Lecture and non-lecture week baseline energy model development and energy prediction in Malaysia educational building

R F Mustapa¹, N Y Dahlan², A I M Yassin³ and A H M Nordin⁴

¹,²,³,⁴Faculty of Electrical Engineering Universiti Teknologi MARA, 40500 Shah Alam, Malaysia
¹,⁴Faculty of Electrical Engineering Universiti Teknologi MARA Johor Branch, Pasir Gudang Campus, 81750 Masai, Johor, Malaysia

E-mail: rijalulfahmi@yahoo.com

Abstract: The development of baseline energy models and prediction of energy consumption in educational buildings especially universities are heavily depending on its operation period. The main operation period can be divided into two period i.e. lecture week and non-lecture week. Possible independent variable candidates that may have an effect towards energy consumption during this two period differ with each other. In addition, spaces that occupies the educational building such as classrooms, laboratories and office rooms within the same building operates differently depending on its operation period. In order to achieve accurate baseline energy models in educational buildings, the operation period have to be considered based on the independent variables that will have an effect towards the energy consumption. Thus, the twofold objectives of this paper are to develop a baseline energy model for two operation period in educational buildings and predicting the energy consumption using multiple linear regression model. One building in a university compound was selected as a case study for modelling and prediction purposes. Independent variables were selected based on the two-period mentioned and from the modelling and prediction results, the independent variables that were selected gives a high coefficient of correlation (R²) value which suggest that the independent variables effect the educational building’s energy consumption.

1. Introduction

Energy consumption modelling and prediction in educational building is important to ensure energy conservation measures (ECM) and energy efficiency (EE) project is being implemented flawlessly. Through baseline energy models, the energy consumption modelling and prediction have created scenarios that enlightened engineers, building owners and utilities on how to plan, conduct and manage the ECM and EE projects. Baseline energy models by definition is a tool exists to assist related personnel in energy department to study the trend of energy consumption in a particular building if any changes are being made to the buildings. The development of baseline energy models is the most crucial tasks that decide whether the implementation of ECM and EE projects is successful or a major failure to quantify the savings achieved from it. Quantification of energy savings is calculated by subtracting the difference of predicted energy consumption with the measured energy consumption after ECM and EE project have been implemented. Such standard to facilitate the quantification of energy saved from ECM and EE projects is available in the International Performance Measurement and Verification Protocol (IPMVP) [1].

The acceptance of linear regression model in the IPMVP standard as a tool for the development of baseline energy model and prediction purpose have been widely used in[2-5]. This is due to the fact the linear regression model is a deterministic model in nature [6] and is easy to implement for modelling and prediction purposes [7]. In addition, multiple linear regression (MLR) model the
variant of the linear regression model accept several independent variables in one equation have made the model able to adapt on the versatility of any system that is intended to be modelled. The less complex model of a linear regression model made its computational demand lower than other complex models. In energy consumption field, MLR model have been fully utilized to predict future energy consumption in a hypermarket situated in United Kingdom[8], the prediction of whole-building energy consumption for single-family homes in[9] and investigating the influence factor for the increase of heating energy consumption in China[10]. Apart from energy modelling and energy consumption prediction field, linear regression model have enjoy modelling variety of discipline such as is being used for modelling solar storage tanks [11] and aero-materials consumption prediction for aviation equipment maintenance [12].

Substantial researches pertaining to baseline energy modelling in educational buildings have been implemented utilizing linear regression model in[13-20]. Authors in [13, 20] made a comparison between linear regression model and non-linear model in a library buildings and amphitheater energy consumption with its respective variables. Factors that affecting energy consumption such as technology and occupancies in educational building is being investigated using linear regression model [14]. A calorifier in a dormitory educational building were modelled using linear regression model for retrofitting purposes [15]. Energy consumption prediction that incorporates ambient temperature, outside temperature in the United Kingdom through multiple linear regression model have establish good prediction value[16]. Comparison between linear regression model with artificial intelligence model in [18]shows that prediction value between the two model is having minimal difference. A comparison between non-linear models in [17] shows complex non-linear model have to be constructed before modelling and prediction purposes.

The mentioned research that have been implemented in educational building on its own ways have presented splendid result in developing baseline energy modes and predicting the energy consumption from the developed baseline energy models. But, to the best of the knowledge from the gathered research in developing baseline energy model and predicting energy consumption in educational building [13-20], there are no separation of lecture week and non-lecture week which is deemed to be crucial. This is due to the fact that educational buildings operate in two different window of operation i.e. lecture week and non-lecture week. The distinguishing of lecture week and non-lecture week pertaining to baseline energy model development and energy consumption prediction is vital because energy consumption between this two period may differ with each other. Furthermore, certain educational buildings contain classrooms, laboratories, office rooms and other specific spaces that are located within the same building. The utilization of these spaces during the two-operation period hypothetically indicates that energy consumption is differ with each other. In addition, modelling and prediction of energy consumption in educational buildings during the two-operation window is depending extremely on the selection of possible candidates to become the independent variables that governs the energy consumption in the buildings.

Thus, the main intention of this research is to develop baseline energy models that differentiate the operation of educational building during lecture week and non-lecture week. In addition to the main intention, the second intention is to perform a prediction of energy consumption using the baseline energy model developed during the two-different operation period in educational buildings. Multiple linear regression model will be used to achieve the two intention of this research. The results will be discussed on the performance of the multiple regression model on its coefficient of correlation ($R^2$) value, Mean Square Error (MSE) value, Root Mean Square Error value and Mean Average Percentage Error value. Thus, reflecting the intentions of this research, there are twofold contribution which is the first fold is developing the baseline energy models in educational buildings during two different period and the second fold is prediction of energy consumption from the developed baseline energy models.
2. Methodology

Several methodology steps have been executed to achieve the objectives of this research. The research starts with selecting educational building as its study case. Faculty of Electrical Engineering Universiti Teknologi MARA Johor branch Pasir Gudang campus's building have been chosen as the study case for this research. Energy consumption were logged using data logger and the independent variables that governed the energy consumption in the building were selected intuitively. Baseline energy model were then developed using multiple linear regression model and energy consumption prediction were performed using the developed model. The minimum threshold of the coefficient correlation (R²) value will be based on IPMVP standard. Several explanations on the methodology will be elaborate in the next few subsections. In this research, two data set will be logged and collected named data set A and data set B. Data set A consists of energy consumption and independent variables that will be logged and collected during March 2017 - May 2017 and March 2018 – June 2018 for non-lecture week and lecture week respectively. Data set A will be used for developing the baseline energy model and performed an energy consumption prediction. Data set B is a new independent variable and energy consumption that will be logged and collected during December 2018 – January 2019 and September 2018 – December 2018 for non-lecture and lecture week respectively. Data set B will be used in the model develop with data set A to further test the strength of energy consumption prediction using model developed by data set A.

Educational Building
The educational buildings that were chose in this research is the Faculty of Electrical Engineering (FKE) Universiti Teknologi MARA (UiTM) Johor branch Pasir Gudang campus. The FKE’s building is shown in Figure 1. The building start commencing its operation on March 2014. The building is a 6-story building and is having 9206.16m² area that can fit up to 1000 students. The building consists of classrooms, laboratories, lecturer’s rooms and meeting rooms. The total connected load and the maximum demand designed for the building is 400.72kW and 335.46kW respectively. The building is using 36W and 18W fluorescent type for its main lighting loads. Classrooms, laboratories and meeting rooms is having a centralized chiller air conditioning system. Lecturer’s office rooms air conditioning unit is a split unit system. The building doesn’t have any smart building monitoring system to monitor the energy consumption. The building is fully occupied during lecture week where most of classrooms and laboratories were heavily used for academic purposes. During non-lecture week, the building behaves like an office building because only lecturer’s that is occupying the building for office duty. Thus, the utterly difference in behaviour during lecture and non-lecture week in the FKE’s building made it vital for modelling and prediction of energy consumption during the two-period.

Figure 1: Faculty of Electrical Engineering (FKE) UiTM Johor Branch Pasir Gudang Campus’s Building

Energy Consumption Measurement and Independent Variables Data Collection
The energy consumption of the building will be logged and record using Fluke 1750 data logger. It is installed in the main switch room of the building. The main switch room of the building received a 415V three phase voltage after it was stepped down by a 11/0.415 kV transformer. During non-lecture
and lecture week, the energy consumption was logged during March 2017 until May 2017 and March 2018 until June 2018 respectively for data set A. The energy consumption for data set B was logged during December 2018 – January 2019 and September 2018 – December 2018 for non-lecture and lecture week respectively. The sampling interval for logging purpose were selected for 15-minutes. The logged data were then will be aggregated to 30-minutes resolution. The baseline energy model will be developed by using the hourly interval of the 30-minutes resolution. This main reason to use hourly interval is to avoid heavy oscillation that might decreases accuracy of the develop model and prediction answers. In addition, the building electricity is being supplied by a utility company from a grid connected power system. There are no renewable energy sources that were used in the building. Grid connected electricity and no renewable energy sources were used in the building indicates that it is having a continuous electricity supply and there is no depreciation of renewable energy sources hence hourly energy consumption interval from the 30-minutes resolution aggregated data is suitable for model development and energy consumption prediction purposes.

The independent variables data that govern the energy consumption during lecture and non-lecture week was selected intuitively. During lecture week, the independent variables data that will be collected is occupancy of staff, occupancy of students in classrooms, occupancy of students in laboratories and the outside temperature. The independent variables were reduced to occupancy of staff and outside temperature during non-lecture week. Occupancy of students in classrooms and laboratories will be collected based on the total students that have registered for subjects that is displayed in the lecture’s timetable session. Occupancy of staff will be counted from recorded biometric attendance system. All staff have to clock in and clock out their attendance with their fingerprint. The clock in and clock out will be saved in a database system. Outside temperature was retrieved from the nearest weather station satellite available in www.weatherunderground.com. Staff occupancy in the building will be counted during office hour 8.00 a.m. until 5.00 p.m. and student’s occupancy in class rooms and laboratories will be counted during timetable lecture hour.

Linear Regression Model
Linear regression model is a linear model that equates two or more variables linearly. Linear regression model display the interchange amount that was experienced in a variable by the changes that occurred in the other variables. Such interconnection between two variables was distinguished by defining one variable as the independent variable and the other as a dependent variable. The dependent variable is the variable that will be effected by the change experienced by the independent variable. A multiple linear regression model equation is shown in Equation (1).

\[ Y = \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \beta_0 + \epsilon \]  

(1)

In equation 1, \(X\) is the independent variables that equates the dependent variable \(Y\). In other terms, \(X\) and \(Y\) is the input and output of the multiple regression model respectively. \(\beta\) in equation (1) is the coefficient of the independent variables. Normally, \(\beta\) in equation (1) is approximated by least square method. The incremental change of \(X\) will increase of decrease the value of \(Y\) which further demonstrate concrit proof that linear regression model is inherenting a deterministic modelling technique.

As being mentioned earlier, data set A that consists of lecture week and non-lecture week energy consumption and independent variables will be used to develop baseline energy models for both of the period. The baseline energy model development process for the lecture week and non-lecture week is shown in Figure 2 and Figure 3 respectively. In Figure 2, March 2018 energy consumption and independent variables data will be the testing data that will be fed in the multiple regression model. The resulting multiple linear regression model will generate a multiple linear equation model and this equation will be the baseline energy model during the lecture week period. The remaining independent variables from April 2018 – June 2018 will be inserted into the linear equation model and the output will become a predicted energy consumption. The predicted output will be compared with the actual energy consumption from April 2018 – Jun 2018. Similar pattern is observed in Figure 3 for
the development of non-lecture week baseline energy model and energy consumption prediction using data set a March 2017 – May 2017. In Figure 3, the training data will used the whole March 2017 energy consumption and independent variables data. The rest of the data will be the testing data that will fed in the multiple linear equation model for energy consumption prediction purpose during the non-lecture week period. The predicted output will be compared with the actual energy consumption from April 2017 – May 2017.

Data set B during lecture week and non-lecture week will be used for model testing purposes. The block diagram for this purpose is shown in Figure 4 and Figure 5 for lecture week and non-lecture week energy consumption prediction respectively. In Figure 4, the multiple linear equation model that have been developed using data from March 2018 in data set A will be used to perform energy consumption prediction using lecture week data set B. All the independent variables data will fed into the model and will produce a predicted energy consumption. This predicted energy consumption will be compared with the actual energy consumption measured during September 2018 – December 2018. In Figure 5, data set B that consists of energy consumption during non-lecture week from December 2018 – January 2019 will be used for the same purpose in the block diagram of Figure 4. All the comparison of predicted data and actual data in Figure 2 – Figure 5 will be assessed with statistical error measurement Mean Squared Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Figure 2: Block Diagram Development of Lecture Week Baseline Energy Model and Energy Consumption Prediction Using Data Set A March 2018 – June 2018

Figure 3: Block Diagram Development of Non-Lecture Week Baseline Energy Model and Energy Consumption Prediction Using Data Set A March 2017 – May 2017

Figure 4: Block Diagram of Developed Model (from data set A) for Lecture Week Energy Prediction Using Data Set B September 2018 – December 2018
3. Results and Discussion

The results of this research will be presented and discussed in two separate sections which is the
lecture week and non-lecture week. The results will discuss the outcome of the statistical value of
correlation coefficient \( R \), and the coefficient of determination \( R^2 \) to demonstrate the strength of the
model developed using data set A. The results of energy consumption prediction using data set A and
prediction to test the developed model using data set B will be presented. The comparison of all the
predicted energy consumption with the actual energy consumption statistical error measurement will
be discussed.

**Lecture Week**

In data set A, a total of 1464 energy consumption aggregated data was used for modelling and
prediction purpose. A total of 456 data were used as training data for the development process of the
multiple regression model. The 456 data that were fed into the multiple regression model yields
multiple linear equation model in Equation (2).

\[
Y = 1.3664x_1 + 0.0154x_2 - 0.0024x_3 + 3.0735x_4 - 59.4566
\]

In Equation (2) \( x_1, x_2, x_3 \) and \( x_4 \) is the occupancies of staff, occupancies of students in classrooms,
occupancies of students in laboratories and temperature respectively. The coefficient of the
independent variables is positive for \( x_1, x_2 \) and \( x_4 \) but \( x_3 \) is having a negative coefficient value. The
regression statistics of the multiple linear equation model is shown in Table 1. In Table 1, the value of
correlation coefficient \( R \) is 0.89 which can be considered that the linearity of the independent variable
with respect to the energy consumption is very high. The coefficient of determination has passed the
minimum value of 0.75 in IPMVP standards which further suggest that strong relationship exist
between the independent variables and energy consumption and the independent variables that have
been chosen does having an impact towards energy consumption.

From the developed multiple linear equation model in equation (2), the remaining independent
variables were inserted in the equation and the output \( y \) of the multiple linear model equation is the
predicted energy consumption. The predicted energy consumption is being shown in Figure 6. In Figure 6,
the predicted energy consumption is being compared with the measured energy consumption
with dashed line and bold line respectively. It can be seen that the predicted output is having similar
pattern of energy consumption with minimal deviation on the higher and lower peak. The performance of multiple linear equation model in Equation (2) is further tested with independent
variables data set B. A total of 1152 independent variables data point was inserted in Equation (2).
The prediction answer is shown in Figure 7. In Figure 7, the comparison between predicted output
(dashed line) and measured output (bold) displays a similar behavior where predicted energy
consumption where its behavior similarity is close enough with the measured energy consumption.
The comparison between predicted energy consumption and measured energy consumption statistical error measurement is shown in Table 3. The MSE and RMSE for data set A and data set B is
234.43kWh and 226.01kWh respectively. The respective MSE for data set A and data set B is 15.03
and 15.31 respectively. The MSE and RMSE for both data set doesn’t have a huge difference between
each other. Furthermore, the MAPE which represent the average deviation from predicted and
measured energy consumption is 0.32 and 0.26 for data set A and data set B. Thus, from this result it
indicates that the developed multiple linear regression equation model in Equation (2) using data set A
does represent the dynamic behavior of energy consumption with respective independent variables.
with minor variation from the actual energy consumption. Table 2 shows the statistical error measurement between predicted energy consumption and measured energy consumption in a lecture week.

![Figure 6: Predicted Energy Consumption using Independent Variables April 2018 – June 2018 (Data Set A)](image)

**Table 1. Regression Statistics Lecture Week Multiple Regression Model**

| Correlation coefficient (R) | 0.89 |
|----------------------------|------|
| Coefficient of Determination (R²) | 0.80 |
| Standard Error | 16.83 |

![Figure 7: Predicted Energy Consumption using Independent Variables September 2018 – December 2018 (Data Set B)](image)

**Table 2. Statistical Error Measurement Between Predicted Energy Consumption and Measured Energy Consumption Lecture Week**

| Prediction Data | MSE | RMSE | MAPE |
|----------------|-----|------|------|
| Data Set A     | 234.43 | 15.31 | 0.32 |
| Data Set B     | 226.01 | 15.03 | 0.26 |

**Non-lecture Week**

The non-lecture week data consumption in data set A consist of 976 data points. The energy consumption and independent variables were measured and collected during March 2017 – May 2017. 384 data points during March 2017 was inserted to the multiple regression model as a test data for the multiple regression model. From the multiple regression model, it yields multiple linear equation model in equation (3)

\[
y = 1.1139x_1 + 3.7878x_2 - 83.9928
\]  

(3)

In Equation (3), \(x_1\) and \(x_2\) is the occupancy of staff and the outside temperature respectively. The coefficient of \(x_1\) and \(x_2\) is a positive value which implies that there is a significant impact of the related independent variables with respect to energy consumption. The regression statistics of the test data is shown in Table 3. In Table 3, the value of R indicated that the correlation between variable is strong with the value of 0.87. The R² value is 0.76 which is just above the minimum value of R² in IMPVVP. This indication shows that certain parts of dynamic behavior may not fully captured by the multiple regression model. The remaining data from April 2017 – May 2017 was inserted in Equation (3) and gives a predicted output that is shown in Figure 8. In Figure 8, the predicted output (dashed line) was deemed to be similar with the measured output.

The independent variables in data set B that was measured during December 2018 – January 2019
was inserted in Equation (3) for model testing purposes. The predicted energy consumption is shown in Figure 9. In Figure 9 there was an obvious deviation majority parts of the predicted energy consumption compared to the measured energy consumption during December 2018 – January 2019. From the outcome of the results, the model can’t represent the measured energy consumption during December 2018 – January 2019. Even though it is a non-lecture week. This prediction result was strengthened with the statistical error measurement shown in Table 4. In Table 4 the data set A and MSE and RMSE is 215.45kWh and 14.67kWh respectively. Meanwhile, data set B MSE and RMSE value is 432.76kWh and 20.80kWh respectively. The MSE and RMSE value difference between two data set is almost half. In addition, the MAPE value for data set A and data set B is 0.39 and 0.54 hence implies that the model developed using multiple linear model equation in equation (3) is not good enough to predict the energy consumption during December 2018 – January 2019 non-lecture week period due to its average deviation (MAPE) is 0.54. Furthermore, the deviation may result from the difference behavior of independent variables between two period in March 2017 – May 2017 and December 2018 – January 2019.

| Table 3. Regression Statistics Lecture Week Multiple Regression Model |
|---------------------------------------------------------------|
| Multiple R | 0.87 |
| R Square (R²) | 0.76 |
| Standard Error | 14.56 |

Figure 8: Energy Consumption Prediction Using Independent Variables April 2017 – May 2017 (Data set A)

Figure 9: Energy Consumption Prediction Using Independent Variables December 2018 – January 2019

| Table 4. Statistical Error Measurement Between Predicted Energy Consumption and Measured Energy Consumption Non-Lecture Week |
|---------------------------------------------------------------|
| Data Set | Prediction Data | MSE | RMSE | MAPE |
| A | April 2017 – May 2017 (Data Set A) | 215.45 | 14.67 | 0.39 |
| B | December 2018 – January 2019 (Data Set B) | 432.76 | 20.80 | 0.54 |

4. Conclusion

This research has developed baseline energy models using multiple regression model in an educational building during lecture week and non-lecture week period. Two data sets have been measured and collected to fulfil the stated objectives. The first data set A was used to for model developing and energy consumption prediction purposes. The second data set B was used for model
testing purposes. The modelling and prediction performed well in lecture week data set A and data set B with the value of MSE, RMSE and MAPE is within the same range. But during non-lecture week, the modelling and prediction does not perform well with data set B due to different behaviour of independent variables and energy consumption during March 2017 – May 2017 in data set A. From this research, the importance of differentiating lecture week and non-lecture week for baseline energy modelling and prediction purposes is important due to the fact that the energy consumption and independent variables behave differently between this two period of operation. MLR model has successfully model the energy consumption with respect to its independent variables but certain weakness was encountered due to the fact that MLR model can’t relate certain dynamic behaviour of energy consumption. Thus, it may require other modelling technique for future work improvement.

Acknowledgments
Authors in general would like to thank Yayasan Munarah Negeri Sembilan darul Khu sus for providing special research grant UiTM File No (100- IRMI/GOV 16/6/2 (017/2017) to conduct this research work.

References

[1] Efficiency, Valuation, and Organization, International Performance Measurement and Verification Protocol: Core Concepts, June 2014.

[2] N. Razali and N. Dahlan, "Whole Facility Measurement for Quantifying Energy Saving in an Office Building Malaysia," Applied Mechanics and Materials, vol. 785, 2015.

[3] F. M. A. Rahman, N. Y. Dahlan, and N. S. Razali, "Modelling Adjusted Baseline Energy In an Office Building using Artificial Neural Network," Applied Mechanics and Materials, 2015.

[4] S. M. Aris, N. Y. Dahlan, M. N. M. Nawi, T. A. Nizam, and M. Z. Tahir, "Quantifying Energy Saving For Retrofit Centralized HVAC Systems at Selangor State Secretary Complex," vol. Jurnal Teknologi, pp. 93-100, 2015.

[5] F. Barnard and L. Grobler, "Baseline Service Level Adjustment Methodologies for Energy Efficiency Projects on Compressed Air Systems in The Mining Industry," in The 9th Industrial and Commercial Use of Energy Conference, 2012, pp. 1-8.

[6] W. M. III, R. J. Beaver, and B. M. Beaver, Introduction to Probability and Statistics: Cengage Learning.

[7] F. Lei and P. Hu, "A Baseline Model for Office Building Energy Consumption in Hot Summer and Cold Winter Region," in International Conference on Management and Service Science MASS 09, Wuhan, 2009, pp. 1-4.

[8] M. R. Braun, H. Altan, and S. B. M. Beck, "Using regression analysis to predict the future energy consumption of a supermarket in the UK," Applied Energy, vol. 130, pp. 305-313, 2014/10/01/ 2014.

[9] N. Fumo and M. A. Rafe Biswas, "Regression analysis for prediction of residential energy consumption," Renewable and Sustainable Energy Reviews, vol. 47, pp. 332-343, 2015/07/01/ 2015.

[10] Y. Wang, F. Wang, and H. Wang, "Influencing factors regression analysis of heating energy
consumption of rural buildings in China," Procedia Engineering, vol. 205, pp. 3585-3592, 2017/01/01/ 2017.

[11] R. Kicsiny, "Black-box model for solar storage tanks based on multiple linear regression," Renewable Energy, vol. 125, pp. 857-865, 2018/09/01/ 2018.

[12] Y. Yang, L. Sun, and C. Guo, "Aero-Material Consumption Prediction Based on Linear Regression Model," Procedia Computer Science, vol. 131, pp. 825-831, 2018/01/01/ 2018.

[13] H. R. M. L. Pombeiro and C. A. S. Silva, "Linear, fuzzy and neural networks models for definition of baseline consumption: Early findings from two test beds in a University campus in Portugal," in 2014 Science and Information Conference, 2014, pp. 481-487.

[14] M. Jafary, M. Wright, L. Shephard, J. Gomez, and R. U. Nair, "Understanding Campus Energy Consumption -- People, Buildings and Technology," in 2016 IEEE Green Technologies Conference (GreenTech), 2016, pp. 68-72.

[15] S. Tangwe, N. Mzolo, M. Simon, and E. Meyer, "Modeling the demand of a Calorifier to establish the baseline before retrofitting it with a commercial air source heat pump," in 2014 International Conference on the Eleventh industrial and Commercial Use of Energy, 2014, pp. 1-8.

[16] K. P. Amber, M. W. Aslam, A. Mahmood, A. Kousar, M. Y. Younis, B. Akbar, et al., "Energy Consumption Forecasting for University Sector Buildings," Energies, vol. 10, 2017.

[17] H. R. Khosravani, M. D. M. Castilla, M. Berenguel, A. E. Ruano, and P. M. Ferreira, "A Comparison of Energy Consumption Prediction Models Basen on Neural Networks of a Bioclimatic Building," Energies MDPI, vol. 9, 2016.

[18] J. Massana, C. Pous, L. Burgas, J. Melendez, and J. Colomer, "Short-term load forecasting in a non-residential building contrasting models and attributes," Energy and Buildings, vol. 92, pp. 322-330, 2015/04/01/ 2015.

[19] R. Rueda, P. M. Cuéllar, M. Molina-Solana, Y. Guo, and C. M. Pegalajar, "Generalised Regression Hypothesis Induction for Energy Consumption Forecasting," Energies, vol. 12, 2019.

[20] H. Pombeiro, R. Santos, P. Carreira, C. Silva, and J. M. C. Sousa, "Comparative assessment of low-complexity models to predict electricity consumption in an institutional building: Linear regression vs. fuzzy modeling vs. neural networks," Energy and Buildings, vol. 146, pp. 141-151, 7/1/ 2017.