Fuzzy Approaches Improve Predictions of Energy Performance of Buildings

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Abstract: The energy consumption in Europe is, to a considerable extent, due to heating and cooling used for domestic purposes. This energy is produced mostly by burning fossil fuels with a high negative environmental impact. The characteristics of a building are an important factor to determine the necessities of heating and cooling loads. Therefore, the study of the relevant characteristics of the buildings with respect to the heating and cooling needed to maintain comfortable indoor air conditions, could be very useful in order to design and construct energy efficient buildings. In previous studies, statistical machine learning approaches have been used to predict heating and cooling loads from eight variables describing the main characteristics of residential buildings which obtained good results. In this research, we present two fuzzy modelling approaches that study the same problem from a different perspective. The prediction results obtained while using fuzzy approaches outperform the ones described in the previous studies. Moreover, the feature selection process of one of the fuzzy methodologies provide interesting insights to the principal building variables causally related to heating and cooling loads.

1 INTRODUCTION

In recent years there has been a substantial increase of research in the area of energy performance of buildings. The aim is to design and construct more energy-efficient buildings with the goal of reducing their energy consumption and CO2 emissions. During the last four years the European Commission boosted the research in this area with a programme framed in the Seventh Framework Programme for Research (FP7) (European Commission, 2013).

Fuzzy logic-based methods have been applied sparingly to the energy performance estimation of buildings; however, there is a considerable amount of research that uses fuzzy logic instead of classical controllers to develop advanced control systems with several building energy goals. The overall objective is the management of indoor environment including user preferences. The development of fuzzy controllers to control thermal comfort, visual comfort, and natural ventilation, with the combined control of these subsystems has led to remarkable results (Dounis and Caraiscos, 2009); (Kurian et al., 2005). There are also studies that focus on more specific control purposes such is, for example, the control of electrochromic windows. In this research the authors develop an algorithm to control the solar transmittance of the electrochromic glazing unit, both in terms of energy and the quality of the indoor environment (Assimakopoulos et al., 2004).

Another interesting area within the analysis of energy in buildings where fuzzy logic has been applied is in multiple criteria decision-making (FMCDM). We can find works in the literature that use these techniques with very different goals. For instance, in (Lee, 2010) a FMCDM is developed to evaluate and rank the energy performance of office buildings because it is relevant for energy agencies and authorities. In (Hsieh et al., 2004) this approach is used for selecting planning and design alternatives in public office building. However, FMCDM has been used mainly in energy planning, in application areas such are renewable energy, energy resource allocation, building energy management, transportation energy management or electric utility (Pohekar and Ramachandran, 2004).

Although, as has been already mentioned, fuzzy logic has been used scarcely for the prediction of energy performance of buildings, machine learning strategies have been already used to deal with this

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issue (Tsanas and Xifara, 2012). In the research presented in this paper the work of Tsanas and Xifara is taken as a basis to study the performance of fuzzy approaches for the problem at hand. The approaches reported in (Tsana and Xifara, 2012), i.e. classical linear regression approach called Iteratively Reweighted Least Squares (IRLS) and nonlinear non-parametric method called Random Forests (RF), are compared with the two fuzzy approaches presented in this work, the Fuzzy Inductive Reasoning (FIR) and the Adaptive Neuro-fuzzy Inference System (ANFIS) from the prediction capability perspective and as feature selection tools.

The next section provides an insight into these two fuzzy approaches. Section 3 presents the data used for this study and describes the fuzzy models construction. Section 4 presents and discusses the results obtained. Finally, section 5 presents the main conclusions of this work.

2 METHODS

Both, the fuzzy inductive reasoning (FIR) and the adaptive neuro-fuzzy inference system (ANFIS) are hybrid methodologies that combine mainly soft computing approaches. FIR combines fuzzy logic with machine learning techniques and ANFIS combines fuzzy logic with neural networks.

2.1 Fuzzy Inductive Reasoning (FIR)

The conceptualization of the FIR methodology arises of the General System Problem Solving (GSPS) approach proposed by Klir (Klir and Elias, 2002). This methodology of modeling and simulation is able to obtain good qualitative relations between the variables that compose the system and to infer future behavior of that system. It has the ability to describe systems that cannot easily be described by classical mathematics or statistics, i.e. systems for which the underlying physical laws are not well understood.

FIR offers a model-based approach to predicting either univariate or multi-variate time series (Nebot et al., 2003); (Carvajal and Nebot, 1998). A FIR model is a qualitative, non-parametric, shallow model based on fuzzy logic.

Visual-FIR is a tool based on the Fuzzy Inductive Reasoning (FIR) methodology (runs under Matlab environment), that offers a new perspective to the modeling and simulation of complex systems. Visual-FIR designs process blocks that allow the treatment of the model identification and prediction phases of FIR methodology in a compact, efficient and user friendly manner (Escobet et al., 2008).

FIR methodology has two main processes: a feature selection process, that allow to develop a model, and the prediction or simulation process, that uses the model obtained to infer the future behaviour of the system.

A FIR model consists of its structure (relevant variables) and a set of input/output relations (history behavior) that are defined as if-then rules.

Feature selection in FIR is based on the maximization of the models' forecasting power quantified by a Shannon entropy-based quality measure. The Shannon entropy measure is used to determine the uncertainty associated with forecasting a particular output state given any legal input state. The overall entropy of the FIR model structure studied, H_s, is computed as described in equation 1.

$$H_s = -\sum_{\forall i} p(i) \cdot H_i \,, \tag{1}$$

where *p(i)* is the probability of that input state to occur and H_i is the Shannon entropy relative to the i^{th} input state. A normalized overall entropy H_n is defined in equation 2.

$$H_n = 1 - \frac{H_s}{H_{\max}} \tag{2}$$

H_n is obviously a real-valued number in the range between 0.0 and 1.0, where higher values indicate an improved forecasting power. The model structure with highest H_n value generates forecasts with the smallest amount of uncertainty.

Once the most relevant variables are identified, they are used to derive the set of input/output relations from the training data set, defined as a set of if-then rules. This set of rules contains the behaviour of the system. Using the five-nearest-neighbours (5NN) fuzzy inference algorithm the five rules with the smallest distance measure are selected and a distance-weighted average of their fuzzy membership functions is computed and used to forecast the fuzzy membership function of the current state, as described in equation 3.

$$Memb_{out_{new}} = \sum_{j=1}^{5} w_{rel_j} \cdot Memb_{out_j} \tag{3}$$

The weights w_{rel_j} are based on the distances and are numbers between 0.0 and 1.0. Their sum is always equal to 1.0. It is therefore possible to interpret the relative weights as percentages.

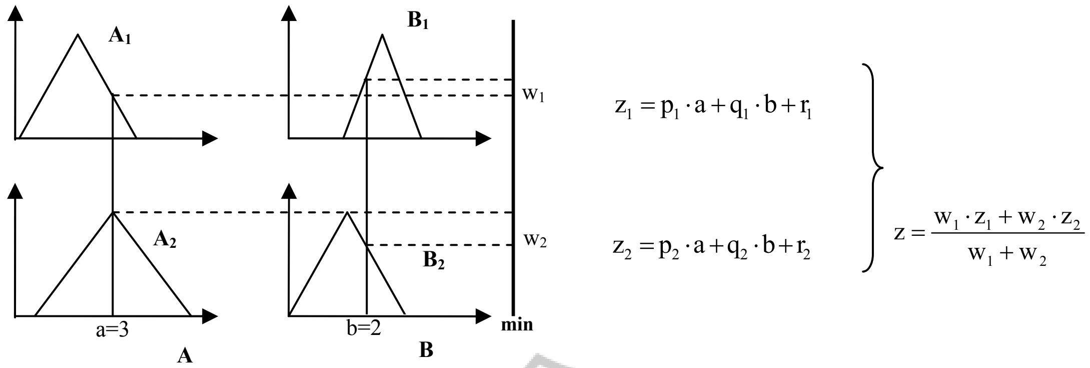

Figure 1: Example of how a Sugeno model works (evaluation of two fuzzy rules with two input variables or antecedents, i.e. A and B).

For a more detailed explanation of the fuzzy inductive reasoning methodology refer to (Escobet et al., 2008).

2.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS), developed by Jang, is one of the most popular hybrid neuro-fuzzy systems for function approximation (Nauck et al., 1997). ANFIS represents a Sugeno-type neuro-fuzzy system. A neuro-fuzzy system is a fuzzy system that uses learning methods derived from neural networks to find its own parameters. It is relevant that the learning process is not knowledge-based but data-driven.

The main characteristic of the Sugeno inference system is that the consequent, or output of the fuzzy rules, is not a fuzzy variable but a function, as shown in equation 4.

$$\begin{aligned} &\text{R1: If A is } A_1 \text{ and B is } B_1 \text{ then } z = p_1 * a + q_1 * b + r_1 \\ &\text{R2: If A is } A_2 \text{ and B is } B_2 \text{ then } z = p_2 * a + q_2 * b + r_2 \end{aligned} \quad (4)$$

Figure 1 describes graphically the inference process of a Sugeno model composed by the two rules described in equation 4 works.

The first step of the Sugeno inference is to combine a given input tuple (in the example of figure 1: a=3 and b=2) with the rule's antecedents by determining the degree to which each input belongs to the corresponding fuzzy set (left panel of Fig. 1). The min operator is then used to obtain the weight of each rule, w_i, which are used in the final output computation, Z (right panel of Fig. 1). Notice that the Sugeno inference has two differentiated set of parameters. The first set corresponds to the membership functions parameters of the input variables. The second set corresponds to the parameters associated to the output function of each rule, i.e. p_i, q_i and r_i.

ANFIS is the responsible of adjusting in an automatic way these two set of parameters by means of two optimization algorithms, i.e. back-propagation (gradient descendent) and least square estimation. Back-propagation is used to learn the parameters of the antecedents (membership functions) and the least square estimation is used to determine the coefficients of the linear combinations in the rules' consequents. ANFIS is a function of the Fuzzy toolbox that runs under the Matlab environment. For a more detailed explanation of the ANFIS methodology refer to (Nauck et al., 1997).

3 DATA

The data used for this study stems from the UCI machine learning repository (UCI, 2013) and is called energy efficiency data set. The data was created by (Tsanas and Xifara, 2012) in the following way. They generated 768 simulated buildings using Ecotet. Ecotet is a sustainable building design software tool that allows the design of buildings performing a whole building energy, thermal performance and water usage analysis, among other functionalities (Ecotet, 2013).

All the buildings have a volume of 771.75 m^3, but different surface areas and dimensions. All of them are created with the same materials, that were selected taking into account the newest and most common materials in the building construction industry and the lowest heat loss in each building element, i.e. wall, floor or roof (U-value).

The simulation assumes that the buildings are located in Athens, Greece, and are residential buildings.

They used three types of glazing areas, expressed as percentages of the floor area: 10%, 25%, and 40%. Furthermore, five different distribution scenarios for each glazing area were simulated: 1) uniform: with 25% glazing on each side, 2) north: 55% on the north side and15% on each of the other sides, 3) east: 55% on the east side and 15% on each of the other sides, 4) south: 55% on the south side and 15% on each of the other sides, and 5) west: 55% on the west side and 15% on each of the other sides. In addition, they obtained samples with no glazing areas. Finally, all shapes were rotated to face the four cardinal points.

Each one of the 768 simulated buildings can be characterized by eight building parameters which are: Relative Compactness (RC), Surface Area (SA), Wall Area (WA), Roof Area (RA), Overall Height (OH), Orientation (O), Glazing Area (GA) and Glazing Area Distribution (GAD). These parameters correspond to the input variables. Also, they recorded the Heating Load (HL) and the Cooling Load (CL), which correspond to the output variables. The authors of the data claim that the data generated represent actual real data with high probability, enabling energy comparisons of buildings (Tsanas and Xifara, 2012).

In the work of Tsanas and Xifara basic statistical analysis of the data were performed and show that linear techniques are not appropriate for the available data in this application due to the fact that the scatter and density plots do not follow a Gaussian distribution.

3.1 Model Evaluation

In order to test the generalization performance of FIR and ANFIS fuzzy models we use cross validation, in this case 10-fold cross validation (CV). The model parameters are derived using the training subset and errors are computed using the testing subset. For statistical confidence, the training and testing processes are repeated 10 times with the whole dataset randomly permuted in each run prior to splitting in training and testing subsets.

Two error measures were used to evaluate the performance of each of the models. These are: the mean square error (MSE) and the mean absolute error (MAE), described in equations 5 and 6, respectively. These are the same error measures used in (Tsanas and Xifara, 2012), in order to compare accurately the methodologies presented in that paper with the fuzzy methodologies presented in this work.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|^2 \tag{5}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{6}$$

where $\hat{y}(t)$ is the predicted output, $y(t)$ the system output and N the number of samples.

3.2 Fuzzy Models Development

In this section the development of ANFIS and FIR models is described. As mentioned before, in this application we have two output variables, i.e. heating load and cooling load, and we want to study if it is possible to estimate each output by using the eight input variables that represent different building parameters. Both, ANFIS and FIR methodologies allow developing models that have a single output, i.e. SISO or MISO models. Therefore, for each methodology two sets of models are obtained, one for each possible output. The input variables for both sets of models are the eight variables previously described. We talk about sets of models because for each methodology and each output we obtain a model for each of the 10 folds, and this is repeated 10 times. Therefore, 100 models are derived and validated for each of the two methodologies and outputs studied.

Both fuzzy approaches need to discretized the quantitative data into qualitative data. To this end, it becomes necessary to define, at least, two parameters, the number of classes (also called granularity) chosen for each input variable (and also for the output variable in the case of FIR models), and the shape of the membership functions of the input variables (and also for the output variable in the case of FIR models).

In this research we have decided to discretize the input variables RC, SA, WA and GAD into three classes and RA, OH, O and GA into only two classes. The output variable is discretized into three classes in the case of the FIR models. Remember that ANFIS does not have fuzzy consequents, i.e. the rules' output is a function (see Figure 1). A triangular shape has been used to discretize all the variables.

These discretization parameters have been chosen based on the analysis of the data. The variable OH can take only two possible values, and therefore it is represented into two classes. Variables RA, O and GA can take four different values, and some of these values appear only few times. A discretization with more than two classes does not enhance the model prediction power and, instead, a higher number of classes can lead to a curse of dimensionality problem. Therefore, it was found that two classes are enough for these variables to obtain good models. The variables discretized into 3 classes have a uniform distribution in their dimensionality space, and, therefore, an odd number of classes seem more reasonable. Three is the lowest number of classes that give good results.

3.2.1 ANFIS Models

In order to obtain ANFIS models it is necessary to define two sets of parameters: the ones related to the discretization process of the input variables, which have been explained before, and the parameters related to the training process. The parameters needed to perform the training process are: the type of the output function (i.e. constant or linear), the optimization method to train the fuzzy inference system and the number of training epochs.

In this research we use a constant output function, a hybrid optimization method and 50 epochs. A constant output has been chosen instead of a linear one because the prediction power of the resulting models were equivalent and the training process is much more time consuming when the linear function is used, due to the additional number of parameters involved that need to be estimated in the optimization process.

ANFIS uses the eight input variables to predict each output, i.e. heating and cooling loads, and does not perform any kind of feature selection.

3.2.2 FIR Models

As in the case of ANFIS, the first step in order to obtain the FIR models is to discretize the data, i.e. to convert quantitative values into fuzzy data. To this end, it is necessary to specify the two parameters described before, i.e. granularity and shape of the membership functions, but also a parameter that refers to the discretization algorithm. Depending on the algorithm chosen the distribution of the membership functions in the variable space may vary and this has a direct impact to the reasoning process, and, therefore, to the model predictions. Contrarily to FIR, ANFIS does not have this discretization parameter. ANFIS distributes uniformly all the membership functions that describe a specific variable. Figure 2 shows an example of uniform (upper plot) and non-uniform (lower plot) distribution of the membership functions of a variable.

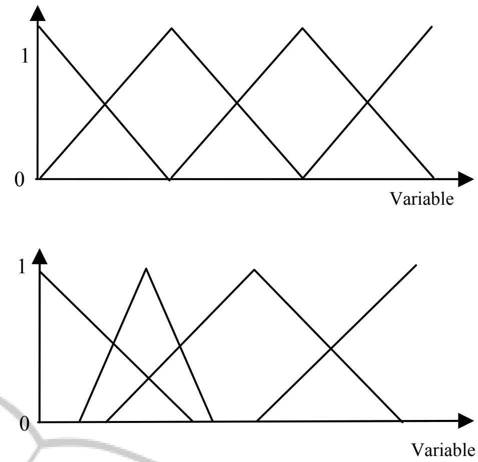

Figure 2: Example of uniform (upper plot) and non-uniform (lower plot) membership functions distribution of four classes that represent a given variable.

In this research, FIR uses the equal with partition (EWP) algorithm for the discretization of the RA and OH variables, and the equal frequency partition (EFP) algorithm for the discretization of the rest of the variables. The EWP algorithm is the one that performs a uniform distribution of the membership functions. The EFP algorithm distributes the membership functions of a variable in such a way that all the classes contain the same number of data points. Visual-FIR allows the modeller to choose between 15 discretization algorithms, some of them belonging to the hierarchical family and others to the fuzzy family (Escobet et al., 2008).

Once the data has been discretized, FIR methodology performs a feature selection process where the more relevant causal relations between the input variables and the output variable are identified. To this end, we used the model structure identification process of the fuzzy inductive reasoning methodology that performs a feature selection based on the entropy reduction measure as described in section 2.

FIR founds that for both outputs, HL and CL, the features that have higher relevant causal relation are Relative Compactness (RC) and Glazing Area (GA). The use of the other variables does not improve the predictive power of FIR models. Therefore, these two variables represent the minimum subset of variables needed to accurately estimate the heating load and cooling load.

4 RESULTS AND DISCUSSION

The MSE and MAE obtained by ANFIS and FIR models, for both HL and CL output variables are summarized in tables 1 and 2, respectively. In both tables, the prediction results reported in (Tsanas and Xifara, 2012) for the Iteratively Reweighted Least Squares (IRLS) and Random Forest (RF) algorithms are also included in order to study their performance when compared with fuzzy approaches. IRLS is a linear regression algorithm that adjusts weights in the coefficients of the classical regression scheme in order to diminish the effect of the outliers when obtaining the fitting curve (Bishop, 2007). RF is a non-linear method which was first put forward by Breiman (2001). RF is a set of classification and regression trees, where the training sample set for a base classifier is constructed by using the Bagging algorithm (Breiman, 1996). When building a base classifier, inner nodes are spitted with a random candidate attribute set. The final classification rule or regression function is the simple majority voting method or the simple average method.

In tables 1 and 2 the errors of ANFIS and FIR models over the 10 cross validation realisations were averaged. Tsanas and Xifara performed 100 cross validations for both, IRLS and RF models. Tables 1 and 2 show the average errors of these 100 CV. We found out that the models errors for each realisation were very similar and, therefore, we think that 10 CV are enough to ensure a fair comparison.

Table 1: Mean square prediction errors obtained by the methodologies: IRLS, RF, ANFIS and FIR, for the HL models and the CL models. The results are given in the form of mean ± standard deviation.

MSE	IRLS	RF	ANFIS	FIR
HL	9.87±2.41	1.03±0.54	0.49±0.1	0.24±0.07
CL	11.46±3.63	6.59±1.56	3.04±0.62	2.96±0.73

Table 2: Mean absolute prediction errors obtained by the methodologies: IRLS, RF, ANFIS and FIR, for the HL models and the CL models. The results are given in the form of mean ± standard deviation.

MAE	IRLS	RF	ANFIS	FIR
HL	2.14±0.24	0.51±0.11	0.52±0.05	0.35±0.04
CL	2.21±0.28	1.42±0.25	1.06±0.11	1.09±0.16

From tables 1 and 2 it can be seen that the linear regression approach, IRLS, has the lowest performance. All the non-linear approaches have good results and FIR is the one that performs much better for both outputs. It is interesting to notice that FIR mean square errors are a 75% and 50% lower than the errors obtained by the RF, for HL and CL models, respectively. The ANFIS errors are also significantly lower (50%) than the MSE of the RF models. Therefore, both fuzzy approaches outperform the RF in the application at hand. It is relevant to mention that the standard deviations obtained by ANFIS and FIR models are really much lower than the ones obtained by RF models. A low standard deviation indicates that all the predictions errors (100 as described in the previous section) tend to be very close to the mean.

An important issue is that FIR, which is the methodology that has a better performance, is the only one that performs a feature selection process. FIR finds that two of the eight input variables, i.e. relative compactness (RC) and glazing area (GA), are highly causally related to the outputs, and therefore, FIR models only use these two building characteristics to predict the heating and cooling loads. This is a very interesting result because, in the one hand, is consistent with Tsanas and Xifara outcomes that claim that the GA is the most important predictor for both HL and CL.

On the other hand, it allows concluding that the rest of the six variables, i.e. surface area (SA), wall area (WA), roof area (RA), overall height (OH), orientation (O), and glazing area distribution (GAD), are redundant or irrelevant. Again, this is consistent with the previous work that infer that variables RC, SA, WA, RA and OH appear reasonably strongly associated with the output variables, and at the same time founds that some input variables are highly correlated. Based on the FIR feature selection process, it becomes reasonably to think that the relative compactness variable, RC, includes the information of other relevant variables involved in the study, as SA or RA. In fact, this is true because there is an analytic formula linking the RC the SA and the volume (Tsanas and Xifara, 2012). The WA variable is clearly directly related to the GA, so it is redundant. Therefore, the five variables that appear reasonably strongly associated with the output variables contain redundant information if SA and GA are already selected.

Figure 3 shows real versus predicted ANFIS and FIR results for HL and CL models. In both cases we present the fold that gives larger MSE, in order to show that even for the worse prediction results the difference with the real data is almost indistinguishable, especially in the case of the heating load model.

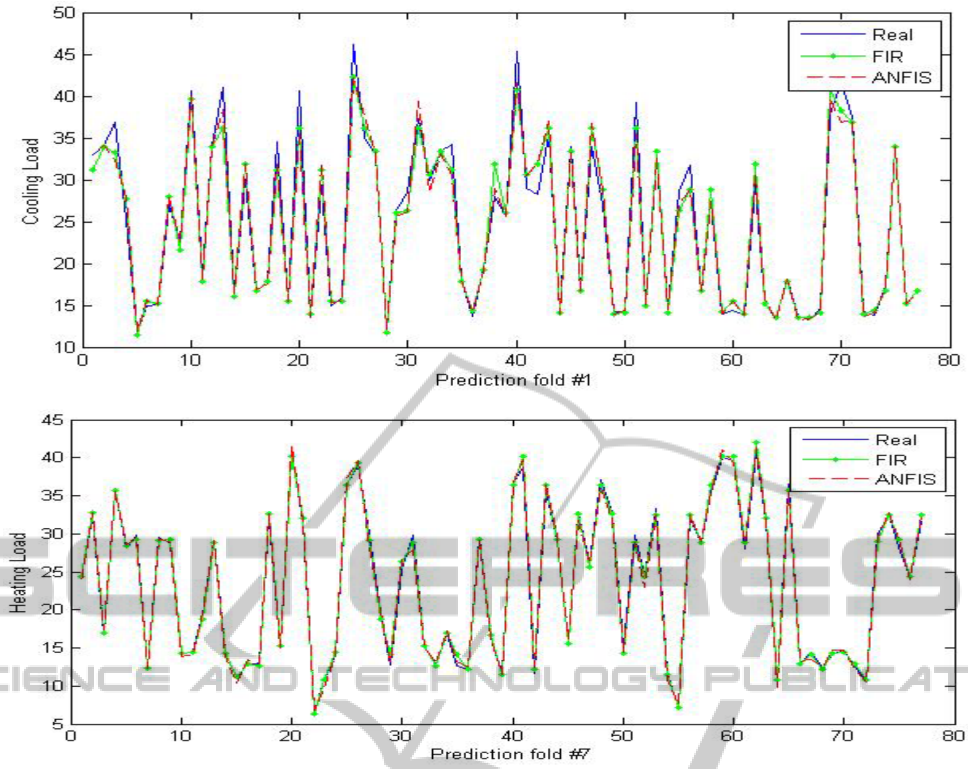

Figure 3: Real vs. ANFIS and FIR prediction results for the Cooling Load (upper plot) and Heating Load (lower plot) models. The results of the Cooling Load correspond to fold #1 in one of the 10 iterations. The MAE and MSE obtained by the ANFIS model in this fold are 1.08 and 2.91, respectively. The MAE and MSE obtained by the FIR model in this fold are 1.16 and 3.03, respectively. The results of the Heating Load correspond to fold #7 in one of the 10 iterations. The MAE and MSE obtained by the ANFIS model in this fold are 0.54 and 0.46, respectively. The MAE and MSE obtained by the FIR model in this fold are 0.42 and 0.38, respectively.

5 CONCLUSIONS

The main goal of this work is to study the feasibility of fuzzy approaches to estimate the energy performance of buildings. The characteristics of a building are an important factor to determine the necessities of heating and cooling loads. Therefore, the study of the relevant characteristics of the buildings with respect to the heating and cooling needed to maintain comfortable indoor air conditions, could be very useful in order to design and construct energy efficient buildings. This work follows a previous study (Tsanas and Xifara, 2012), that creates a set of 768 buildings with different characteristics by means of the Ecotet software, with the goal of predict the heating and cooling load of buildings taking into account eight variables that represent different building characteristics, i.e. relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area and glazing area distribution.

Two fuzzy methodologies have been studied, the fuzzy inductive reasoning (FIR) and the adaptive neuro-fuzzy inference system (ANFIS). In order to test the generalization performance of FIR and ANFIS fuzzy models we use 10-fold cross validation. The training and testing processes are repeated 10 times with the whole dataset randomly permuted in each run prior to splitting in training and testing subsets. Therefore, 100 models are derived and validated for each of the two methodologies and outputs studied.

The results obtained by ANFIS and FIR methodologies are compared with the ones presented in the work of Tsanas and Xifara, where the linear regression Iteratively Reweighted Least Squares (IRLS) algorithm and the non-linear Random Forest (RF) algorithm are used to predict heating and cooling loads.

From the results it can be concluded that the non-linear approaches (RF, ANFIS and FIR) perform much better than the IRLS. All the non-linear approaches have good results and FIR is the one that performs much better for both models, i.e. heating and cooling loads. Both fuzzy approaches outperform the RF in the application at hand. Moreover, the standard deviations obtained by ANFIS and FIR models are really much lower than the ones obtained by RF models.

An interesting result is that the feature selection process of FIR methodology finds that only two input variables, i.e. relative compactness and glazing area, contain the relevant information needed to predict accurately the heating and cooling loads.

The results are very encouraging and we think that these fuzzy methodologies can be good alternatives to deal with different energy analysis problems in the context of the smart grid.

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