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Fuzzy Model for Estimation of Energy Performance of Residential Buildings

Shirley Urdaneta[1],Emilio Zapata[1] andJuan Contreras[1,2, a]

[1] *Department of Engineering, InstitutciónUniversitaria ITSA, Barranquilla, Colombia.*

[2] *Department of Engineering, Escuela Naval Almirante Padilla, Cartagena, Colombia.*

[a]ORCID: 0000-0001-9730-9263 & Scopus Author ID: 35104582500

Abstract

Residential and commercial buildings have contributed significantly to the total energy demand and are responsible of about 40% of primary energy demanded in developed countries. D, there is growing interest for development of tools to evaluate the energy performance of buildings and to identify the parameters with significantly influence in future energy demand. This article presents the application of a training algorithm which could improve accuracy and interpretability of data, through a fuzzy singleton model, for the prediction of heating load and cooling load in residential buildings

Keywords: building energy performance, estimation of energy performance, heating load, cooling load, fuzzy model.

INTRODUCTION

According to the U.S Energy Information Administration (EIA) in 2016, about 40% of total U.S. energy consumption was consumed in residential and commercial buildings, butjust about 21% was consumed in residential buildings. Besides this, according to information supplied by European Commission in 2016, buildings are responsible for 40% of energy consumption and 36% of CO2 emissions in the European Union EU.

The constant use of air conditioners and heaters result in high levels of energy consumption in residential buildings. In order to reduce the use of such equipment, energy-efficient buildings able to maintain the desired indoor climate conditions should be designed, considering estimation and analyzing of heating and cooling loads [1], [2]. One of the most important aspect for designing energy efficient buildings is to identify the parameters with significantly influence in future energy demand, for instance: overall height, relative compactness, surface area, wall area, roof area, orientation, glazing area, and glazing area distribution of building [3].

Recently, there is growing interest for the development of approach for predicting energy performance of residential buildings [4], [5].Many techniques have been proposed for modeling building energy demand. Some of these techniques are based on traditional regression methods [6], statistical linear regression model, which focus on demographic, household behavior and building appliance influences on household electricity demand [7], least square support vector machine (LS-SVM) [3], Incremental Radial Basis Function Network (IRBFN), designing a Linear Regression LR as a global model and refining it through local RBFN [8], Bees Algorithm, a nature-inspired intelligent optimization method based on the foraging behavior of honey bees [9].

This article is organized as follows: Section2 presents a description of the data set which has been used for training and testing of fuzzy models. Section 3 describes how the fuzzy model is trained. Section 4 shows the obtained results and a comparison between the proposed system and other state-of-the-art methods. Finally, Section 5 summarizes the contributions of this research.

DATA SET DESCRIPTION

The dataset comprises 768 samples and 8 features, aiming to predict two real valued responses (heating load and cooling load). It could also be used as a multi-class classification problem if the response is rounded to the nearest integer. This dataset performs energy analysis using 12 different building shapes. As there are two responses, it could be derived two datasets from it. The features are reported in Table 1.

Table 1: Input variables(Attributes)

Item	Variable	Discrete Values	Range
1	Relative Compactness	12	[0.62, 0.98]
2	Surface Area	12	[514.5, 808.5]
3	Wall Area	7	[245.0, 416.5]
4	Roof Area	4	[110.25, 220.5]
5	Overall Height	2	[3.5, 7.0]
6	Orientation	4	[2.0, 5.0]
7	Glazing Area	4	[0.0, 0.4]
8	Glazing Area Distribution	6	[0.0, 5.0]

Table 2: Responses

Item	Outcome	Mean	Range
1	Heating Load	22.3072	[6.01, 43.10]
2	Cooling Load	24.5878	[10.9, 48.03]

The prediction task is to use various building characteristics, such as a surface area and a roof area, in order to predict the energy efficiency of a building, which is expressed in the form of two different metrics—heating load and cooling load. All experiments were completed with a typical 60%–40% split between the training and testing data subsets.

FUZZY MODEL

The fuzzy algorithm used in this research has been applied in the identification and classification of problems [10]-[12]. For each input variable an uniform partition was built using normalized triangular sets with overlapping of 0.5 between two successive fuzzy sets. There were two triangular membership functions with their modal values placed in the minimum and the maximum of the universe of discourse. This fuzzy partition was considered a Strong Fuzzy Partition (SFP) because it satisfies the following semantic constraints [13]: distinguishability; overlapping in 0.5; coverage; normality; convexity and the number of fuzzy set is no upper than 9.Fuzzy singletons were used for the consequent membership functions.

For each triangular membership function of each input variable a singleton consequent was generated and there were so many rules as singleton consequents (or triangular membership function). Therefore, the distribution of the membership functions generated p x n rules, where p is the number of input variables and n is the number of membership functions for each input variable.

The inference formula of the singleton fuzzy model proposed is given by

$$f(x^{(i)}) = \sum_{j=1}^{p}\sum_{l=1}^{n} \delta_{jl} u_{A_{jl}}(x^{(i)}) \qquad (1)$$

The previous equations could be expressed in a matricial form as

$$\underbrace{\begin{bmatrix} y^{(1)} \\ y^{(2)} \\ \vdots \\ y^{(N)} \end{bmatrix}}_{Y} = \underbrace{\begin{bmatrix} w_{11}^{(1)} & \cdots & w_{1n}^{(1)} & w_{21}^{(1)} & \cdots & w_{2n}^{(1)} & \cdots & w_{p1}^{(1)} & \cdots & w_{pn}^{(1)} \\ w_{12}^{(2)} & \cdots & w_{1n}^{(2)} & w_{21}^{(2)} & \cdots & w_{2n}^{(2)} & \cdots & w_{p1}^{(2)} & \cdots & w_{pn}^{(2)} \\ & & & & \cdots & & & & & \\ w_{12}^{(N)} & \cdots & w_{1n}^{(N)} & w_{21}^{(N)} & \cdots & w_{2n}^{(N)} & \cdots & w_{p1}^{(N)} & \cdots & w_{pn}^{(N)} \end{bmatrix}}_{W} \underbrace{\begin{bmatrix} \delta_{11} \\ \vdots \\ \delta_{1n} \\ \delta_{21} \\ \vdots \\ \delta_{2n} \\ \vdots \\ \delta_{p1} \\ \vdots \\ \delta_{p1} \end{bmatrix}}_{\theta} \qquad (2)$$

where

$$w_{jl}^{(i)} = u_{A_{jl}}(x^{(i)}) \qquad (3)$$

Given a collection of experimental input and output data $\{x_l^{(i)}, y\}$, i =1,..., N, where x_l is the p-dimensional input array $x_1^{(i)}, x_2^{(i)}, \cdots, x_p^{(i)}$ and y is the one-dimensional output array, the algorithm is defined by the following steps:

Step 1. Organization of the N pair set of input – output data $\{x_l^{(i)}, y^{(i)}\}$ with $i = 1 \ldots N; l = 1,\ldots, p$,, where $x_l^{(i)} \in \Re^p$ are input arrays and $y^{(i)}$ are output scalars.

Step 2. Determination of universe ranges of each variable, according to maximum and minimum values of associated data $\left[x_l^-, x_l^+\right]$, $[y^-, y^+]$.

Step 3. Uniform distribution of triangular membership functions over each universe of discourse. As a general condition the vertex with ownership value one (modal value) falls at the middle of the region covered by the membership function while the other two vertexes, with membership values equal to zero, fall in the middle of the two neighboring regions. See Fig 1. The algorithm starts with two triangular membership functions (n = 2) for each input variable with their modal values placed, respectively, in the minimum and the maximum of the universe of discourse.

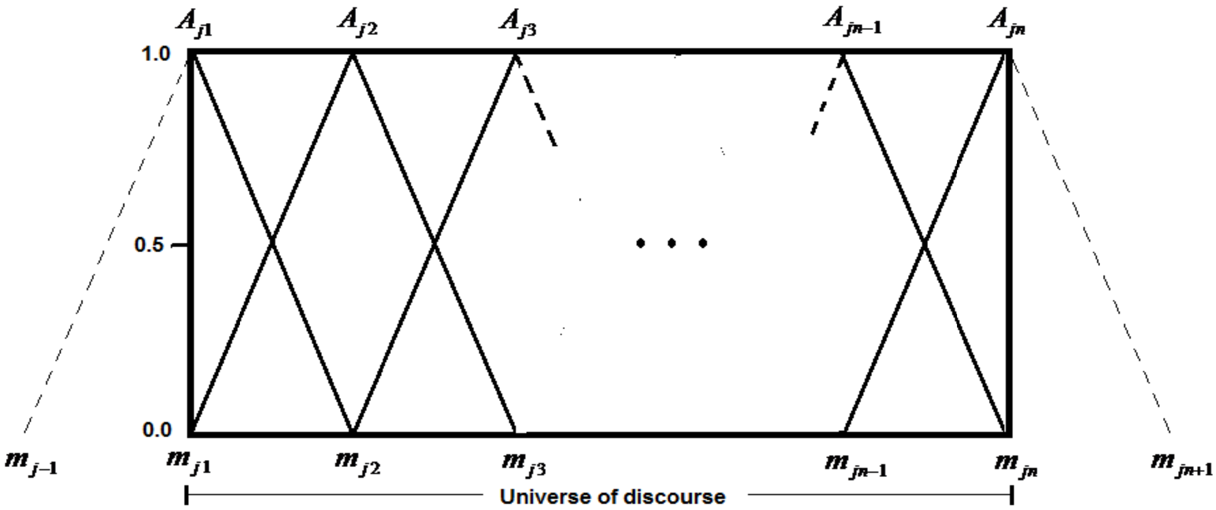

Figure 1. Triangular sum-1 partition

Step 4. Calculate the singletons consequents using recursive least square estimation

$$\theta(k) = \theta(k-1) + P(k)W(k)e(k)] \tag{4}$$

where

$$e(k) = y(k) - f(x(k)) = y(k) - w(k)\theta(k) \tag{5}$$

$$P(k) = \frac{P(k-1)}{\lambda}\left[I - \frac{w(k)w(k)^T P(k-1)}{\lambda - w(k)^T P(k-1)w(k)}\right] \tag{6}$$

At the beginning, the covariance matrix P(0) = identity matrix. λ is the forgetting factor (0< λ <1).

Step 5. End if either the resulting error measure is smaller than an error criterion or the number of membership functions is more than 9. In any other case, increment by 1 the number of sets in the input variable (the number of partition member) and turn back to step 3

RESULTS

The fuzzy identification algorithm was used to approximate the functions represented by the data sets: heating load and cooling load.Then, two fuzzy models were obtained.The dataset was divided into two subsets randomly: 60% of the dataset was used for training (453 samples) and the rest of data (40%) was used to test and validate (315 samples). Figure 2and Figure 3 show the variation of the Mean Squared Error MSE between the output of fuzzy model 1 and the heating load and between the output of the fuzzy model 2 and the cooling load. For training process 2 to 9 triangular membership functions were used for the following inputs: Relative Compactness and Surface Area. For the rest of the input a number of triangular membership functions equal to the number of discrete valueswere considered.

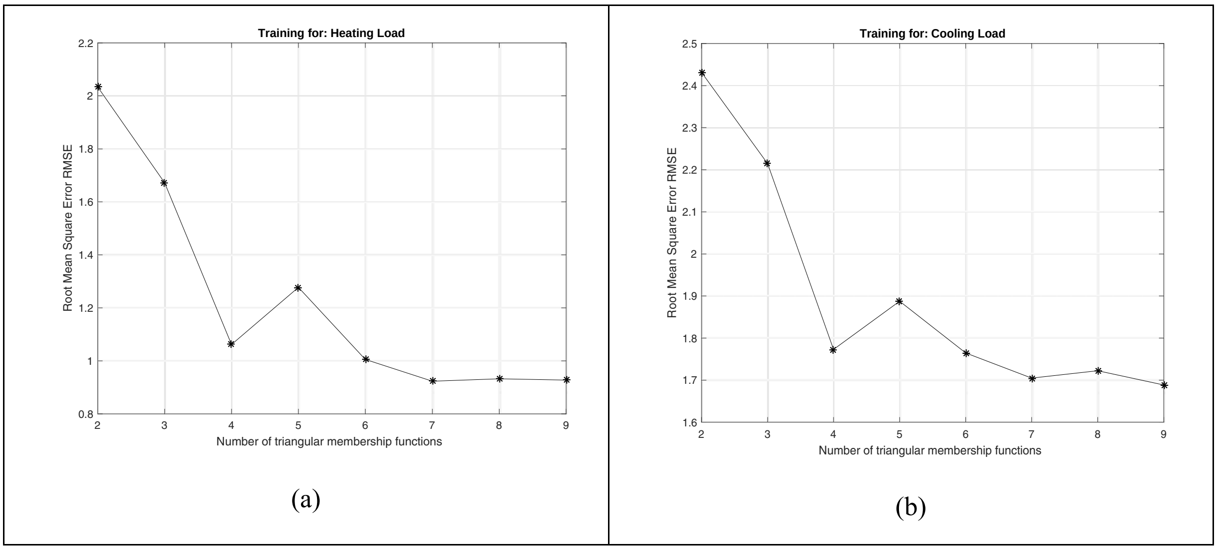

Figure 2. Root Mean Square Error between the output of fuzzy model and the responses: heating load (a) and cooling load (b)

The best option was 7 triangular membership funtios for each input: Relative Compactness and Surface Area.

The figure 3, shows a comparison between the output of the fuzzy model (o) and the real value of load, heating and cooling.

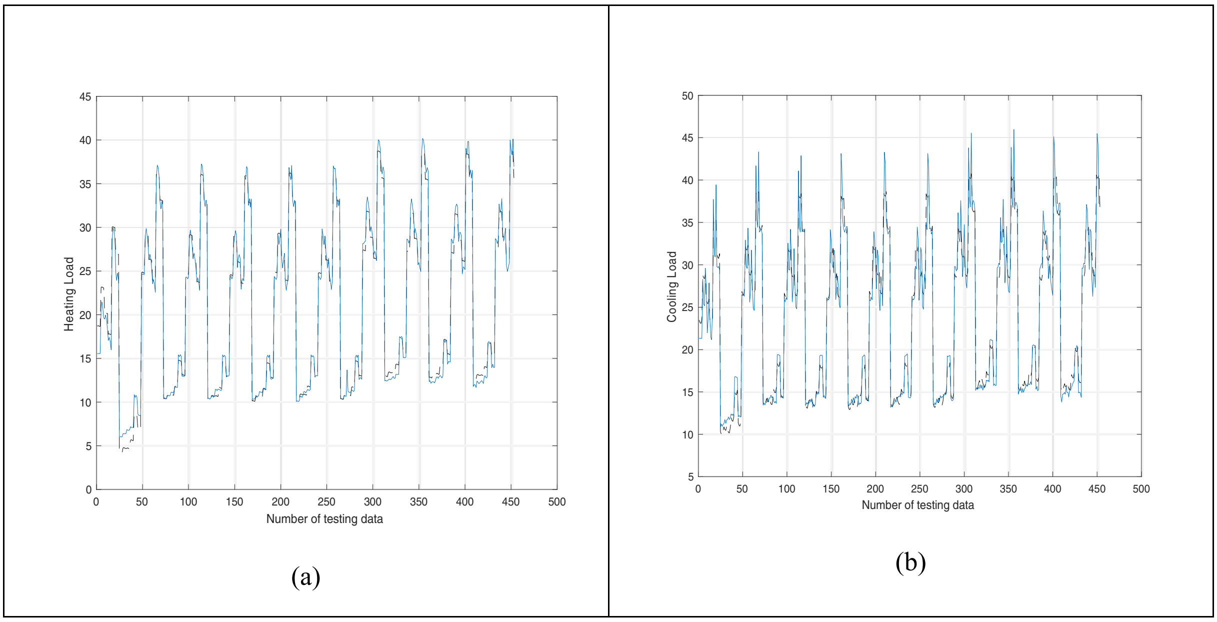

Figure 3. Prediction performance for heating load (a) and cooling load (b) in training process

The resulting fuzzy model has the following specifications:

Table 3: FuzzyModel

Variable	Number of Triangular Membership Functions	Number of singleton consequents
Relative Compactness	12	12
Surface Area	12	12
Wall Area	7	7
Roof Area	4	4
Overall Height	2	2
Orientation	4	4
Glazing Area	4	4
Glazing Area Distribution	6	6
Number of rules		51

Table 4: Comparison results of fuzzymodel for prediction of heating load [8]

Method	RMSE (Training)	RMSE (Testing)
LR	2.936	2.911
MLP	2.833	2.890
RBFN	3.707	5.199
RBFN(CFCM)	2.767	3.106
LM	4.084	4.388
IRBFN LSE	2.284	2.826
IRBFN BP	2.353	2.730
Our approach	**0.9608**	**1.217**

Table 5: Comparison results of fuzzymodel for prediction of cooling load [8]

Method	RMSE (Training)	RMSE (Testing)
LR	3.180	3.208
MLP	3.176	3.226
RBFN	3.601	4.812
RBFN(CFCM)	2.866	3.388
LM	3.866	4.296
IRBFN LSE	2.462	3.102
IRBFN BP	2.555	3.089
Our approach	**1.3057**	**1.745**

CONCLUSIONS

In thisstudy, a fuzzy identification algorithm for the prediction of energy performance of residential buildings was proposed. The method guarantees the completeness of the rule base and it constrains the exponential growth of the rule base as the number of inputs increases as it occurs with classical methods. This is becausethe proposed method generated p x n rules, where p is the number of input variables and n is the number of membership functions for each input variable. Each fuzzy region was covered with a fuzzy rule and there was no redundancy in the rule base. The results showedthat fuzzy models obtained could predict the heating load and cooling load of residential buildings with reasonable accuracy.

For further research, we propose to include in the fuzzy identification algorithm the gradient descent method to adjust triangular membership function. The triangular membership functions are parameterized by using only their modal values for preserving the overlap of 0.5 and to reduce the number of parameters to be tuned.

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