COMPARISON OF PREDICTIVE MODELS FOR FORECASTING BUILDING HEATING LOADS

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ABSTRACT

This paper is concerned with the development of data-driven predictive models capable of forecasting commercial building heating loads based on BEM (Building Energy Management) systems recorded variables, as well as weather data. To address the lack of available complete datasets from actual commercial building BEM systems, a detailed representation of a reference building using EnergyPlus was implemented as a benchmark. Data analysis of the simulated results is used to detect relationships between variables and select input variables for the predictive models. Various regression and machine learning models are investigated for their ability to forecast building heating loads. The most suitable model is selected by comparing the accuracy of the predictions.

INTRODUCTION

The building sector consumes 35% of global final energy use and is responsible for about 17% of total direct energy-related CO_2 emissions from final energy consumers. Space and water heating as well as space cooling account for nearly 55% of global building energy use and represent the largest opportunity to reduce building energy consumption (International Energy Agency, 2013). Retrofit of existing buildings offers significant opportunities for achieving reductions in energy consumption and greenhouse gas emissions (Ma et al., 2012). The most common retrofit measures used include; envelope upgrade, improved Heating Ventilation and Air-Conditioning (HVAC) control and installation of more efficient HVAC systems. One of the most cost-effective approaches to decrease the energy usage and increase compliance with the European Directives on the energy performance of buildings (European Commission, 2010) is the enhancement of HVAC control, particularly in commercial buildings. The use of efficient energy management systems in buildings is expected to generate a maximum saving of 8% of the energy consumption in the EU (Ferreira et al., 2012). Before retrofit measures can be considered, an accurate and easily implemented methodology for assessing building thermal loads is a useful and increasingly important first step. Predicting the load of HVAC systems is important for energy management especially during peak energy demand hours (Kudiak et al., 2010).

Predictions of building heating load can be estimated using appropriate simulation software (U.S. D.O.E., 2011) when detailed data such as building geometry, occupancy as well as environmental variables are available. In reality, such data are often unknown, especially for older buildings, where uncertainty arising from parameter and occupancy estimation can lead to significant additional modelling efforts (Kwok and Lee, 2011). An alternative way to forecast these loads is to take advantage of BEM systems recorded data. These data records include underlying information regarding building thermal response and can be introduced to data-mining models, which utilise extensive assessment of input and output variables, in order to produce accurate predictions (Foucquier et al., 2013). In the context of developing data-driven models capable of forecasting heating loads of commercial buildings, pre-analysis of BEM systems data, is a prerequisite.

The main objectives of the current paper are to describe an approach of selecting useful information from BEM systems data in order to be used in predictive models, as well as the development of predictive models of heating loads for commercial buildings. The input variables under examination in this paper should be recorded and easily obtained from the BEM systems or any other source for a long period of time. Therefore, weather and indoor conditioning data are investigated as possible input variables. A commercial building, located in Cork, Ireland is utilised as a testbed building for the development stage of the predictive models. Data are extracted on a time step basis in order to analyse them for the investigation of possible correlations between variables. Incomplete datasets are often acquired when extracting the data. Rates of less than 1% missing data are generally considered trivial, 1-5% manageable. However, 5-15% requires sophisticated methods to handle, and more than 15% may severely impact any kind of interpretation (Acuña and Rodriguez, 2004). In order to preclude missing data and their implications, a detailed representation of the testbed building is implemented using EnergyPlus (U.S. D.O.E., 2015).

The growing interest in forecasting building energy performance in city or even national scale, leads to long processing time when developing such models, therefore reducing model complexity is an important issue. The ultimate goal of this data mining process is to assist with building heating load prediction, specifically the issue of the selection of input variables. This selection is critical for the construction of the predictive model, since redundant input variables introduce unnecessary increases in the complexity during the development of the models. Once the input variables for the predictive models are identified, various models are developed by implementing both regression-based and machine learning prediction methods.

BACKGROUND

Building energy models use varied number of inputs to produce useful results. However, the influence of some characteristics is stronger than others on the modelled energy performance of the building (Turner et al., 2014). Numerous academic studies have used sensitivity analysis to identify which building characteristics have the greatest impact on energy results from building models (Turner et al., 2014).

Lam and Hui (1996) performed a sensitivity analysis on inputs for a modelled office building in Hong Kong and found that the annual building energy consumption was most sensitive to internal loads, then window systems, indoor temperature set points and HVAC system efficiencies. Macdonald (2002) performed an extensive sensitivity analysis on the different variables of a building simulation and concluded that the variables with the greatest impact on the final energy solution are the internal loads, the air infiltration rate, the conductivity of the building insulation, and the weather file used to specify the outdoor environment. Heller et al. (2011) also performed sensitivity analysis on building simulation variables for commercial buildings and discovered that the factors which had the largest effect on simulated energy performance were the internal loads, the building envelope and the HVAC system.

Amongst the most common methods used in the literature to achieve forecasting of building thermal loads without the use of simulation software are Regression, Artificial Neural Network (ANN) and Support Vector Machine (SVM). However, during the development of these data-driven models, the selection (or justification) of input variables has not been subjected to the same level of academic scrutiny as for physics-based whole-building simulation models.

Aranda et al. (2012) used linear regression models to predict the annual energy consumption in the Spanish banking sector. The energy consumption of a single building was predicted as a function of its construction characteristics, climatic area and energy performance. Catalina et al. (2008) worked on the development of regression models to predict monthly heating demand for the single-family residential sector. The inputs for the regression models were building shape factor, envelope U-value, window to floor area ratio, building time constant and climate. The average error was 2% between the predicted and simulated values. An update to the aforementioned work, in an attempt to simplify the model to obtain fast predictions, used as inputs the building global heat loss, south equivalent surface and difference between indoor and ambient temperature (Catalina et al., 2013).

ANNs have been applied to analyse various types of building energy consumption, as well as heating loads. Kalogirou et al. (1997; 2001) implemented ANN at an early design stage to predict the required heating load of buildings. Input data included the areas of windows, walls and floors, the type of windows and walls, roof classification and the room temperature. The relative error of the network was 3.5%. Gonzalez and Zamarreno (2005) used an ANN approach to predict the hourly energy consumption in buildings. The inputs of the network were current and forecasted values of temperature, the current load, the hour and the day. The performance of adaptive ANN models that are capable of adapting themselves to unexpected pattern changes in the incoming data was evaluated by Yang et al. (2005). Two adaptive models were proposed and evaluated, accumulative training and sliding window training. These models can be used for real-time on-line building energy prediction. Moreover, they used both simulated (synthetic) and measured datasets. More recently, Ekici and Aksoy (2009) used an ANN to predict building energy needs benefitting from orientation, insulation thickness and transparency ratio. A back propagation network was preferred and available data were normalised before being presented to the network. The calculated values compared to the outputs of the network gave satisfactory results with a deviation of 3.4%.

SVM models have been used more recently for predicting energy consumption in buildings. Dong et al. (2005) were the first to introduce the use of SVM for the prediction of the energy consumption of four commercial buildings. The input variables were mean outdoor dry-bulb temperature, relative humidity and global solar radiation. The obtained results were found to have coefficients of variance less than 3% and percentage of error within 4%. Li et al. (2009) used a SVM model in regression to predict hourly building cooling load for an office building. The outdoor dry bulb temperature and solar radiation intensity were the input parameters for this model. Results indicated that the SVM method can achieve accurate predictions and that it is effective for building cooling load prediction. A comparison of the developed SVM model against a back propagation neural network, a radial basis function neural network and a general regression neural network was published by Li et al. (2009). Simulation results revealed that the SVM and general regression neural network methods achieved better accuracy.

The research field related to building thermal loads forecasting has been very active, involving various regression and data mining techniques. Nevertheless, it is clear from the literature that little attention has been given to the justification of the selection of the input variables to their predictive models. Hence, the investigation of which variables and why they should be considered as inputs to such a model should be a priority towards the development stage of the model. In the next section, the methodology for selecting input variables and the development of the predictive models is described.

METHODOLOGY

The process of data analysis implemented in this paper to detect interrelationships between variables consists of three stages: (1) the examination of the distribution of each variable (e.g. adhering to a Gaussian distribution), (2) investigation of linear correlation by calculating the Pearson correlation coefficient, and (3) investigation of monotonic correlation by calculating the Spearman correlation coefficient.

The initial task of the data analysis process is the selection of BEM systems variables to be assessed. All of the variables are selected based on the sensors already installed at the testbed building. These variables are divided into two categories, input and output variables. Inputs are the ones introduced to the predictive model and output is the heating load, which will be forecasted from the models. Selection of input variables is validated with the implementation of widely-known statistical techniques, which reveals the existence and importance of correlation with the output variables. Data analysis is based on simulated data obtained by an EnergyPlus model of the testbed building, due to the fact that available measured data was for a period of less than one year. Furthermore, the use of simulated data precludes the possibility of dealing with incomplete data sets that are often acquired when extracting recorded data in BEM systems. The EnergyPlus model provides one year of simulated data at 15-minute intervals. The examination of the correlation between input and output variables was carried out with the use of two different weather data files from Cork, Ireland and London, United Kingdom, available from EnergyPlys (U.S. D.O.E., 2015). The selection of two cities with almost the same climate was made in order to validate the obtained results. The Cork data includes two years of data from 2011 and 2012, whereas the London data is based on nine years of data from 1983 until 1991.

Subsequent to the selection of input variables, numerous regression models alongside several ANN models are developed. All of the developed predictive models are tested and evaluated regarding their ability to forecast heating loads in order to identify the most accurate.

Testbed Building Description

The NIMBUS building (Valdivia et al., 2014) is a two storey quadrangle-type office building, used for research purposes, hosting researchers and students from Cork Institute of Technology (CIT) located in Cork, Ireland. It has a low pitch roof varying in height from 7.7 to 8.7 m and the ratio of transparent to opaque envelope is approximately 34 %. A view of the building and the EnergyPlus model are shown in Figure 1.

Figure 1: NIMBUS building and its EnergyPlus model

The heating system of the building incorporates a 50 kW electrical / 82 kW thermal combined heat and power (CHP) unit, two gas boilers of 175 kW, a 2000 litre water calorifier. The CHP creates an interconnection between the electrical and the thermal system. The boilers produce heat by delivering hot water, which is distributed to the main header and at each building floor through two mixing valves. Finally, radiators are used in each zone for local heating, thereby satisfying user comfort requirements. An extensive network of meters and sensors has been deployed to facilitate measurement and necessary data collection for the control and monitoring of electrical and thermal systems. These measurements together with relevant information about gas and electricity power consumption measurements and prices, as well as heating/electrical loads and weather forecast, are available from the Supervisory Control and Data Acquisition System and the BEM systems.

Selection of Input Variables

The procedure followed for analysing the data and examining the existence of a correlation between input and output variables was based on statistical techniques. Initially the selected input and output variables were tested to check if they follow a

Gaussian distribution. This was achieved with the use of statistical tests (Justel et al., 1997). Next, the existence of a linear correlation between input and output variables was investigated by performing a Pearson correlation (Spiegel et al., 2013), which measures the linearity between paired data. When the paired variables are normally distributed, Pearson correlation coefficient provides a complete description of their relationship. In a sample of data, it is denoted by r_P and is constrained between -1 and 1, where positive values denote positive linear correlation, while negative values denote negative linear correlation and a value of zero denotes no linear correlation. The correlation coefficient does not relate to the gradient beyond sharing its positive or negative sign. The strength of correlation can be verbally described using the following guide for the absolute value of r_P where:

- 0.00 – 0.19 "very weak"
- 0.20 – 0.39 "weak"
- 0.40 – 0.59 "moderate"
- 0.60 – 0.79 "strong"
- 0.80 – 1.00 "very strong"

Furthermore, the existence of monotonic relationships can be identified as well through the Spearman correlation coefficient (Spiegel et al., 2013). A monotonic relationship is one that the dependent variable either never increases or never decreases as the independent variable increases. The Spearman correlation coefficient is a statistical measure of the strength of a monotonic relationship between paired data and is denoted by r_S. It is also used when the paired variables do not follow the normal distribution and is robust to outliers (unlike Pearson correlation coefficient). The principles of Spearman correlation are the same as the Pearson correlation coefficient.

The statistical analysis was carried out using the IBM SPSS Statistics 20 software (IBM Corp., 2013). The most commonly measured variables in BEM systems of commercial buildings are chosen as possible input variables and are grouped according to weather data and indoor variables, as given in Table 1. Heating load of the testbed building is the output variable and as an extra output, the variable of gas consumption is examined regarding its correlation to heating load.

The selection process of the input variables that will be introduced to the predictive models is based on the calculated Pearson and Spearman correlations between input and output variables. Absolute values of the calculated Pearson and Spearman coefficients are used to simplify this process. Only "moderate", "strong" and "very strong" relationships are of interest, hence the threshold value for introducing an input variable to the predictive model is 0.5. It is important to select carefully the input variables in order to avoid unnecessary increases in the complexity during the development of the models.

Table 1: Input variables under examination

Weather Data	Indoor Data
Ambient Temperature	Zone Air Temperature
Ambient Relative Humidity	Zone Relative Humidity
Wind Speed	Zone Occupancy
Solar Radiation	Zone CO_2 level
Sky Clearness	

Predictive Models Development

The development of the predictive models for the testbed building is initiated with the investigation of regression models followed by the examination of ANN models.

In order to investigate all possible scenarios different types of regression and ANN models have been developed using different input variables, different resolution of data acquisition as well as different partitioning methods, as given in Table 2.

Multiple linear, multiple non-linear and generalized linear regression models have been implemented in the development stage of the regression models. Moreover, multilayer perceptron and radial basis ANN methods were considered for the development of machine learning models. Ambient Temperature, Ambient Relative Humidity, Solar Radiation and Zone Air Temperature are the input variables used in multiple combinations. Furthermore, the datasets acquired from the simulated model of NIMBUS building are divided into training and testing partitions. The training partition is used to develop and train the predictive models, while the testing partition is utilised for the evaluation of the accuracy of the models. The predictions generated from the models are compared with the actual values of the testing partition. Two ways of separating the datasets were examined. The first is that the training partition includes data from January to June and the second is that training consists of all data from the first fifteen days of each month. In addition, the synthetic dataset was generated with 15-minutes, 30-minutes and hourly resolution to detect if the time step interferes with the accuracy of the predictions.

The development of the predictive models was achieved with the use of the IBM SPSS Modeler 14.2 software (IBM Corp., 2011). The accuracy of each model was calculated based on the following equation:

$$Accuracy(\%) = \left(1 - \frac{MAE}{Max_{pr.val.} - Min_{pr.val.}}\right) \times 100$$

where, MAE is the mean absolute error in prediction, $Max_{pr.val.}$ is the maximum predicted value and $Min_{pr.val.}$ is the minimum predicted value.

Table 2: Possible scenarios for predictive models development

Regression Models	ANN Models	Resolution of Dataset	Training Partition	Input Variables
Multiple linear	Multilayer Perceptron	15 minutes	January to June	Amb. Temp., Amb. R.H., Sol. Rad.
Multiple non-linear	Radial Basis Function	30 minutes	First 15 days of each month	Amb. Temp., Amb. R.H., Sol. Rad., Zone Temp.
Generalized linear		Hourly		Amb. Temp., Sol. Rad., Zone Temp.
				Solar Rad., Zone Temp.
				Zone Temp.

RESULTS AND DISCUSSION

Input Variables Selection

The first task of the data analysis was the examination of the hypothesis that individual parameters follow a Gaussian (normal) distribution. The results of the normality tests are illustrated in Table 3, for the Cork and London weather data. It can be seen that certain variables are normally distributed, including Ambient Temperature, Zone Air Temperature and Zone Relative Humidity. In addition, the results reveal that the distribution is not influenced by the different weather data. The only variable that is not consistent is Wind Speed.

Table 3: Normality test results for input and output variables

Variable	Normally distributed, Cork	Normally distributed, London
Ambient Temperature	YES	YES
Ambient Rel. Humidity	NO	NO
Wind Speed	YES	NO
Solar Radiation	NO	NO
Sky Clearness	NO	NO
Zone Air Temperature	YES	YES
Zone Rel. Humidity	YES	YES
Zone CO_2 level	NO	NO
Zone Occupancy	NO	NO
Heating Load	NO	NO
Gas Consumption	NO	NO

The next step was the examination of linear correlation using the Pearson correlation analysis and the most interesting results are shown in Table 4. Both normally and non-normally distributed variables were included in the examination process in order to apprehend the linear relationship between all variables.

The Pearson coefficients indicate correlations between well-established variable pairs, including: Solar Radiation with Sky Clearness and Zone Occupancy with Zone CO_2 levels. The correlation of Heating Load and Gas Consumption with other variables is “strong” when Cork weather data is used but is “weak” when London weather data is applied.

The lack of consistency implies that the correlation may be monotonic instead of linear.

Table 4: Pearson correlation results for Cork and London weather data

Variable 1	Variable 2	Cork. r_P	London r_P
Solar Radiation	Sky Clearness	very strong	very strong
Zone CO_2 level	Zone Occupancy	very strong	very strong
Zone Air Temperature	Ambient Temperature	strong	strong
Zone Air Temperature	Sky Clearness	moderate to strong	moderate to strong
Zone Air Temperature	Solar Radiation	moderate to strong	moderate to strong
Zone Rel. Humidity	Ambient Rel. Humidity	moderate to strong	moderate to strong
Heating Load	Gas Consumption	strong	weak
Heating Load	Ambient Temperature	strong	weak
Gas Consumption	Zone Air Temperature	strong	weak

To clarify if this case is valid, a Spearman analysis is performed. The outcome of the examination for monotonic relationships between data is displayed in Table 5.

Table 5: Spearman correlation results for Cork and London weather data

Variable 1	Variable 2	Cork r_S	London r_S
Solar Radiation	Sky Clearness	very strong	very strong
Zone CO_2 level	Zone Occupancy	strong	strong
Zone Air Temperature	Ambient Temperature	moderate to strong	very strong
Zone Air Temperature	Sky Clearness	moderate to strong	moderate to strong
Zone Air Temperature	Solar Radiation	moderate to strong	moderate to strong
Zone Rel. Humidity	Ambient Rel. Humidity	strong	moderate to strong
Heating Load	Gas Consumption	very strong	very strong
Heating Load	Ambient Temperature	very strong	strong
Gas Consumption	Zone Air Temperature	strong	weak

Based on the Spearman analysis, the existence of correlation between variables that had been discovered with Pearson coefficient is verified. Table 5 reveals that the correlation between Heating Load and Gas Consumption can be better described as a monotonic one, since results yield a “moderate” to “strong” correlation. Another interesting finding from the Spearman analysis is the correlation between Heating Load and Ambient Temperature, which is consistent. The relationship between Gas Consumption and Zone Air Temperature is not consistent when changing the location, but the fact that there is a “strong” to “very strong” correlation for one of them cannot be neglected.

Through this analysis, two pairs of input variables that include the same type of information were identified. Sky Clearness and Solar Radiation is the first pair. These two variables have a “very-strong” correlation, but this was expected since when the sky is clear, higher solar radiation reaches the building. Heating Load and Gas Consumption is the second pair of variables. Initial results from the Pearson correlation coefficient indicated that using different weather data can interfere with their linear correlation. A deeper analysis of the Spearman correlation coefficient revealed nevertheless that they have a “very-strong” monotonic correlation.

Predictive Models

Combination of all possible scenarios in Table 2 led to the development of 90 regression and 60 ANN models. The average accuracy of the regression models is 74.52% and of the ANN models 83.31% as illustrated in Figure 2.

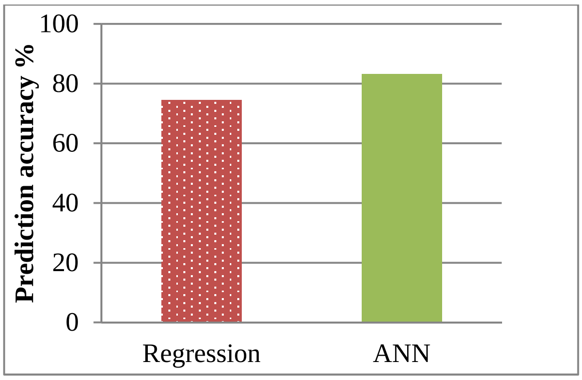

Figure 2: Average accuracy of Regression and ANN models

The most accurate regression model was found to have 92.1% of accuracy regarding generating predictions for the heating load of the NIMBUS building, while the least accurate was only 34.5%. Regarding the developed ANN models, the most accurate achieved 97% and the least accurate 39.7%, as shown in Table 6.

Table 6: Most and least accurate predictive models, using regression and ANN

Model Type	Most Accurate	Least Accurate
Regression	92.1%	34.5%
ANN	97.0%	39.7%

The most accurate regression and ANN models both used as inputs the Ambient Temperature, the Ambient Relative Humidity, the Solar Radiation and the Zone Air Temperature at a 15 minute time step resolution for the dataset. The generalised linear regression method was implemented for the development of the most accurate regression model. Furthermore, the multilayer perceptron method was utilised for the generation of the most accurate ANN model.

The obtained results from the predictive models were assessed to examine possible influences from the different training partitions and resolutions of the datasets used. The assessment indicated that neither the training partition nor the resolution of the dataset significantly affect the accuracy of the predictions, as depicted in Figures 3 and 4.

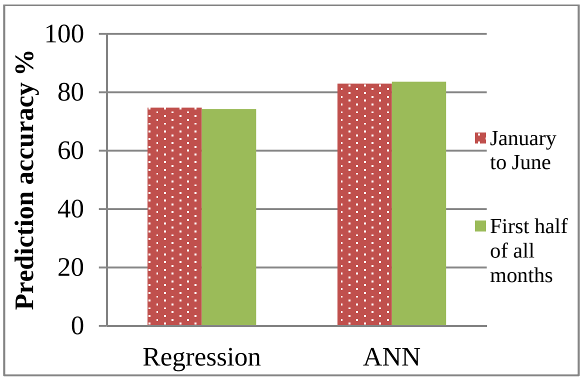

Figure 3: Average accuracy of Regression and ANN Models using different training partitions

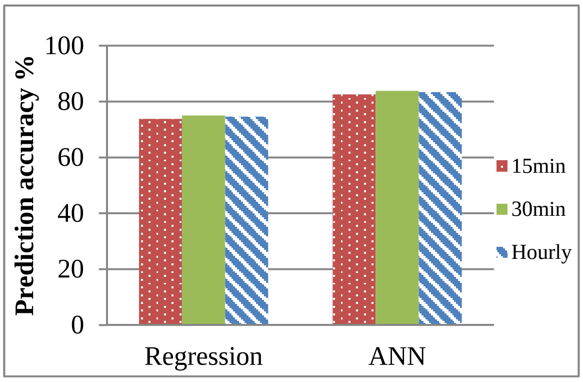

Figure 4: Average accuracy of Regression and ANN Models using different resolutions for the dataset

An interesting finding during the assessment of the obtained results was the influence of the Zone Air Temperature as an input variable, which is highlighted in Figure 5.

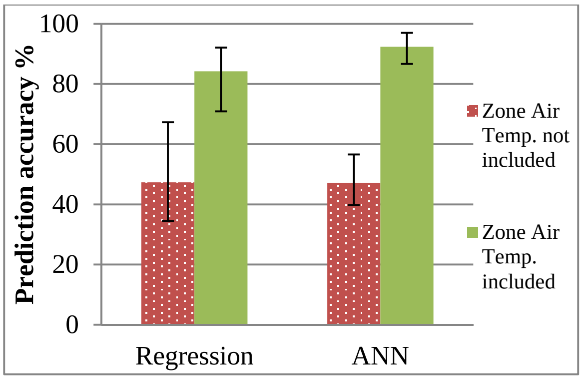

Figure 5: Effect of Zone Air Temperature on the average accuracy of Regression and ANN Models

The average accuracy of the regression models without Zone Air Temperature as an input is 47.35%, while when it is present as an input the average accuracy rises to 84.23%. Likewise, the average accuracy of the ANN models without Zone Air Temperature as an input is 47.15%, while when it is present as an input the average accuracy rises to 92.35%.

CONCLUSIONS

It is clearly shown that the variables that affect Heating Load are Ambient Temperature, Ambient Relative Humidity, Solar Radiation and Zone Air Temperature for the case of the testbed building. The relationship between Zone Air Temperature and Heating Load required further examination, since based on the variables selection process, their correlation was not consistent when different weather data were used. During the development of the predictive models, Zone Air Temperature proved to be a critical variable for the generation of accurate predictions. Moreover, regarding the predictive models, results indicate that machine learning models can achieve higher accuracy in predictions, compared to the regression models. To summarise, the input variables under consideration for the predictive models are Ambient Temperature, Ambient Relative Humidity, Solar Radiation and Zone Air Temperature, while ANN models performed better in forecasting the Heating Load. Future research work includes the application of the methodology to different types of commercial buildings in various climates. In this way, the existence of a pattern related to the selection of input variables will be investigated and the effectiveness of machine learning techniques in forecasting heating loads of commercial buildings will be examined.

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