlation analysis, between the electricity demand of Huatacondo and solar power, speed of wind, temperature, moisture and solar radiation, from December, 2010 to July, 2011. Results show that those variables do not have a high correlation coefficient, because of the almost non-variable weather conditions in Huatacondo; therefore the model uses only the historical demand. Thus, the inputs for the fuzzy model are the demand of the previous day with a sampling time of 15 minutes (96 steps). Finally, the fuzzy model has the following structure:

$$R_i: If\ y(t-1) is\ A_{i,1}\ and \ldots and\ y(t-96) is\ A_{i,96}$$
$$then\ y_i(t) = a_{i,1}y(t-1) + \cdots + a_{i,96}y(t-96) \quad (15)$$

with $y(t)$ the load forecast for t.

3) Structural optimization

To choose the appropriate method for the number of rules, and the regressors to be selected in the model, the parameters will be identified using the two least square methods, described in section II.B.4. Different numbers of rules, and the RMSE index of the test set are evaluated.

4) Parameters identification

For the parameter identification, the two least square methods, described in section II.B.4, are used. The model that uses the first method will be called T&KS11, and the one that uses the second method will be called T&KS21 from here onward. In the next section both methods are evaluated based on the comparison of the RMSE index. The premise identification is performed using fuzzy clustering.

5) Model Validation

The RMSE index for different numbers of rules, using both models, is shown in Figures 4. The obtained model T&KS11 is discarded because the RMSE test increases with more rules. The second method is chosen, and therefore the T&KS21 model is used for load forecast. The number of rules chosen is 4 or 8, because of the slight difference in RMSE and the short time of processing.

Based on theorems 1 and 2, described in Section II.C, the stability is analyzed to T&S models with 4 and 8 rules. Thus, both models are written in their state space form, obtaining 4 and 8 state matrices respectively. The stability of every matrix is analyzed. For the 8 rules model only one is stable, so the model is unstable. All the matrices of the 4 rule model were stable, so all the matrices are multiplied among them to verify conditions of theorem 2, obtaining 16 matrices. For this model, the 16 matrices are stable, so the 4 rule model is stable and is the one used to forecast electric load.

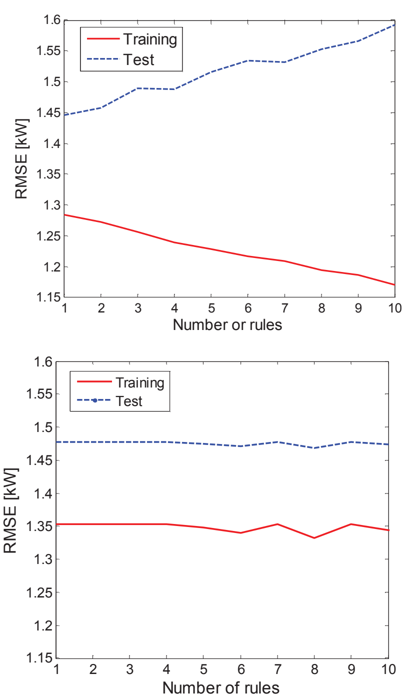

Fig 4: RMSE for the a) T&KS11 model and b) T&KS21 model

Figure 5 shows the behavior of the selected model using validation data, considering two-days ahead for load forecasting. It also shows that the model predicts the load adequately with the exception of load peaks, where the model underestimates it. This is because the training data does not present many peaks in the daily behaviour of the load.

In the next section, the proposed load forecasting using the Takagi & Sugeno fuzzy model is compared with a neural-network based model. The validation steps including the proper real time training frequency and the right amount of data will be considered in the comparison.

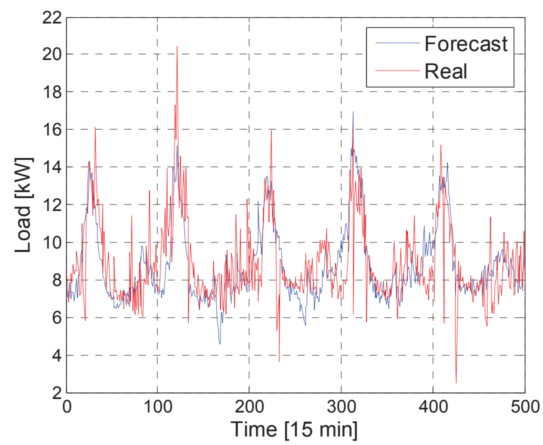

Fig 5: Two-day-ahead- forecasting of load and real load from Huatacondo micro-grid. Validation set.

E. Comparative analysis

The T&S model obtained is compared with the neural networked reported in [15]. The neural network consists of 3 layers: one hidden layer, 96 neurons in the input layer, 8 neurons in the hidden layer, and one neuron in the output layer. The training method used is back-propagation.

The comparison is made through the RMSE and MAPE indices, for 1 hour, 24 hour, and 48 hour prediction horizons. This was made using rolling horizon methods, making the load prediction for the next N hours in every step, using real data. For each prediction the RMSE and MAPE defined in (4) and (14) respectively, are calculated. Table 2 shows the mean of both sets for the fuzzy-based (T&S) and the neural-network based (NN) forecasting models.

The data used for both models consists of 14,976 measurements of electric load, of which 60% is for training, 30% for testing, and 10% for validation. Taking into account that the error increases as the demand behavior starts to differ significantly from the training set, and that the validity of the model depends on the amount of data used for training, real-time training is analyzed.

Table 3 and Table 4 present the prediction error (MAPE and RMSE) at one-hour, 24-hours and 48-hours ahead for electric load, using the rolling horizon strategy and training every 7, 15, and 30 days. For each case, three models are used, trained with 30, 60, and 90 days.

In this case, improvement is observed when the amount of data for training increases, getting a reduction of approximately 10% in the MAPE index from using 30 to 90 days of data. The differences for the different training frequencies are not considerable. Therefore, it is more important to have a large amount of data for training than to train the model with varying frequencies. However, for future work, analyzing, the training frequency with the data of a whole year to see the effect of the seasons is recommended.

TABLE II
Error for the T&S-based and NN-based forecasting models.

	48-hours ahead		24-hours ahead		1-hour ahead	
	T&S	NN	T&S	NN	T&S	NN
RMSE [kW]	1.71	1.72	1.54	1.80	1.53	1.65
MAPE [%]	14.83	15.98	12.80	15.47	13.37	14.12

TABLE III
Real-time training MAPE

Mean MAPE [%]				
Prediction horizon	Data for training	Training frequency		
		7 days	15 days	30 days
48 hours ahead	30 days	15.9003	15.6955	16.1343
	60 days	15.5700	15.4568	15.5245
	90 days	14.1630	14.1987	14.2569
24 hours ahead	30 days	15.5260	15.2391	15.6270
	60 days	15.2763	15.2345	15.2777
	90 days	13.9682	13.9801	14.0975
1 hour ahead	30 days	15.5171	15.6394	16.2135
	60 days	15.4031	15.4151	15.4399
	90 days	14.4017	14.3877	14.5323

TABLE IV
Real-time training RMSE

Mean RMSE [kW]				
Prediction horizon	Data for training	Training frequency		
		7 days	15 days	30 days
48 hours ahead	30 days	1.7947	1.7846	1.7978
	60 days	1.7761	1.7653	1.7781
	90 days	1.6956	1.6959	1.7051
24 hours ahead	30 days	1.7210	1.7195	1.7288
	60 days	1.6837	1.6798	1.7034
	90 days	1.6564	1.6560	1.6713
1 hour ahead	30 days	1.4447	1.4453	1.4795
	60 days	1.4234	1.4249	1.4390
	90 days	1.4256	1.4243	1.4291

IV. Conclusions

Demand forecasting is an important stage for the EMS systems applied to micro-grids where any kind of change of energy use has significant effects on the microgrid load, and resource availability is also uncertain. In this paper a demand forecast application that makes use of Takagi & Sugeno fuzzy models is presented. This model uses daily data to perform predictions, and its stability is established by means of system matrix analysis. The model delivers forecasts with a horizon of 48 hours each 15 minutes; it was compared with a neural network-based model, obtaining better results with the fuzzy model.

Finally, both training frequency and the amount of data required for obtaining good results for forecasts of 1 hour, 24 hours, and 48 hours in advance were analyzed. Results show that good model behavior is obtained when a data set of 90 days is used for training purposes regardless of the training frequency. For future work, it will be useful if the data set comprises a whole year to analyze training frequency issues and to optimize a robust fuzzy model structure.

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