Energy Consumption Forecasting using Neuro-Fuzzy Inference Systems: Thales TRT building case study

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Abstract— **Electrical energy consumption forecasting is, nowadays, essential in order to deal with the new paradigm of consumers' active participation in the power and energy system. The uncertainty related to the variability of consumption is associated to numerous factors, such as consumers' habits, the environmental temperature, luminosity, etc. Current forecasting methods are not suitable to deal with such a combination of input variables, with often highly variable influence on the outcomes of the actual energy consumption. This paper presents a study on the application of five different methods based on fuzzy rule-based systems. This type of method is able to find associations between the distinct input variables, thus creating rules that support and improve the actual forecasting process. A case study is presented, showing the results of applying these five methods to predict the consumption of a real building: the Thales TRT building, in France.**

Index Terms— **Energy consumption, Forecasting, Fuzzy rule-based systems, TRT building**

I. INTRODUCTION

Time series forecasting is an attractive domain in the power and energy systems field, as it is essential to enable and adequate energy resources management. With the increase of renewable generation with an intermittent nature, and the consequent need for the increase in consumers' flexibility, forecasting energy generation and consumption, in addition to other factors, such as market prices, environmental variables, among many others, becomes crucial [1]. In this scope, regression approaches and Artificial Intelligence (AI) based methods, such as Artificial Neural Networks (ANN) are the most common approaches. Because of their attractive characteristics, Support Vector Machines (SVM) has been attracting high interest in the scientific community and many have been the extensions proposed to the basis algorithm. The application of SVM based methods to forecast energy consumption is also widely found in the literature. A method with two dimensional SVM is proposed in [2] for load forecasting. The method contains two main procedures, the first one is to identify the bad data and smooth the daily curve load, and the second is to train the smoothed historical load data and predict the needed future load. A combination of DWT (discrete wavelet transform) and SVM are used for load forecasting in [3]. In [4] the combination of two methods for predicting the medium and long-time electricity consumption is proposed. In [5] a new model which integrates a SVM with the reduction attributes of Rough Sets (RS) based on Immune Genetic Algorithm (IGA) is proposed to form a new load forecasting model. The forecast of electricity consumption in Malaysia based on ANN is presented in [6]. The work presented in [7] demonstrates the forecast of electricity consumption by separating the periodic variable and decompositions the pattern. In [8] the author applies an ANN in order to forecast the consumption of an office building.

Most of these works achieve acceptable results. However, the integration of correlated external variables, which can improve the results of the energy consumption forecasting, such as the influence of temperature, brightness, among others, is still insufficiently studied. In fact, the major limitations found in the methods used in the literature are: (i) to consider a wide variety of data relevant to the forecast, and (ii) to correlate different types of data from different sources.

This paper presents a study regarding the application of five methods based on Fuzzy Rule-Based Systems (FRBSs) for energy consumption forecasting. These methods have the ability of combining different variables that influence energy consumption by creating association rules between these variables. These fuzzy rules are then used to enhance the forecasting process, usually undertaken by ANN. The application of these methods is assessed using real consumption data from the Thales Group TRT building, in France.

II. FUZZY RULE-BASED SYSTEMS

FRBSs are based on the fuzzy concept proposed by Zadeh [9]. These systems rep-resent the reasoning of human experts in production rules (a set of IF-THEN rules) to handle real-life problems from domains such as control, prediction and inference, data mining, bioinformatics data processing, robotics, and speech recognition. Many different approaches have been implemented using FBRS in order to have a better performance in different real-life problems. These methods are divided into five groups based on the actual FRBS implementation.

1. FRBS based on space partition
2. FRBS based on neural networks
3. FRBS based on clustering approach
4. FRBS based on genetic algorithms
5. FRBS based on the gradient descent method

Five different forecast methods based on FRBS are used in this work in order to forecast the total energy consumption the TRT building for following hours.

1) Wang and Mendel's Method

The Wang and Mendel's model, proposed in [10], is known as a simple method with good performances. This method implements the FBRS based on space partition. The generation of the fuzzy rules is put into effect by means of the four steps below:

Step 1: Divide equally the input and output spaces of the given numerical data into fuzzy regions as the database. It may be obtained from the expert information (if it is available) or by a normalization process. If the latter is the case, perform a fuzzy partition of the input variable spaces dividing each universe of discourse into a number of equal or unequal partitions, select a kind of membership function and assign one fuzzy set to each subspace. In our case, we will work with symmetrical fuzzy partitions of triangular membership functions (Figure 1).
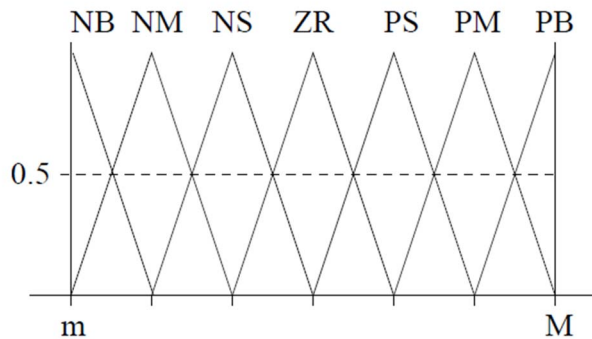

Figure 1 - Graphical overview of a uniform fuzzy partition

Step 2: Generate fuzzy IF-THEN rules by covering the training data. In this step, the generation of fuzzy rules includes the training data, using the database from step1. First, the degrees of the membership functions are calculated for all values in the training data. For each instance in the training data, a linguistic term having a maximum degree in each variable will be determined.

Step 3: Determine a degree for each rule. Degrees for rules are determined by aggregating the degree of membership functions in the antecedent and consequent parts.

Step 4: The ρ candidate rules are first divided in g different groups, each one of these groups composed of all the candidate rules presenting the same antecedent. It will note by R_{ji}, the j-th rule in the i-th group. To compose the final rules, the rule with the highest importance degree is chosen in each group i, $i = 1,..,g$. Hence, g will be both the number of different antecedent combinations in the candidate rule set and the number of linguistic rules in the final generated rule base.

2) Hybrid neural Fuzzy Inference System (HyFIS)

This method was proposed by J. Kim and N. Kasabov [11] and is one of the methods that uses the FRBSs on neural networks. The learning method in HyFIS includes two phases:

- The first phase concerns the structure learning, i.e. finding the rules by using the knowledge acquisition module.
- The second phase regards the parameter learning phase for tuning fuzzy membership functions [12] to achieve a desired level of performance.

In the learning phase, the neuro-fuzzy model in the HyFIS uses a multilayered perceptron (MLP) network based on a gradient descent learning algorithm for adapting the parameters of the fuzzy model [13]. The architecture simplifies learning from data and approximate reasoning, as well as knowledge acquisition. It allows using the combination of both numerical data and fuzzy rules thus producing the synergistic benefits associated with the two sources.
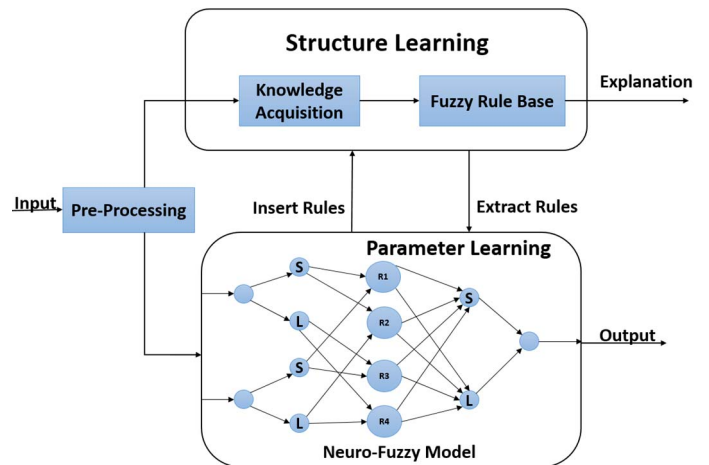

Figure 2 - General schematic diagram of the HyFIS [14]

The proposed neuro-fuzzy model in the HyFIS is a multilayer ANN, based on a combination with fuzzy systems, with five layers; where the input and output nodes are the input state and output control/decision signals respectively. The hidden layers detain the responsibility of representing the membership functions and rules.

3) Genetic fuzzy systems for fuzzy rule learning based on the MOGUL methodology (GFS.FR.MOGUL)

The GFS.FR.MOGUL method implements a Genetic Algorithm (GA) determining the structure of the fuzzy IF-THEN rules and the membership function parameters and was proposed by Herrera et al. [15]. This implementation includes two general types of fuzzy IF-THEN rules which are the Descriptive rules and the Approximate/free semantic approaches. In the first type, the linguistic labels illustrate a real-world semantic and the linguistic labels are uniformly defined for all rules, while in the approximate approach there is any associated linguistic label.

Modeling a fuzzy IF-THEN rule on a chromosome that consists of the parameter values of the membership function shows that every rule has the own membership function values. A population contains many such generated chromosomes, based on the iterative rule learning approach (IRL). IRL means that the chromosomes will be generated one by one, considering the fitness value and covering factor, until there are sufficient chromosomes in the population. After obtaining the population, the GA is started, using the genetic operators: selection, mutation, and crossover.

In order to present a good behavior, an FRBS needs to consider many important statistical properties [16]. In the Generated Fuzzy Rule Bases (GFRB) obtained from MOGUL, two of these properties are considered: the completeness and consistency.

Both properties will be based on the existence of a training data set, Ep, composed of p numerical input-output problem variable pairs. These examples pre-sent the following structure (1):

$$e_l = (ex_1^l, ex_2^l, ..., ex_n^l, ey^l), \quad l = 1, ..., p \quad (1)$$

4) Genetic lateral tuning and rule selection of linguistic fuzzy systems (GFS.LT.RS)

GFS.LT.RS is a GA based method and was proposed by R. Alcala et al [17]. It includes genetic lateral tuning and rule selection of linguistic fuzzy systems. This method implements an evolutionary algorithm for post processing in constructing the FRBS model. A new rule representation model based on the linguistic 2-tupples representation that allows the lateral displacement of the labels is used. To design the evolutionary tuning algorithms, the method includes five main components: (i) Coding scheme and initial gene pool; (ii) Chromosome evaluation; (iii) Crossover operator; (iv) Restarting approach; (v) Evolutionary model.

First, the Wang & Mendel's approach [10] is used to construct the population. For calculating the chromosome evaluation, the Mean Squared Error (MSE) is considered. This method performs BLX-a in crossover process.

5) The simplified TSK fuzzy rule generation method using heuristics and gradient descent method (FS.HGD)

The FS.HGD was proposed by H. Ishibuchi, et al [18] and uses the FRBS based on the gradient descent method. This method implements the simplified TSK fuzzy rule generation method using heuristics and gradient descent method and is considered to solve regression tasks. It uses fuzzy IF-THEN rules with non-fuzzy singletons (i.e. real numbers) in the consequent parts. To generate the antecedent part, the techniques of space partition are implemented, while the initial consequent part of each rule is determined by the weighted mean value of the given training data. Then, the gradient descent method updates the value of the consequent part. Furthermore, the heuristic value given by the user affects the weight of each data.

III. TRT BUILDING

TRT-France building is located in Palaiseau, in the South of Paris, and specifically in the Paris-Saclay area which is a research- and business-intensive cluster.

The building includes 5000 m² of laboratories out of which 3600 m² are clean rooms, and the rest is mainly composed of offices and meeting rooms.

The clean rooms, have thermal, hygrometric, dust and pressure constraints. In order to meet these constraints specific HVAC systems, have to be used, such as Air Handler Units containing particular filtering racks, air extractors, heating and cooling coils, recirculated air ducts.

All this dedicated equipment amounts to about 80% of the total energy consumption of the building. This is continuously monitored over several aggregated consumption points called low-voltage switchboards and which aim at balancing the overall consumption throughout the building. Moreover, different regimes are established for working and non-working ours in terms of clean-rooms conditions, with less strict thresholds outside the working hours range.

A platform stores the power readings for these low voltage switchboards on an hourly basis. Since most of the power budget is taken by the air handlers, the energy consumption can be easily linked to external conditions such as weather data, therefore the dataset also includes readings of the external temperatures for the considered timeframe.

IV. CASE STUDY

The main objective of this study is to improve the forecasting of energy consumption for the following hour. In order to achieve these results, five different forecast methods based on FRBSs have been employed. These methods are developed in R language and use the same set of data as the inputs to forecast the energy consumption of the following hours. A java based application has been developed to execute the methods, based on R's FBRS Package [19]. This application is connected to the database and collects the energy consumption and related data of the TRT buildings to feed the training process of the algorithms.

1)   Input structure

To forecast each value every method needs a set of three tables as the input: (i) Training input, (ii) Training output, and (iii)Testing input. The main input of the method is the Testing input table which includes the energy consumption of every hour since the beginning of the day until one hour before the hour which is meant to be forecasted. Table 1 shows an example of the Testing input table for forecast the energy consumption of 12 hours of 20/12/2013.
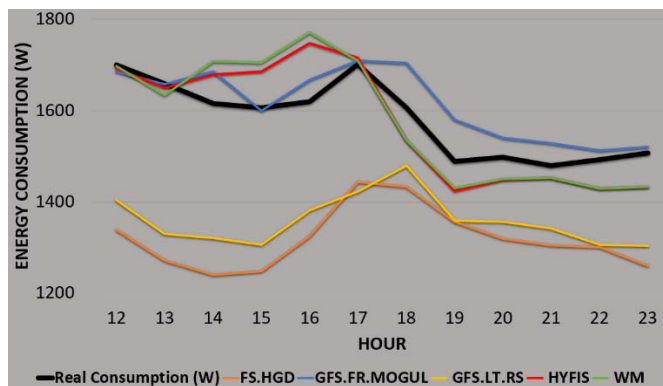
Table 1 - Test input table to forecast the Energy consumption of 12H of 20/12/2013

Hour	0:00	1:00	...	10:00	11:00
Consumption (W)	1487	1497	...	1985	1845

The Train input and Train output tables are used in order to train the methods and generate the fuzzy rules. The Train input table includes the same set of data as the Test input table but from the last 10 days before the target day. And the Train output table has the value of the energy consumption of the same hour as the target hour but from the past 10 days. For every forecasted value, every method will be trained by the data from the last 10 days before the target day.

2)   Results and discussion

The validation process of the forecasting methods uses as target the energy consumption of a set of 12 hours (namely from 12h to 24h of 21/12/2013) to be forecasted based on using the TRT building data. Figure 3 presents the real consumption value of these 12 hours as well as the forecasted values by every forecasting method.

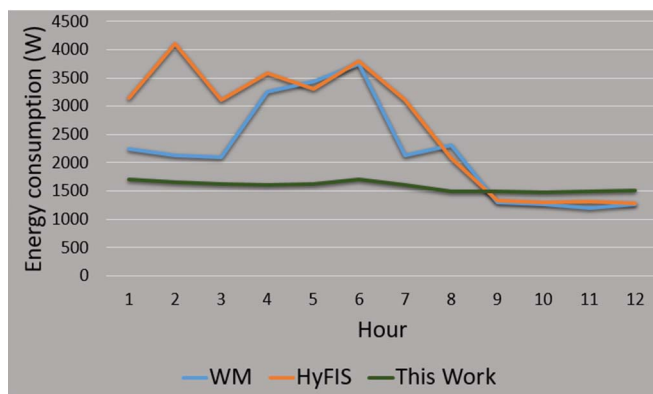**Figure 3 -** Energy consumption forecasting results of 12 hours of 20/12/2013

Fig. 3 shows that all the forecasted values by FS.HGD and GFS.LT.RS are lower than the real consumption, but they are still able to detect the consumption tendency throughout the hours (e.g. the peak around hour 17). On the other hand, the three other methods have more reliable results. The results of HyFIS and WM show that these two methods have a similar behavior and the forecasted values for each hour by these methods are very close. In order to compare the forecasted values to the real consumption, the MAPE (Mean Absolute Percent Error) has been used. Table 2 shows the MAPE error of each forecasted value as well as the average error for each method.

Table 2 - MAPE errors of the forecasted values

HOUR	FS.HGD	GFS.FR.MOGUL	GFS.LT.RS	HYFIS	WM
12:00	20.70%	0.82%	17.39%	0.48%	0.18%
13:00	23.32%	0.06%	19.80%	0.58%	1.48%
14:00	23.26%	4.33%	19.64%	3.86%	5.73%
15:00	22.29%	0.40%	18.64%	4.99%	6.18%
16:00	18.15%	2.99%	14.63%	7.90%	9.40%
17:00	19.80%	0.47%	16.42%	0.79%	0.47%
18:00	10.76%	6.06%	7.95%	4.46%	4.50%
19:00	8.86%	6.07%	6.37%	4.32%	3.88%
20:00	11.88%	2.87%	9.42%	3.24%	3.15%
21:00	11.82%	3.24%	9.31%	1.77%	1.77%
22:00	15.20%	1.27%	12.45%	4.21%	4.21%
23:00	16.32%	0.89%	13.45%	4.84%	4.84%
AVG.	**16.86%**	**2.46%**	**13.79%**	**3.45%**	**3.82%**

As the Table 2 shows, the closest forecasted value to the real consumption is at 13h by the GFS.FR.MOGUL, which accounts for an error of 0.06%. The highest achieved error belongs to the FS.HGD by 23.32% also at 13h. The averages of the errors of each method show that between these five FRBSs methods the GFS.FR.MOGUL has the best performance and the FS.HGD has the highest error.

In [14] and [20] two case studies using HyFIS and WM methods to forecast the energy consumption of an office building for a set of 12 hours of an official day have been presented. The average MAPE error in these two studies is 12.42% for HyFIS and 18.41% for WM, while in this work the average MAPE error for HyFIS is 3.45% and for WM is 3.82%. The reason of this difference between the results is the variation between the real consumption values. The figure 4 shows a comparison between the used Real consumption values in previous works and this work.

Figure 4 - Comparison between the real consumptions from previous works and this work

As the figure 3 presents, the used values in previous works have much more variation during these 12 hours than the used values in this work. The standard deviation in the previous works are 1039.59W (in case of HyFIS) and 848.01W (in case of WM) while the standard deviation of the used values in this

work is 80.43W. It means that while there is less variation in the energy consumption values the forecast method can present a more reliable profile for energy consumption in the following hours.

V. RESULTS AND DISCUSSION

This paper presented a case study on energy consumption forecast based on five FRBSs forecast methods, namely FS.HGD, GFS.FR.MOGUL, GFS.LT.RS, HYFIS and WM. The total energy consumption of the TRT office building in Paris, France had been chosen to be forecasted in this work. The results of these five forecast methods shows that the GFS.FR.MOGUL presents the most trustable energy consumption profile for the following hours, followed by the HyFIS and WM methods.

The comparison between the results of this paper and two previous works, which use the HyFIS and WM methods to forecast the energy consumption, shows that while the energy consumption value has less variation throughout the hours, the results of the methods are closer to the real value.

The future works will include using these five methods to forecast different variables such as the electricity production and the influence of using a combination of different variables in order to forecast the electricity consumption.

REFERENCES

[1] Conejo, A.J., Carrión, M., Morales, J.M. (Eds.), "Decision Making Under Uncertainty in Electricity Markets", Journal of the Operational Research Society, Springer, 66, 174, December 2014

[2] Jingfei Yang and J. Stenzel, "Application of two-dimensional support vector machine in short-term Load forecasting," Power Tech, 2005 IEEE Russia, St. Petersburg, 2005, 1-4.

[3] J. Pahasa and N. Theera-Umpon, "Short-term load forecasting using wavelet transform and support vector machines," Power Engineering Conference, 2007.Singapore, 2007

[4] D. Niu, J. Li and J. Li, "Middle - long Electric Power Load Forecasting Based on Co-integration and Support Vector Machine," Natural Computation, 2007. ICNC 2007. Third International Conference on, Haikou, 2007, pp. 596-600., doi: 10.1109/ICNC.2007.472

[5] J. Wang, Z. Liu and P. Lu, "Electricity Load Forecasting Using Rough Set Attribute Reduction Algorithm Based on Immune Genetic Algorithm and Support Vector Machines," Risk Management&Engineering Management. International Conference on, Beijing, 2008,

[6] M. S. M. Othman, D. Johari, I. Musirin, T. K. A. Rahman and N. F. N. Ismail, "Artificial neural network-based forecast for electricity consumption in Malaysia," Power and Energy (PECon), 2010 IEEE International Conference on, Kuala Lumpur, 2010, pp. 24-28.

[7] S. F. Ghaderi, A. Azadeh, H. S. Keyno, "Forecasting electricity consumption by separating the periodic variable and decompositions the pattern," Industrial Engineering and Engineering Management, IEEE International Conference on, Singapore, 2007, pp. 292-296.

[8] E. Vinagre, L. Gomes and Z. Vale, "Electrical Energy Consumption Forecast Using External Facility Data," Computational Intelligence, 2015 IEEE Symposium Series on, 2015.

[9] L. A. Zadeh, "Fuzzy Sets," Information and Control, vol. 8, pp. 338-353, 1965.

[10] L. X. Wang, J. M. Mendel, "Generating fuzzy rules by learning from examples", IEEE Transactions on Systems, Man and Cybernetics, vol.22, no.6, p.1414-1427, 1992.

[11] J. Kim, N. Kasabov, HyFIS: adaptive neuro-fuzzy inference systems and their application to nonlinear dynamical systems, Neural Networks, 12, 9, November 1999, 1301-1319,

[12] F. Gomide and W. Pedrycz, "Notions and Concepts of Fuzzy Sets", Fuzzy Systems Engineering: Toward Human-Centric Computing, 2007.

[13] K. Rudd, G. Di Muro and S. Ferrari, "A Constrained Backpropagation Approach for the Adaptive Solution of Partial Differential Equations," IEEE Trans. on Neural Networks and Learning Systems, vol. 25, no. 3, pp. 571,584, Mar. 2014.

[14] Aria Jozi, et al, "Energy Consumption Forecasting based on Hybrid Neural Fuzzy Inference System", IEEE Symposium Series on Computational Intelligence, December 2016

[15] F. Herrera, M. Lozano, and J.L. Verdegay, "A learning process for fuzzy control rules using genetic algorithms", Fuzzy Sets and Systems, vol. 100, pp. 143 - 158 (1998).

[16] Driankov, D.; Hellendoorn, H.; Reinfrank, M. An Introduction to Fuzzy Control;Springer-Verlag: Berlin, 1993.

[17] R. Alcala, J. Alcala-Fdez, and F. Herrera, "A proposal for the genetic lateral tuning of linguistic fuzzy systems and its interaction with rule selection", IEEE Trans. on Fuzzy Systems, Vol. 15, No. 4, pp. 616 - 635 (2007).

[18] H. Ishibuchi, et al, "Empirical study on learning in fuzzy systems by rice taste analysis", Fuzzy Set and Systems, vol. 64, no. 2, pp. 129 - 144 (1994).

[19] Lala Septem Riza, Christoph Bergmeir, Francisco Herrera, and Jose Manuel Benitez," Fuzzy Rule-Based Systems for Classification and Regression Tasks"

[20] Aria Jozi, et al," Wang and Mendel's Fuzzy Rule Learning Method for Energy Consumption Forecasting considering the Influence of Environmental Temperature", 2016 Global Information Infrastructure and Networking Symposium (GIIS), Porto, 2016, pp. 1-6.