Forecasting Heating and Cooling Energy Demand in an Office Building using Machine Learning Methods

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***Abstract*—Forecasting heating and cooling energy demand in buildings plays a critical role in supporting building management and operation. Thus, analysing the energy consumption pattern of a building could help in the design of potential energy savings and also in operation fault detection, while contributing to provide proper indoor environmental conditions to the building's occupants.**

This paper aims at presenting the main results of a study consisting in forecasting the hourly heating and cooling demand of an office building located in Lisbon, Portugal, using machine learning models and analysing the influence of exogenous variables on those predictions. In order to forecast the heating and cooling demand of the considered building, some traditional models, such as linear and polynomial regression, were considered, as well as artificial neural networks and support vector regression, oriented to machine learning. The input parameters considered in the development of those models were the hourly heating and cooling energy historical records, the occupancy, solar gains through glazing and the outside dry-bulb temperature.

The models developed were validated using the mean absolute error (MAE) and the root mean squared error (RMSE), used to compare the values obtained from machine learning models with data obtained through a building energy simulation performed on an adequately calibrated model.

The proposed exploratory analysis is integrated in a research project focused on applying machine learning methodologies to support energy forecasting in buildings. Hence, the research line proposed in this article corresponds to a preliminary project task associated with feature selection/extraction and evaluation of potential use of machine learning methods.

Keywords— Energy Forecasting in Buildings; Heating and Cooling Demand; Machine Learning

I. Introduction

According to [1], the buildings sector represents approximately 36% of the global final energy consumption and 39% of the energy-related carbon dioxide (CO2) emissions. As stated by [2], in 2012, 63% of the final energy consumed in the services sector was used for heating and cooling, with 62% representing space heating and 19% for cooling needs (space cooling and other cooling processes). Forecasting those demands can play a major role in supporting building management and operation, as highlighted in [3], [4] and [5].

In existing non-residential buildings equipped with energy metering systems, particularly those equipped with Building Management and Control Systems (BMCS), it is possible to gather energy consumption data and other related parameters (e.g. occupancy, indoor air temperature, etc.) to feed and update machine learning models.

To achieve that goal, there are conventional approaches, such as linear regression or polynomial regression; machine learning strategies, including Artificial Neural Networks (ANN) and Support Vector Machine (SVM), can also be adopted to this purpose [3] [4] [5]. In these studies, machine learning approaches are presented as providential tools as they surpass accuracy derived from conventional strategies, can be easily extended to different types of buildings and make use of smart technology installed and are able to highlight non-linear relationships between exogenous variables and consumptions (not evident during correlation analysis). On the other hand, it must be stressed out that these methods are strongly dependent on the type and quality of available data and there is often room for further investigation related with better tuning of these methods.

A. Linear Regression

Linear regression is one of the most common models used in forecasting problems. The idea behind linear regression is attempting to find a linear relationship between the target and the input variables, i.e., finding the straight line that best fits the data and minimizes the associated deviations as much as possible [6].

B. Polynomial Regression

If a linear regression is not able to find a linear relationship between the input variables and the target, there may be the need to increase the complexity of the model and use a polynomial function to fit the training data. It increases the degree of the equation to find a curve that provides a better fit for the data.

C. *Artificial Neural Networks*

The ANN's principle is based on the way biological nervous systems process information. It consists of: (i) a first layer, the input layer, accommodating all of the model´s input variables, (ii) the final layer, with each neuron representing a different output of the model, and (iii), in between the former, the hidden layer(s), in which the data given by the input layer is analysed by a variable number of neurons in search of a pattern in the relationship between the different input variables and the target. That pattern is translated into weights and biases given to the connection between each neuron and the neuron in the layer ahead. The weights show the strength of each connection and the biases are a factor added to the weights to impose offsets and approximate the forecasted time series values to the real ones. The activation function allows the ANN model to learn from the training data, eventually detecting non-linearities whenever a non-linear activation function is chosen and calculating those weights and biases to forecast the outputs as accurately as possible [7]. Given the flexibility of ANN models, they can be configured to only one output or multiple outputs. In this study, the ANN models were designed to predict 24 outputs at once, corresponding to the hourly values of energy associated with thermal demands (heating or cooling) for the following day. Fig. 1 shows the configuration of an ANN model used in this study, using two historical days load profiles (one and two weeks before) as inputs to estimate hourly load values for the predicted day (24 outputs).

D. *Support Vector Machine*

SVM has been widely used for classification purposes but can also be applied to regression based on the same principles. Its core idea, while addressing regression problems, is to try to find an optimal hyperplane to lie as close as possible to the majority of data points, i.e., that minimizes the distances between the hyperplane and the data points [8]. To optimize the SVM model, some parameters, such as the kernel function, kernel parameter (gamma), cost parameter and epsilon (error margin) need to be tuned. The kernel function, which is best equipped to deal with non-linearities, quite common in energy demand problems, is the Radial Basis Function (RBF). Gamma defines the level of non-linearity of the SVM model (Fig. 2), according to the width of the resulting bell-shaped function (RBF). The cost parameter (C) is a regularization parameter of SVM to avoid model overfitting to the training dataset [9]. Epsilon's variation and influence in regression problems is briefly described in Fig. 3 [10].Some studies were already conducted using machine learning strategies to forecast thermal and electric demands of service buildings.

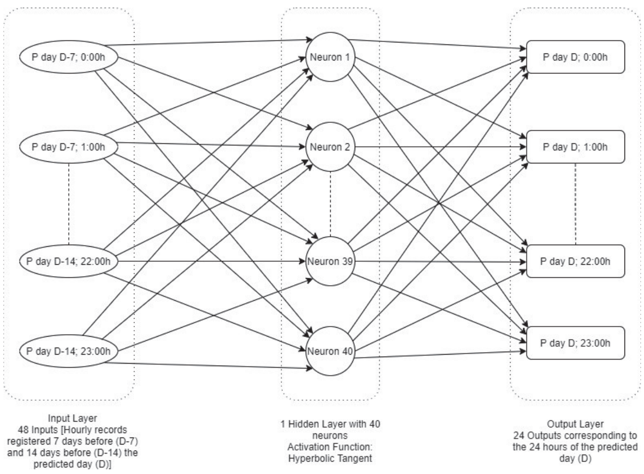

Fig. 1 Representation of the adopted multivariable Artificial Neural Network

In [11], the authors made a comparison between ANN and a physical principle based model (EnergyPlus) to forecast the energy consumption in an administrative building of the University of São Paulo, Brazil.

In [12], the authors studied a load forecasting method for an office building located in Tianjin, China, using wavelet transform, SVM and partial least squares regression.

In [13], the comparison between a linear regression model based only on the outdoor air temperature and three machine learning techniques (decision trees, SVM and ANN) was studied to predict the aggregated heating demands of a community of 52 residential houses.

This paper is organized as follows: in Section 0, the case study building is presented, as well as the data used to feed the models, its pre-processing techniques (including data split into training, validation and test subsets and the exogenous variables considered), the adaptation of the machine learning models to focus on thermal load forecasting and the error metrics used to score the models. In Section III, a sensibility analysis is followed to evaluate the effect of historical data and some exogenous variables in the forecast of thermal energy demands and a comparison is made between the different models to evaluate their accuracy in forecasting thermal demands. In Section IV some conclusions are pointed out and further research is proposed to be applied to similar cases.

II. Methodological Approach

A. *Building Description*

The case study building is a modern office building located in Lisbon, Portugal, built in 2007, equipped with an advanced building automation and control system. The net floor area is of about 12000 sq. mt., where 7000 sq. mt correspond to offices (eight floors above ground) and 5000 sq. mt. to underground parking (three floors below ground). Regarding the building envelope, all four façades are mostly

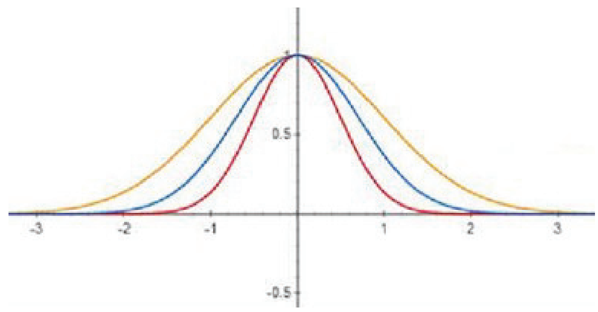

Fig. 2 Influence of gamma variation in RBF function. Yellow, blue and red functions represent, respectively, gamma = 0.5, 1 and 2

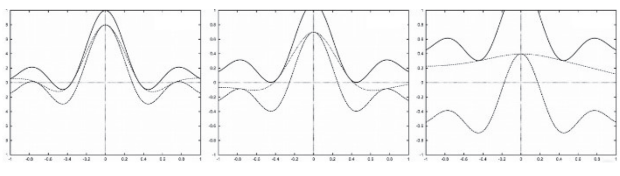

Fig. 3 From left to right: approximation of the function with precision ε = 0.1, 0.2, and 0.5

glazed and exposed to the elements, with partial shading only on the south-facing façade. The roof is made of an XPS-covered horizontal concrete slab and an outer layer of pebbles.

Heating and cooling for the building are provided by a combined cooling, heating, and power (CCHP, or trigeneration) plant and distributed via hot/cold water networks. Thermal energy is transferred by plate heat exchangers located on a substation on floor -2.

B. Data Description

The dataset available for this study included hourly measurements of the occupancy profile, solar gains through glazing, outdoor dry-bulb temperature and heating fluid and cooling fluid consumption from a complete year obtained through a calibrated building energy performance simulation model. The cooling period was considered to occur from April to September and the heating period from January to March and from October to December, with the first 80% of the data, approximately, used to train the models and the remaining 20% used for testing in both heating and cooling demand forecast. Regarding the input variables, the effect of the historical data was considered, corresponding to the values registered 7 days before and 14 days before the predicted days, and the exogenous variables for the predicted days. To level off the different variables, a normalization stage was introduced, using the minimum and maximum values of the training dataset as scaling factors.

C. Machine Learning models adaptation for Load Forecasting Purposes

In this section, a brief description of how machine learning approaches were followed to enable the desired analysis is presented.

For ANN models, the activation functions used were the hyperbolic tangent function and linear function for the hidden layer and output layer respectively, the solver for weight optimization was 'adam', only one hidden layer was considered and 20% of the data was set aside for validation to terminate the training phase if the validation score stopped improving. The option related to one single hidden layer corresponds to the recommended choice to represent any type of function, while the approximation ability is still dependent on the choice of activation functions and on the number of neurons. To optimize the ANN models, some tests were made by training the models 10 times, using 10, 20, 30, 40 and 50 neurons. Then, by comparing the error metrics associated to each set of simulations, the best of the studied options was the 40 neurons structure. It can be summarized that simulations with a number below 40 neurons led to a generalized ability loss to estimate heating/cooling demand while a larger number of neurons would cause overfitting (loss of generalization ability to estimate new load values).

For SVM models, some different combinations were tested between parameters C (100; 500), gamma (0.1; 0.5) and epsilon (1; 0.5) to check which combination performed better with the given dataset. The combination that provided the lowest MAE and RMSE for the test dataset was C=500, gamma=0.5 and epsilon=0.5.

D. Error Metrics

To score the results given by the models and compare them with the reference values, two error metrics were used.

The first error metric used was the mean absolute error (MAE), which represents the average absolute error between the reference (y) and the predicted values (ŷ) through n observations (1).

$$\text{MAE}=\frac{1}{n}.\sum_{i=1}^{n}|y_i-\hat{y}_i| \qquad (1)$$

The root mean squared error (RMSE) was also used, representing the mean standard deviation of the predicted values compared to the reference (2), as in [14].

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{n}} \qquad (2)$$

The main difference between MAE and RMSE is that MAE treats all errors equally and RMSE penalizes the highest errors. That means that if RMSE is considerably higher than MAE, it could indicate that there may be some predictions very distant from the expected.

III. Results and Discussion

In this section the results of the developed models are presented in order to make possible the evaluation of their accuracy in the forecast of heating and cooling demands for the next day. For both heating and cooling scenarios, the historical data was considered as the main input variable to feed the models and then some exogenous variables, such as outdoor air temperature, occupancy and solar gains through exterior windows were added to check if there were any improvements in the predictions. Outdoor air temperature was the only exogenous variable that improved prediction accuracy, comparing with the models simply based on historical records.

Despite the fact that a strong correlation between the energy consumption and outdoor air temperature (or even indoor air temperature that could more directly reflect heating/cooling needs but is not available) was expected, this validates the methods used and the results obtained while enhancing the importance of evaluating the influence of outdoor temperature for different seasons.

The different models' accuracy was then compared by evaluating their MAE and RMSE between predicted values (obtained from four tested models) and reference values.

A. Models Comparison

To score the different models used in this study and evaluate which ones perform better according to the objective proposed in this paper, the error metrics described in section II.D were considered. The results for heating and cooling demand are summarized in Table I and Table II, respectively.

By analysing Table I and Table II, the ANN model is the most accurate in both heating and cooling demand forecast for all error metrics in both scenarios (simply based on historical records and adding outdoor air temperature). As commented in Section III, by adding outdoor air temperature as an input to the models, the associated error is lower when compared with the predictions simply based on historical records. This is noticeable specially for the cooling demand prediction. According to the dataset available, these models have more difficulty in forecasting cooling demands of this case study building, which is

TABLE I. ERROR METRICS FOR COOLING DEMAND

Cooling Demand	Linear Regression		Polynomial Regression		ANN		SVM	
	Simply based on Historical Data	*Based on Historical Data + Outdoor Air Temperature*	*Simply based on Historical Data*	*Based on Historical Data + Outdoor Air Temperature*	*Simply based on Historical Data*	*Based on Historical Data + Outdoor Air Temperature*	*Simply based on Historical Data*	*Based on Historical Data + Outdoor Air Temperature*
MAE Train (kW)	40,15	40,00	31,28	24,31	21,77	8,00	28,86	23,31
MAE Test (kW)	46,39	48.52	39,63	26,20	34,22	19,47	36,32	24,51
RMSE Train (kW)	72,10	68,11	63,50	47,57	50,87	20,52	65,14	52,11
RMSE Test (kW)	89,38	83,93	80,71	53,08	73,12	43,52	81,17	55,86

TABLE II . ERROR METRICS FOR HEATING DEMAND

Heating demand	Linear Regression		Polynomial Regression		ANN		SVM	
	Simply based on Historical Data	*Based on Historical Data + Outdoor Air Temperature*	*Simply based on Historical Data*	*Based on Historical Data + Outdoor Air Temperature*	*Simply based on Historical Data*	*Based on Historical Data + Outdoor Air Temperature*	*Simply based on Historical Data*	*Based on Historical Data + Outdoor Air Temperature*
MAE Train (kW)	18,32	18,74	16,43	11,60	12,17	3,72	1,12	0,79
MAE Test (kW)	28,26	30,68	27,06	22,09	25,73	14,17	29,24	29,51
RMSE Train (kW)	32,24	30,45	31,02	21,34	24,75	10,16	4,69	3,13
RMSE Test (kW)	47,31	45,90	47,84	39,79	47,03	28,86	51,12	51,21

confirmed by comparing the RMSE for the test dataset in Table I and Table II.

This may be due to the consumption profile in the heating period being more constant throughout the day than the cooling period, i.e., in the cooling period, the occupants could resort to other ways to achieve their thermal comfort, such as opening the windows or using other electrical devices rather than the air conditioner to cool the space. To summarize, it can be concluded that the cooling demand profile is more unpredictable.

In Fig. 4 and Fig. 5 the results of a typical working day are presented regarding cooling and heating consumption, respectively. These predictions are based on four different models (with historical records and outdoor air temperature as inputs) and compared to the reference values registered in that day, relative to the test dataset.

As seen in Fig. 4, for the cooling demand, ANN models are more accurate and have a daily consumption profile very similar to the reference values when compared with the most conventional models and SVM, which tend to be lower. For the heating demand forecast, represented in Fig. 5, the ANN model's profile is also the one that better fits the reference profile, as can be confirmed by checking its

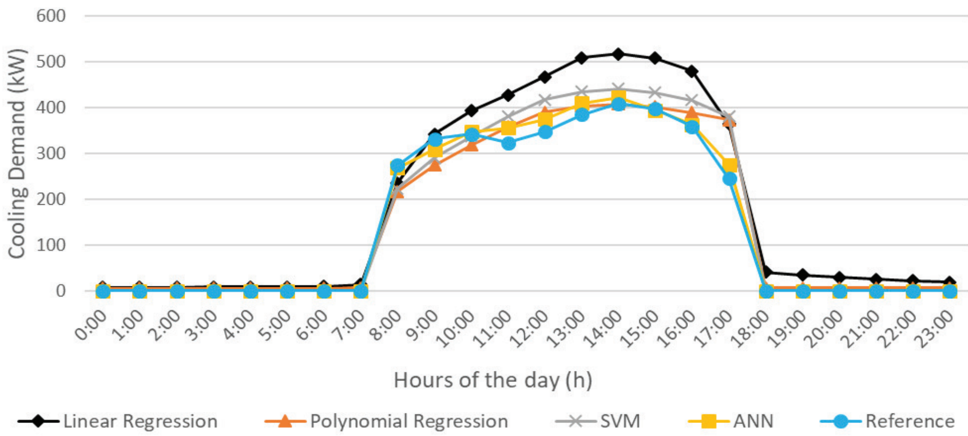

Fig. 4 Cooling demand prediction vs reference in a typical working day during the test period based on historical data and outside temperature

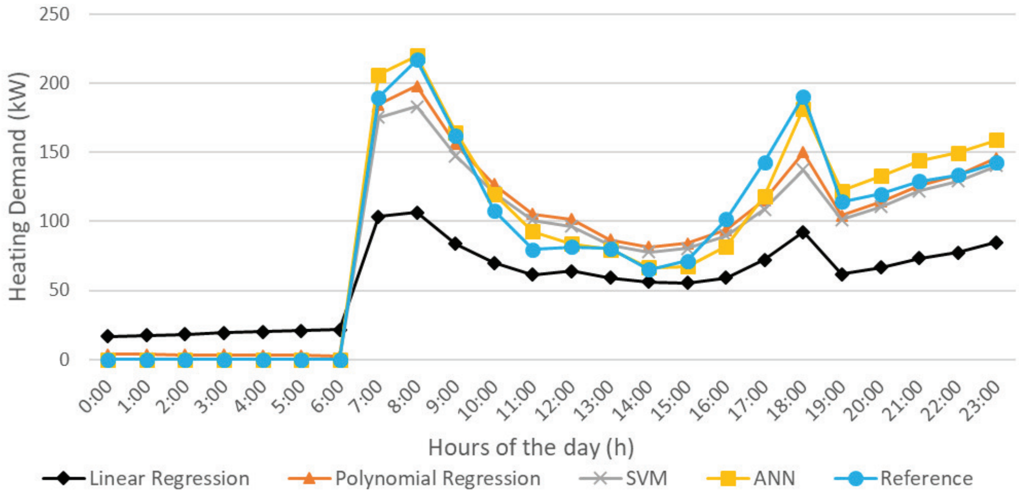

Fig. 5 Heating demand prediction vs reference in a typical working day during the test period based on historical data and outside temperature

associated error in Table II. As the ANN model performed better than the others in forecasting the thermal demands for the case study building, the error associated to each working hour of the day was studied by using a boxplot graphic, which is shown in Fig. 6 for the cooling demand and in Fig. 7 for the heating demand. Fig. 6 shows the range of errors from 8 a.m. to 5 p.m., corresponding to the working hours of the cooling systems.

To highlight the assumptions pointed out when analysing Fig. 4, the error boxplot chart associated to the ANN model in Fig. 6 confirms that the ANN tends to predict higher values than the referenced, but with an average close to zero at all hours of the day. The biggest variations occur between 11 a.m. and 3 p.m., which was expected due to the higher exterior temperatures in this interval. This factor drives the occupants to activate the cooling systems inside the building to maintain their thermal comfort. Fig. 7 shows the range of errors from 7 a.m. to 11 p.m., corresponding to the working hours of the heating systems. Confirming the information given in Table II, the error variation is much smaller than in the cooling period. As expected, the biggest variations occur early in the morning, matching the lower temperatures verified outside the building.

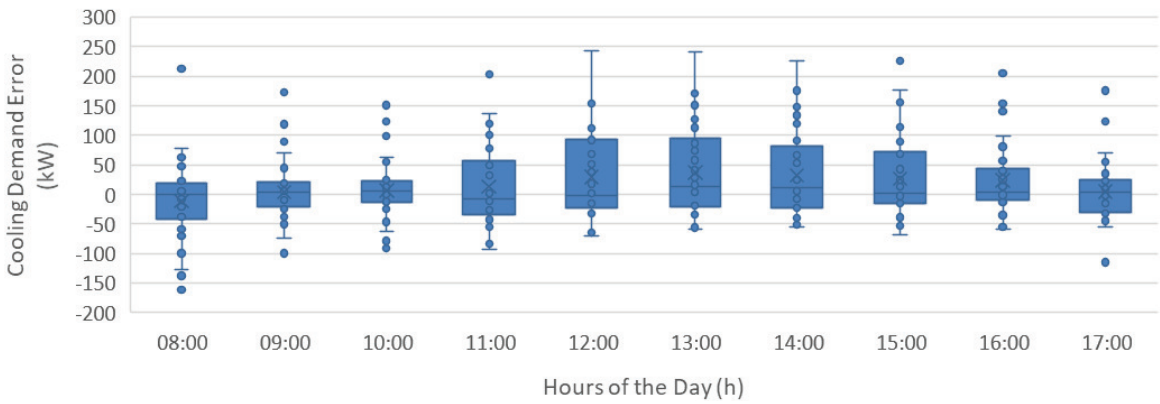

Fig. 6 Boxplot Analysis of Cooling Demand Forecast Errors in a typical working day during the test period based on historical data and outside temperature

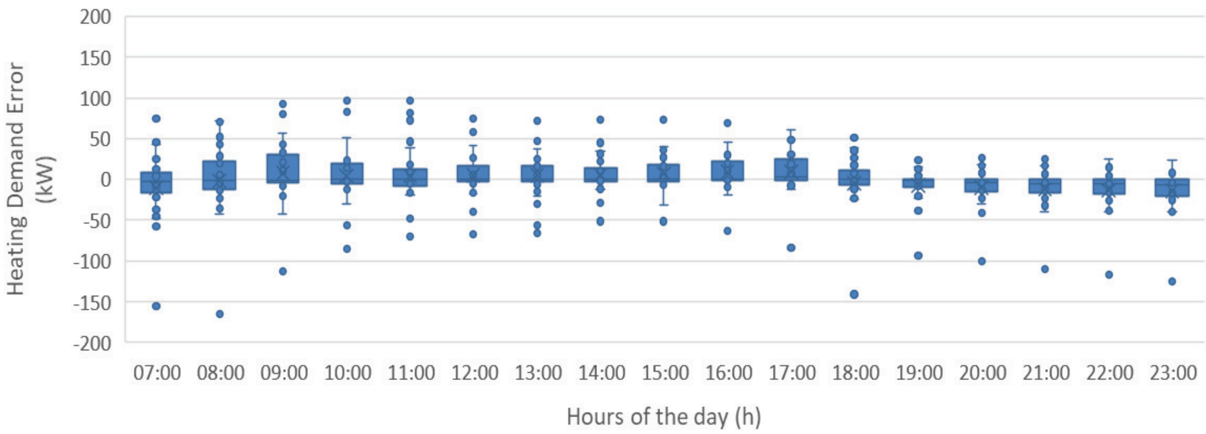

Fig. 7 Boxplot Analysis of Cooling Demand Forecast Errors in a typical working day during the test period based on historical data and outside temperature

IV. CONCLUSIONS AND FURTHER RESEARCH

Machine learning models demonstrate to be more accurate in forecasting thermal demands based on historical data only or adding some exogenous variables, such as outdoor air temperature, when compared to conventional approaches such as linear and polynomial regression models. For the cooling period it has been harder for the models to detect a pattern due to the occupants' behaviour and the variety of alternatives available to cool the offices. Outdoor air temperature has proved to be an improvement to the models in both heating and cooling periods. Although further investigation could be made to study the influence of the occupancy profile in the models' accuracy, it is expected to play a major role in the thermal demand and energy consumption. There is also room for improvement regarding the SVM parameters' optimization, using metaheuristic methods to run multiple combinations of parameters and determine the optimal set for this scenario. Also, by using some pre-processing techniques, such as the wavelet transform, the models' accuracy could be improved by detecting patterns of consumption, or identifying some noise data, especially in the cooling period.

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