Research on Techniques for Building Energy Model

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1 STAGE OF THE RESEARCH

Forecasting of building thermal and cooling loads, without the use of simulation software, can be achieved using data from Building Energy Management Systems (BEMS). Experience in building modelling has shown that data analysis is a key factor in order to produce accurate results. Commercial buildings incorporate BEMS to control the Heating Ventilation and Air-Conditioning (HVAC) system and to monitor the indoor environment conditions. Measurements of temperature, humidity and energy consumption are typically stored within BEMS. These measurements include underlying information regarding buildings' thermal response. Data Mining is utilised to explore the data, to search for consistent patterns and/or systematic relationships between variables, and then to validate the findings by applying the detected patterns to new subsets of data. The process of data mining within the current research project consists of three stages: (1) the initial exploration, (2) model building or pattern identification with validation/verification, and (3) deployment (i.e., the application of the model to new data in order to generate predictions). The data used for the purposes of this research project has been gathered from two commercial buildings, located in Dublin and Cork, Ireland.

The research described in this paper is at its initial stage, where an extensive literature review of building energy modelling has been conducted, the research plan is defined, the research skills are being developed and original research work is initiated. In February 2014, the first year of the three-year programme will be completed.

2 OUTLINE OF OBJECTIVES

This project focuses on a novel approach for cost-effective modelling of actual data from commercial buildings, with models that can be assembled rapidly and deployed easily. This approach will constitute a practical research testbed to optimise multiple objectives related to the buildings' energy modelling research area: i) development of a novel approach for predicting thermal and cooling loads of commercial buildings; ii) highly accurate predictions in terms of thermal and cooling loads; iii) scalability of the new approach to any commercial building and iv) minimum commissioning and maintenance effort requirements.

3 RESEARCH PROBLEM

Predictions of building thermal and cooling load can be obtained using appropriate simulation software. Building simulation software require detailed building geometry as well as physical data, such as construction elements, U-values, etc. in order to simulate the operation of a building. These parameters are often unknown, especially for older buildings, thus introducing rough estimations and significant commissioning effort in real-world applications.

An alternative way to forecast these loads is to take advantage of the data recorder within BEMS. As already mentioned measurements of temperature, humidity and energy consumption are the ones stored within BEMS. Useful information regarding the thermal response of buildings are contained in these measurements.

Utilization of measured data can produce predictions of buildings energy consumption. These predictions can be used to improve the efficiency of the HVAC system and hence reduce the amount of energy consumed. The accuracy of the prediction is a crucial factor regarding the maximization of energy savings. This project will attempt to answer the following research questions:

- Can historical measured data of buildings be used to predict thermal and cooling load?
- Which is the best methodology to adopt for model development?

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- What is the innovation and novelty of the new model?
- How accurate and scalable is the new model?
- Which are the commissioning requirements of the new model?

4 STATE OF THE ART

American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) classify building analytical methods into dynamic and steady state approaches, as summarised in Figure 1 (ASHRAE, 2009). The difference between steady-state and dynamic methods is the consideration of effects such as thermal mass and/or capacitance. Steady-state methods do not take into account effects that cause temperature transients. Conversely, building transient behaviour, which includes effects such as building warm-up or cool-down periods, is captured using the dynamic methods.

Figure 2 illustrates another way to classify the methods outlined in Figure 1. The key difference is that the analytical methods are classified based on the underlying computational methodology rather than a transient/steady-state demarcation. Three categories can be observed using this classification, namely, "White", "Grey" and "Black" box models. "White-box" models use physical principles to calculate the thermodynamics and energy behaviour of the whole building level or of sub-level components (Zhao and Magoulès, 2012). The second category "black-box" models, includes the data-mining methods, which utilises extensive measurement of input and output variables in order to determine correlated relationships between different variable combinations. The third category includes models that use both physical and data-mining methods and are called hybrid or "Grey-box" models. One can observe that the two different approaches for classifying the existing methodologies are two different aspects of the same issue.

All methods use physical principles or data-mining techniques and at the same time are either dynamic or steady-state. This point becomes clearer while using a colour coding as shown in Figure 1 and Figure 2. White, grey and black colours are used in Figure 1 to discriminate the white, grey and black box models. Steady-state methods are coloured with blue and dynamic methods with orange in Figure 2.

White-box methods do not meet the basic requirement of this project, which is the use of historical data and avoidance of detailed building geometry and construction data.

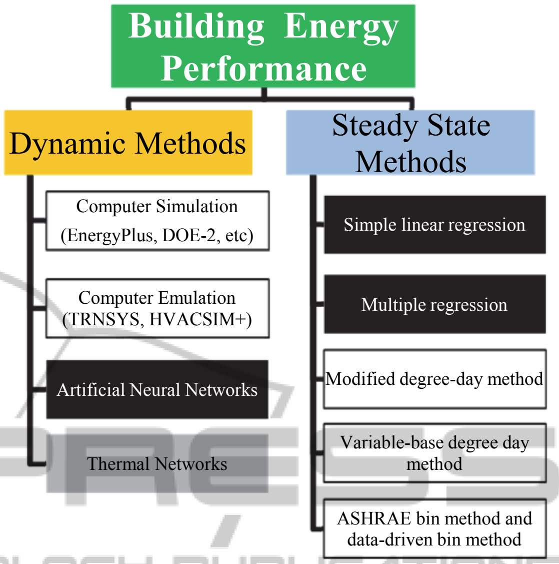

Figure 1: Categorization of methods used to estimate building energy performance based on ASHRAE Handbook (ASHRAE, 2009).

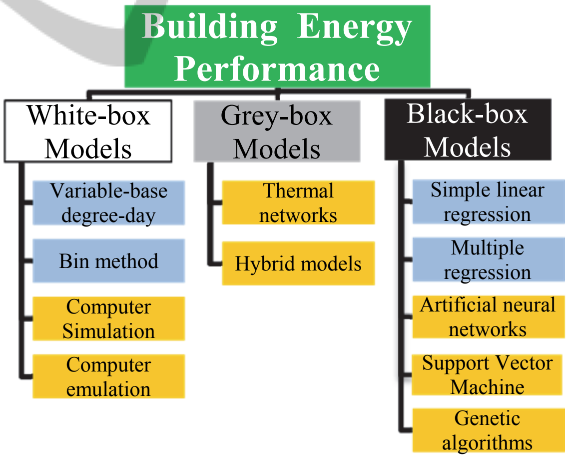

Figure 2: Categorization of analytical methods to estimate building energy performance based on the underlying methodology.

Hence, they are not included in a detailed manner in this research. Furthermore, grey-box methods combine the use of white- and black-box methods thus it is reasonable to eliminate them as well, due to the presence of white-box methods.

Based on the literature review for black-box methods regression, support vector machine (SVM) and artificial neural network (ANN) models seem suitable for generating predictions. Their performance and accuracy will be explored further to determine which one is the most appropriate for this specific application. Genetic algorithms are mainly used for optimization rather than forecasting and for that reason are excluded from deeper investigation.

An overview of regression, SVM and ANN methods including their advantages and disadvantages alongside interesting case-studies follows.

4.1 Regression Models

The correlation of energy consumption with all influencing variables can be achieved with the use of regression models. Development of these empirical models is based on historical performance data, which need to be collected prior to the training of the models. The main objectives of these models are the prediction of energy usage, prediction of energy indices and estimation of important parameters of energy usage. Examples of these parameters are the total heat capacity, total heat loss coefficient and gain factors (Zhao and Magoulès, 2012).

In general, regression models can be divided into simple and multiple regression. Simple regression models were frequently used in the late ’90s to correlate energy consumption with climatic parameters, to obtain building energy behaviour (Bauer and Scrartezzini, 1998); (Westergren et al., 1999). Multiple regression analysis is used to predict a single dependent variable, such as heating demand, by a set of independent variables, such as shape factor, building time constant, etc. Multiple regression shares assumes: linearity of relationships, same level of relationship throughout the range of the independent variable, interval or near-interval data, absence of outliers and data whose range is not truncated (Catalina et al., 2008). Multiple regression models can be separated in two major categories, multiple linear regression models and multiple non-linear regression models.

4.1.1 Multiple Linear Regression

Multiple linear regression models are also known as conditional demand analysis (CDA) models and are usually applied to the building energy forecasting area (Foucquier et al., 2013). The idea of using the linear regression for the prediction of energy consumption in buildings was first proposed by Parti (1980). The deduction of the energy demand from the sum of several end-use consumptions added to a noise term which was the innovation regarding this method.

The underlying principle of multivariate linear regression is the prediction of an output variable Y as a linear combination of input variables ($X_1, X_2, \ldots, X_p$) plus an error term ε_i (Foucquier et al., 2013).

$$Y = \alpha_0 + \alpha_1 \cdot x_{i1} + \alpha_2 \cdot x_{i2} + \ldots + \alpha_p \cdot x_{ip} + \varepsilon_i, \; i \in [1, n] \quad (1)$$

In Equation (1), n is the number of sample data, p is the number of variables and α_0 a bias. For instance, when the output variable is internal temperature the external temperature, humidity, solar radiation and lighting equipment can be considered as input variables (Foucquier, et al., 2013).

Essentially, multiple linear regression models can be applied both for predicting or forecasting energy consumption and for data-mining. The main advantage of these methods is the simplicity of implementation by non-expert users, since no parameter needs to be tuned. Nevertheless, multiple linear regression models imply a major drawback due to their inability to solve nonlinear problems. This causes limitations to the flexibility of the prediction and at the same time presents difficulties to manage the correlation between several variables.

4.1.2 Multiple Non-linear Regression

Non-linear regression models are of the same basic form as linear regression models:

$$Y_i = f(X_i, a) + \varepsilon_i \quad (2)$$

The error terms are usually assumed to have a value of zero, constant variance and to be uncorrelated, just as for linear regression models. Often, a normal error model is utilized which assumes that the error terms are independent normal random variables with constant variance. The correlation between the input and output variables can take different forms in order to fit the available data series. Two examples of non-linear regression models widely applied in practice are exponential and polynomial regression models.

4.1.3 Case Studies

In this section interesting case-studies of regression models are given. At first, two case-studies which applied multiple linear regression models are stated followed by multiple non-linear regression case-studies.

Lam et al., (2010) developed multiple linear regression models for office buildings for the five major climates in China. These models can be used to estimate the potential energy savings during the initial design stage when different building schemes and concepts are being examined. A total of 12 key building variables were identified through parametric and sensitivity analysis and considered as inputs in the regression models. More recently, Aranda et al., (2012) used multiple linear regression models to predict the annual energy consumption in the Spanish banking sector. The energy consumption of a bank branch was predicted as a function of its construction characteristics, climatic area and energy performance. Three models were finally obtained. The first one was used to make predictions for the whole banking sector, while the rest estimated the energy consumption for branches with low winter climate severity (Model 2) and high winter climate severity (Model 3).

Catalina et al., (2008) worked on the development and validation of multiple regression models to predict monthly heating demand for single-family residential buildings in temperate climates. The inputs for the regression models were the building shape factor, building envelope U-value, window to floor area ratio, building time constant and climate, which was defined as a function of temperature and heating set-point. It was found that quadratic (second-order) polynomial models were the most appropriate solution for the problem. In order to validate the models, 270 different scenarios were analysed. The average error was 2% between the predicted and simulated values.

An update to the aforementioned work was published by Catalina et al., (2013). A new model to predict the heating energy demand, based on the main factors that influence the building heat consumption, was introduced. Influencing factors were: the building global heat loss coefficient, south equivalent surface and difference between indoor set point temperature and "sol-air temperature". Once again, polynomial multiple regression models were used and a three input model was found to be the most appropriate for this problem. The model was tested and demonstrated relativly good accuracy considering its simplicity and generality. Human behaviour was also taken into account in the creation of this model, improving the accuracy of the predictions.

4.2 Support Vector Machine

The SVM is an artificial intelligence technique that is usually used to solve classification and regression problems. It was introduced by Vapnik and Cortes (1995). As already described, the regression method is used to characterise a set of data with a specific equation. The type of the regression equation is determined by the user. The technique which allows the demarcation of a set of data in several categories is called classification. Once again, the characteristics of each category are given by the user.

SVM is mainly used with a regression method to predict the energy consumption of buildings. The determination of the optimal generalisation of the model to promote sparsity is the basic principle of the SVM for regression. A given training dataset from a nonlinear problem is $[(x_1,y_1),..,(x_n,y_n)]$, where x_i and y_i is the input and output space respectively. The approach to solve this problem is to overcome the nonlinearity by transforming the nonlinear relation between x and y in a linear map. To achieve that, the nonlinear problem must be sent to a high-dimensional space called the feature space. The aim is to determine the function $f(x)$ that best fits the behaviour of the problem as with all the known regression techniques. A special feature of the SVM is that it authorises an error or an uncertainty ε around the regression function (Foucquier et al., 2013). The form of the $f(x)$ function is the following:

$$f(x) = <\omega, \Phi(x)> + b \tag{3}$$

where, Φ represents a variable in the high-dimensional feature space and <,> is a scalar product, ω and b are estimated by the following optimisation problem.

$$\begin{gathered} \min_{\omega,b,\xi_i,\xi_i^*} \frac{1}{2}\|\omega\|2 + C\sum_{i=1}^{n}\left(\xi_i + \xi_i^*\right) \\ \textit{subject to} \\ y_i - <\omega, \Phi(x_i)> - b \le \varepsilon + \xi_i \\ <\omega, \Phi(x_i)> + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{gathered} \tag{4}$$

where, C is a regularisation parameter, which introduces a trade-off between the flatness of $f(x)$ and the maximal tolerated deviation larger than ε, given by users, ξ_i and ξ_i^* are two slack variables, which allow the constraints to be flexible. In addition, a kernel function defined as a dot product in the feature space $k(x,x') = <\Phi(x),\Phi(x')>$ is created to allow the substitution of the complex nonlinear map with a linear problem without having to evaluate $\Phi(x)$. Examples of kernel function used in regression by SVM are the linear $[k(x_i,x) = x_i \cdot x]$, polynomial $[k(x_i,x) = (x_i \cdot x + c)^d]$ and radial basis function (RBF) kernel (Foucquier et al., 2013).

One of the main advantages of the SVM model is the fact that the optimisation problem is based on the structural risk minimisation principle. The minimisation of an upper bound of the generalization error consisting of the sum of the training error is the objective of this method. This principle is usually encountered at the empirical risk minimisation which only minimises the training error. An additional advantage is that with this method there are fewer free parameters of optimisation. Application of the SVM technique requires the adjustment of the regularisation constant C and the margin ε. At the same time, this adjustment is one of the hardest steps of this method. The main drawback of the SVM method is the selection of the best kernel function corresponding to a dot product in the feature space and the parameters of this kernel (Foucquier et al., 2013).

4.2.1 Case Studies

Support vector machine models have been used for predicting energy consumption in buildings quite recently. Dong et al., (2005) were the first to introduce the use of SVM for prediction of the building energy consumption. The objective of their work was to examine the feasibility and applicability of SVM in building load forecasting area. In order to test the developed SVM model, four commercial buildings in Singapore were selected randomly as case studies. The input variables were the mean outdoor dry-bulb temperature, the relative humidity and the global solar radiation. The kernel function used was the radial basis function kernel. The obtained results were found to have coefficients of variance less than 3% and percentage of error within 4%.

Li et al., (2009) used the SVM model in regression to predict hourly building cooling load for an office building in Guangzhou, China. The outdoor dry-bulb temperature and the 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 newly developed SVM model against different artificial neural networks was published by the same research group later the same year (Li et al., 2009). The SVM model was compared with the traditional back propagation neural network, the radial basis function neural network and the general regression neural network. All prediction models were applied at the same office building in Guangzhou, China. The models were evaluated based on the root mean square error and mean relative error. Simulation results showed that these models were effective for building cooling load prediction. The SVM and general regression neural network methods achieved better accuracy and generalisation than the back propagation neural network and radial basis function neural network methods.

Hou and Lian (2009) also used a SVM model for predicting cooling load of a HVAC system in a building in Nanzhou, China. The performance of the SVM with respect to two parameters, C and ε, was explored using stepwise searching method based on radial-basis function kernel. Actual prediction results showed that the SVM forecasting model, whose relative error was about 4%, may perform better than autoregressive integrated moving average ones.

4.3 Artificial Neural Networks

Artificial neural network (ANN) is a generic denomination for several simple mathematical models that try to simulate the way a biological neural network (for instance human brain) works.

The main characteristic of such models is the capability of learning the ‘‘rule’’ that controls a physical phenomenon under consideration from previously known situations and extrapolate results for new situations. This learning process is called network training. The development of artificial neural networks is based on the observation of the biological neural network behaviour (Neto and Fiorelli, 2008).

Several possible arrangements for artificial network have been suggested, generating different and distinct network models, since it is not well known how a biological neuron is arranged (Fausett, 1994). The feed-forward model is the most known and simple network arrangement, illustrated in Figure 3. In this model, the neurons are placed in several layers. The first one is the input layer, which receives inputs from outside. The last layer, called output layer, supplies the result evaluated by the network. Between these two layers, a network can have none, one or more intermediate layers called the hidden layers. The input layer is usually considered a distributor for incoming signal, hidden layers are signal classifiers, and output layer is the organizer of obtained responses (Neto and Fiorelli, 2008).

An important detail about the feed-forward model is that the neurons of a given layer are only connected with the previous layer and the next one. Other possible more sophisticated network arrangements are possible as well, for instance the Self-Organising Maps creates models in which the network itself changes its arrangement during the training phase.

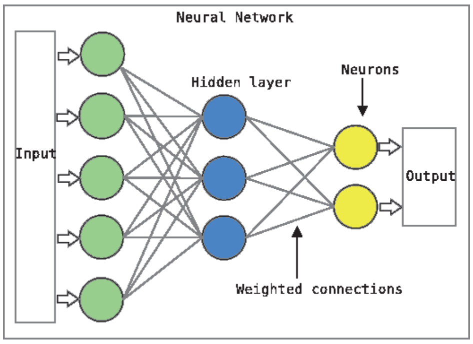

Figure 3: Typical structure of an artificial neural network.

One of the advantages of this method is that it does not need to detect the potential co-linearity included in the problem. Another advantage of the artificial neural networks is its ability to deduce from data the relationship between different variables without any assumptions or any postulate of a model. Moreover, it overcomes the discretisation problem and is able to manage data unreliability. This method suggests a large variability of the predicted variable form (binary 0 or 1, yes/no, continuous value, etc.) and an efficient simulation time.

Conversely, artificial neural networks are significantly limited by the fact that a relevant database should be available in order to be applied. In fact, it is of vital importance to train the network with an exhaustive learning basis, which consists of representative and complete samples. For instance, samples in different seasons or in different moments of the day or during weekend or holidays etc. as well as samples, which contain the same amount of information. An additional disadvantage of the artificial neural network is its large number of undetermined parameters, for which there are no rules to determine (Foucquier et al., 2013).

4.3.1 Case Studies

Artificial neural networks have been applied by researchers to analyse various types of building energy consumption, such as heating and cooling load, under different conditions.

Kalogirou et al., (1997) implemented back propagation neural networks at an early design stage in order to predict the required heating load of buildings. The network was trained based on 250 known cases of heating load, varying from large spaces of 100 m^2 floor area to very small rooms. Input data included the areas of windows, walls, partitions and floors, the type of windows and walls, classification on whether the space has a roof or ceiling, and the design room temperature. Another artificial neural network for the estimation of daily heating and cooling loads was developed by the same group of researchers (Kalogirou et al., 2001). A multi-slab feed-forward architecture having 3 hidden slabs was used and each slab comprised of 36 neurons. The accuracy of this network was within the acceptable level (relative error 3.5%).

The predictions of an artificial neural network can be made on an hourly basis as well. Gonzalez and Zamarreno (2005) were based on a special kind of artificial neural network, which feeds back part of its outputs, to predict the hourly energy consumption in buildings. The network was trained by means of a hybrid algorithm. The inputs of the network were current and forecasted values of temperature, the current load and the hour and the day. The achieved results demonstrated high precision.

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. When synthetic data was used the two models appeared to have equal performance in terms of coefficient of variation (CV). On the other hand, when real measurements were used the sliding window training performed better than accumulative training, CV of 0.26 compared to 2.53 respectively.

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%.

Dombayci (2010) developed an artificial neural network model in order to forecast hourly heating energy consumption of a model house. The hourly heating energy consumption of the model house was calculated with degree-hour method. The model was trained with heating energy consumption values of years 2004–2007 and tested with heating energy consumption values for the year 2008. Best estimate was found with 29 neurons and a good coherence was observed between calculated and predicted values.

A comparison between detailed model simulation and artificial neural network for forecasting building energy consumption was published by Neto and Fiorelli in 2008. EnergyPlus was used as the model based on physical principles. Results of this study indicate that EnergyPlus consumption forecasts present an error range of ±13% for 80% of the tested database. Major source of uncertainties in the detailed model predictions are the improper evaluation of lighting, equipment and occupancy schedules. The artificial neural network model results had an average error of about 10% when different networks for working days and weekends were implemented. The outcome of this study was that both models are suitable for energy consumption forecast.

In the same year Aydinalp-Koksal and Ugursal (2008) compared the use of neural network against conditional demand analysis (CDA) and engineering approaches for modelling the end-use consumption in the residential sector in Canada. The prediction performance and the ability to characterise the consumption of the aforementioned methods were compared in this study. The results indicated that neural networks and CDA are capable of accurately predicting the energy consumption in the residential sector as well as energy simulation programs. Moreover, the effects of socio-economic factors were estimated using the neural network and the CDA model, where possible. Neural network model was proved to have higher capability of evaluating these effects compared to the CDA model.

5 METHODOLOGY

Based on the methodologies described earlier new models will be developed taking account of the key principles outlined in the objectives. In order to achieve this, the sequence presented below will be followed:

- Acquisition of real measured data of a commercial building (testbed 1) from installed sensors;
- Data analysis;
- Development of the new models;
- Improvement of models accuracy;
- Evaluation of new models based on accuracy and on-line training capability;
- Selection of the most suitable model;
- Examination of model scalability with the use of another commercial building (testbed 2);
- Determination of commissioning and maintenance effort for the implementation of the model.

The methodology that is described in this sequence is also illustrated in Figure 4.

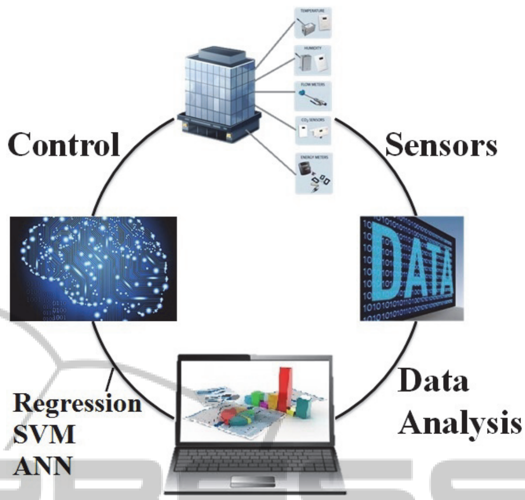

Figure 4: Development of methodology.

The first step of this methodology is to acquire as much data as possible from BEMS already installed in a commercial building. Afterwards, data analysis is employed to replace missing data and correlate variables to obtain a complete and comprehensive dataset. The ultimate goal of this data mining process is to assist with building load prediction, where incomplete data is available.

Data Mining is utilised to explore the data, to search for consistent patterns and/or systematic relationships between variables, and then to validate the findings by applying the detected patterns to new subsets of data.

In order to determine the new model the selection of the optimum model between regression, SVM and ANN models is required. Different multiple regression models will be developed alongside numerous SVM models and several architectures of ANN and tested in order to reach the optimum one. The chosen model amongst the aforementioned will be selected based on its accuracy and tested for its ability to train on-line.

The scalability of the model will be the next thing under examination. Data from a second commercial building will be introduced to the model and its ability for accurate predictions will be tested once again.

Finally, commissioning and maintenance effort for the implementation of the new model will be determined. Hence, the model will be evaluated based on its ability to meet the necessary requirements.

6 EXPECTED OUTCOME

The expected outcome of this project is the development of a novel whole-building energy model. The model will take advantage of historical measured data of commercial buildings in order to generate accurate prediction of heating and cooling load. Data analysis will be one of the milestones of this project, since usually measurements include missing values due to equipment malfunction, maintenance, etc. An efficient method of dealing with missing values related with acquired datasets will be the first outcome of the project.

Once a comprehensive dataset is obtained, the most suitable methodology for this application is going to be selected between regression, SVM and ANN models. An evaluation of the developed models will take place based on the accuracy of each model and its ability to train on-line or not. The selection of the most appropriate model will be the second outcome.

After the selection process, the chosen model will be evaluated based on its scalability. The ability of forecasting heating and cooling loads of two different given building within the same level of accuracy will be the criterion. If the chosen model does not have the desired scalability, then another model will be selected from the previous procedure and examined based on its scalability. Finally, the effort required for commissioning and maintenance of the model should be as little as possible. The final outcome should be a scalable model with minimum commissioning and maintenance requirements.

Ideally, this novel approach of estimating the thermal and cooling load of commercial buildings could be implemented to the control of the BEMS. In this way, the efficiency of the HVAC systems of the building could be improved reducing the energy consumption at the same time. This will also lead to a reduction of the energy cost of commercial buildings.

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