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Forecasting Daily Electricity Consumption of Academic Buildings of UK Higher Education Sector

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***Abstract*—A reliable forecast of electricity consumption helps Energy Managers in numerous ways such as in preparing future energy budgets and setting up energy consumption targets. In this paper, we developed a multiple regression (MR) model using SPSS software to forecast daily electricity consumption of an academic building located at the Southwark campus of London South Bank University in London. The model integrate five important independent variables, i.e. ambient temperature, solar radiation, relative humidity, wind speed and weekday index. Daily values of these variables were collected from year 2007 to year 2011. The data sets from year 2007 to 2010 are used for training the model while 2011 data set is used for testing the model. The predicted test results for the model are analyzed and compared with actual electricity consumption. At the end, some conclusions are drawn about the performance of the model regarding its forecasting capabilities. The results demonstrate that significant variables are the ambient temperature and weekday index. The model demonstrates good result with an adjusted R^2 value of 0.62, RMSE of 46Wh/m²and an overall error of +4.43%. This indicates the strength of this model to forecast daily electricity consumption of the academic building, provided of course that the operation and scheduling of the building are unaltered.**

Index terms -Electricity forecasting, Academic buildings, Multiple Regression

I. INTRODUCTION

Electricity is a key energy source in each country and plays an important role for economic development [1]. In the UK, electricity is generated from conventional power plants and contributes to 30% of the UK's total carbon emissions [2]. Electricity consumption in the UK in 2011 decreased by 6.9% compared to 2007 consumption level [3]. Energy consumption in buildings makes up over 40% of all UK energy use [4]. HE sector in the UK spends £200m every year on its energy bills [5]. Figure 1 shows the sector's annual energy consumption for 2009, 2010 and 2011. In 2011, electricity was directly responsible for 63.4% of the HE sector's total carbon emissions [6].

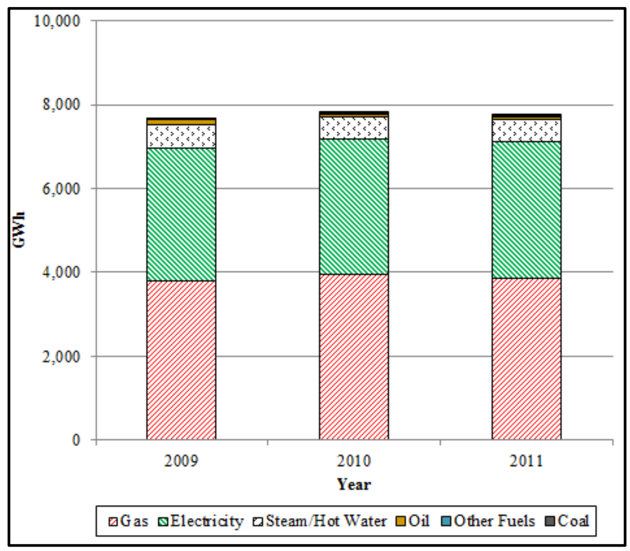

Figure 1. Energy consumption in the UK HE sector

HE campuses have a variety of functions to perform. The morphology of the built environment of campuses reflects these functions, with different buildings having unique energy requirements and consequently consumption profiles. For example, laboratory spaces may require 24 hours electricity and services that require constant electricity, heating or cooling. In contrast, large venues such as lecture halls and auditoriums may only be occupied for a small portion of the day, and require minimal energy supply.

For the evaluation of potential energy usage, it is necessary to understand the types of building and categories of space in a university campus. Figure 2 presents a breakdown of different space types in a typical HE campus. In a typical HE campus in the UK, the academic facilities occupy 43% of the total space of the campus [7].

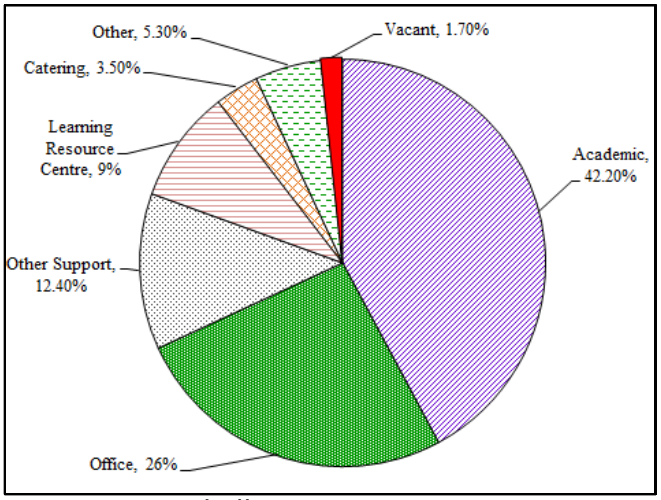

Figure 2 Breakdown of different space types in a typical HE campus

Electricity consumption in the academic buildings mainly occurs in HVAC components, IT equipment, lifts and lighting. In some academic buildings there are kitchens where electricity is used in electric kettles, microwave ovens and coffee machines. A small proportion of daily electricity consumption occurs in the hoovers while the cleaning is carried out and also in mobiles charging. Major components of HVAC system include air conditioners, air handling units, fans, pumps and boilers. Air conditioners are the major energy users (57%) in academic buildings, followed by lighting (19%), lifts and pumps (18%) and other equipment (6%) [8].

Financial year in the UK universities runs from 1 August every year to 31 July of next year. Energy Managers are responsible for preparing a budget forecast for their university buildings. To calculate the annual budget for electricity purchase, a reliable forecast of electricity consumption is vital. Other benefits of a reliable forecast of electricity consumption include:

i. It helps in identifying the variables having significant effect on electricity consumption;
ii. It helps in identifying electricity saving potential;
iii. It helps in estimating electricity consumption of similar types of buildings;
iv. In industries, it helps in policy development and improvement of production and distribution facilities; and
v. For the utility companies, it helps in understanding the peak and base load demands.
vi. It also helps in preparing operation and maintenance (O & M) budget forecasts
vii. Helps in finding operational and maintenance problems

II. Objectives & Overview Of The Proposed Modeling Technique

A. Objectives

In this paper, we propose to develop a Multiple Regression Linear Model to forecast the daily electricity consumption of the academic buildings of the UK Higher Education Sector. Following objectives have been set up;

i. To collect daily electricity consumption data (for minimum five years) of an academic building;
ii. To collect five years data of daily mean values of ambient temperature, solar radiation, wind speed and relative humidity;
iii. To visit the building and to collect information for building's cooling and heating systems;
iv. To develop a MR model using the SPSS software;
v. To test the model against real data.

B. Overview of the Multiple Regression Method

A simple and common method of forecasting buildings energy consumption is using the Multiple Regression Models (MRM). Due to their characteristics such as simple in form, easy to use and fair reliability of results, the MRMs have become a broadly adopted technique for forecasting of buildings energy consumption. However, the accuracy of a regression model depends widely on the length of data. Using a small sample of data for developing the regression models can, unfortunately, lead to significant errors in the prediction of the energy consumption [9].

A multiple linear regression model (MLRM) with more than one explanatory variable may be written as shown in Eq.1:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots \beta n X_n + \varepsilon \qquad (1)$$

Where Y is the output or dependent variable, βi are the regression coefficients (i = 0, 1, 2….n), Xi are the independent variables (i =1, 2, 3 …n) and ε is the random error term.

Once regression coefficients (βi) are obtained, a prediction equation can then be used to predict the value of dependent variable as a linear function of one or more independent variables.

III. Related Work

Signor et al. [10] developed a simple regression model to forecast the electricity consumption of academic buildings, for 14 (fourteen) Brazilian cities. They investigated effect of independent variables which include building size, building shape, the façade composition (window to wall ratio), thermal transmittance and absorptance of roof, the shading coefficient of glazing, the solar protection, façade and roof colors, occupation and electric power density (lights and equipment). They found strong R^2 values (higher than 0.99) for most of the fourteen cities studied.

Aranda et al. [11] used multiple regression models to estimate the annual energy consumption in the Spanish banking sector. A dataset of energy consumption from 55 banks was regressed on eleven independent variables. The results indicated that only three out of eleven independent variables which include summer climatic severity (x_1), office surface area (x_2) and number of automated teller machines (x_3) have significant effect on the annual energy consumption. Eq.2 represents their MRM.

$$E = 14,702 - 4175\, x_1 + 62.5 x_2 + 7,837\, x_3 \qquad (2)$$

Korolija et al. [12] developed two regression models (bivariate and multivariate) for predicting annual energy consumption of five different types of HVAC system (variable air volume system, constant air volume system, fan-coil system, chilled ceiling system with embedded pipes and chilled ceiling system with exposed aluminum panels) as function of building's heating and cooling demands and compared the results of both models. The two models are presented by in Eq.3 and Eq.4;

Bivariate model

$$y(x) = a + b.x^c \qquad (3)$$

Multivariate variate model

$$y(x_1, x_2) = a + bx_1 + cx_2 + d.bx_1^2 + e.x_1.x_2 + f.x_2^2 \qquad (4)$$

Where x denotes cooling or heating demand in bivariate model. In multivariate model, x_1 represents cooling and x_2 represents heating demand.

They found that the multivariate model offers greater accuracy predicting the heating, cooling and auxiliary energy requirements with: above 99.5% within ±20% relative difference range for almost all five HVAC systems.

Noren and Pyrko [13] developed a multiple linear regression model for predicting electricity consumption for 26 Swedish school buildings. They regressed one year hourly measured electricity consumption data (the dependent variable) on four independent variables. Eq.5 represents their MRM.

$$HECI = A_0 + K1.A_1 + K_2.A_2 + D_3.A_3 + T.A_4 \qquad (5)$$

Where:
HECI = Hourly electricity consumption intensity
K_1 = number of meals cooked daily in kitchen
K_2 = Relationship between sports centre area and floor area
D_3 = Dummy variable, 1 for secondary schools, otherwise 0
T = Daily mean outdoor temperature
A_0- A_4 = Regression coefficients

They found that during unoccupied hours (23 – 0600hrs), the three variables K1, K2 and D3 are not significant and R^2 values during these hours are as low as 0.018.

Using the WiFi connections as a proxy for human occupancy, Martani et al. [14] investigated the linear relationship between building occupancy, ambient temperature and energy consumption (electricity, steam and chilled water) for two buildings within the Massachusetts Institute of Technology's campus. The results of their study showed strong relationships ($R^2 = 0.63$ for building one and $R^2 = 0.69$ for building two) between the electricity consumption and occupancy levels. On the other hand, they observed weak relationships between building occupancy and energy consumption through HVAC systems.

Similarly, there are many more studies where multiple regression models (MRM) have been used as a technique for forecasting energy consumption in buildings. This literature review provides sufficient evidence that MRMs are easy and fairly reliable models for forecasting energy consumption in buildings. In this study, a Multiple Regression Model (MRM) is developed for forecasting the daily electricity consumption of an academic building called "Keyworth Centre". Section 3 presents a brief summary of the building.

IV. Description of the Keyworth Centre Building

The Keyworth Centre was built in 2003 and is located at the Southwark campus of London South Bank University in London, UK. Comprises of six floors, the Keyworth Centre has a total Gross Internal Area (GIA) of 8,588m². Building mainly consists of lecture rooms and offices. Figure 3 shows a view of the Keyworth Centre building.

Figure 3 Keyworth Centre

Building's daily operating hours are from 7.30amto 8pm. It remains opened until 10pm when it is closed by the security staff. It is a naturally ventilated building. For space heating, there are six gas fired boilers (each of 160kW) installed in the plant room which is located in the basement. These boilers supply space heating and domestic hot water to all floors through radiators. There are two lifts located near the main reception. Electricity to the building is supplied via a single low voltage (LV) supply. Lighting on all floors is of Compact Fluorescent Lamps (CFL) type. In terms of its annual electricity consumption, the Keyworth Centre consumes nearly 7% of the total annual electricity consumption of London South Bank University.

V. Model Development

For developing a Multiple Regression Model (MRM) for forecasting daily electricity consumption of the Keyworth Centre, actual daily electricity consumption (kWh) data was available from the office of University's Energy Manager. The dataset covers a period of 1 January 2007 to 31 December 2010. The daily electricity consumption was converted from kWh to Wh/m² by using the Eq. 6.

$$E_d = (E_D \times 1000) \div A_g \qquad (6)$$

Where:

E_D *is daily electricity consumption in kWh*
E_d *is daily electricity consumption in Wh/m²*
A_g *is the Gross Internal Area (GIA) of the building in m²*

Daily data covering the same period (January 2007 to December 2010) was available for the following weather and non-weather variables:

a) *Ambient temperature, °K*
b) *Relative humidity, %*
c) *Solar radiation, Watts/m²*
d) *Wind speed, m/s*
e) *Weekday index (1 or 0)*

Daily data for the weather variables, i.e. ambient temperature, RH, SR and WS for the London region was available from the public website of the Environmental Research Group, Kings College [15]. The data was downloaded.

An important parameter effecting the daily electricity consumption in academic buildings is the building occupancy. Unfortunately data was not available for the building's daily occupancy. Therefore a dummy variable "Weekday Index (WDI)" is introduced for the representation of building's occupancy. The WDI has a value of unity for working days and a value of zero for non-working days such as weekend and bank holidays are treated as non-working days. A record of bank holidays for the period January 2007 to December 2010 was available from the website and this was included in the analysis [16].

For developing a Multiple Linear Regression Analysis, the statistical analysis tool "SPSS" is used as this was available. Eq.7 presents the initial model.

$$E_d = \beta_0 + \beta_1.T + \beta_2.w + \beta_3.W_{di} + \beta_4.R + \beta_5.S \qquad (7)$$

Where:

E_d is daily electricity consumption (Wh/m²);
T is mean daily ambient temperature (°K);
w is mean daily wind speed (m/s);
W_{di} is weekday index ;
R is mean daily relative humidity (%);
S is mean daily solar radiation (W/m²); and,
β_0, β_1, β_2, β_3, β_4 *and* β_5 are regression coefficients.

VI. Results And Performance Evaluation

Table 1 presents the results for initial regression analysis. An adjusted R² value = 0.62 indicates that 62% of daily electricity consumption of the Keyworth Centre can be explained by the independent variables.

Table 1 Results of initial regression model 1

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
(Constant)	β_0	1342.8	96.45		13.92	0.000		
T	β_1	-3.734	0.337	-0.247	-11.09	0.000	0.522	1.916
w	β_2	**-1.616**	**1.500**	**-0.018**	**-1.078**	**0.281**	0.982	1.018
Wdi	β_3	139.73	3.098	0.727	45.10	0.000	0.999	1.001
R	β_4	-0.463	0.205	-0.046	-2.256	0.024	0.621	1.611
S	β_5	-0.156	0.032	-0.123	-4.798	0.000	0.397	**2.521**
R^2	0.622							
Adjusted R^2	0.621							

The following checks must be carried out in order to check any possible problematic issues.

i. ***Checking the significance of independent variables***

A variable is considered a significant variable if its t-stat value is equal or greater than 1.6. From Table 1, it is apparent that weekday index (Wdi) is the most significant variable. Only one variable, i.e. Wind speed (w) has low t-stat values thus indicating that it is not a significant variable.

ii. ***Checking the multiple colliniearity among independent variables***

Collinearity among the independent variables can adversely affect the results of a MRM [17]. Last two columns on the RHS of the Table 1 show the results for collinearity statistics. Two parameters, i.e. tolerance and the variance inflation factor (VIF) explain the collinearity. A higher value for VIF indicates a higher multiple collinearity between the independent variables. For some authors, the value 4 corresponds to the highest limited value from which collinearity is a problem. In our model, VIF is less than 4 for each variable, indicating a lack of collinearity between the independent variables [18].

Another way of checking the multiple collinearity among the independent variables is the analysis of the Pearson correlations[1] which are presented in Table 2. It is apparent that solar radiation and relative humidity have correlation coefficients of 0.69 and -0.41 with the ambient temperature, thus showing presence of multi collinearity between these variables.

[1] The Pearson's correlation coefficient, r, measures the linear association between two variables (the extent to which a variable changes with another). The r value is always between −1 and 1.

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Table 2 Pearson Correlations coefficients among different variables

Correlations							
	Variables	E_d	T	w	Wdi	R	S
Pearson Correlation	E_d	1.000	-0.296	-0.017	0.72	0.133	-0.256
	T	-0.296	1.000	-0.009	0.022	**-0.417**	**0.691**
	w	-0.017	-0.009	1.000	-0.011	-0.094	-0.019
	Wdi	0.72	0.022	-0.011	1.000	0.000	0.013
	R	0.133	**-0.417**	-0.094	0.000	1.000	**-0.607**
	S	-0.256	**0.691**	-0.019	0.013	**-0.607**	1.000

It was decided that before making any further checks, three independent variables, i.e. wind speed, relative humidity and solar radiation should be eliminated from the model equation due to the low significance (of wind speed) and due to the multiple collinearity between relative humidity, solar radiation and ambient temperature. The regression analysis was under taken for the second time. Eq. 8 presents the updated regression model for forecasting the daily electricity consumption.

$$E_d = \beta_0 + \beta_1 . T + + \beta_3 . W_{di} \quad (8)$$

Table 3 shows results for the updated regression model 2. It can be seen that both variables are significant (having t-stat values > 1.6) and there exist no collinearity among them. Exclusion of three independent variables, i.e. Wind speed, relative humidity and solar radiation has resulted in a small decrease in adjusted R² value as its value drops from 0.622 to 0.616.

iii. *Checking the distribution of regression residuals*

Another important check for the regression models is to check the distribution of the regression residuals. This can be explained by two parameters, i.e. Skewness and Kurtosis.
Skewness is a measure of symmetry, or more precisely, the lack of symmetry of a distribution. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point. Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. Developing a histogram of the regression residuals is an effective graphical technique for showing both the skewness and kurtosis [19].

Table 3 Results of updated regression model

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
(Constant)	β_0	1572.02	70.01		22.43	0.000		
T	β_1	-4.723	0.245	-0.313	-19.28	0.000	0.999	1.001
Wdi	β_3	139.750	3.12	0.727	44.80	0.000	0.999	1.001
R²	**0.616**							
Adjusted R²	**0.616**							

Figure 4 presents a histogram of frequency distribution of regression standardised residuals of daily electricity consumption. The distribution is positively skewed (+0.36, standard error 0.064), hence demonstrating a longer tail to the upper end of the rating scale. The distribution demonstrates negative kurtosis (-0.45, standard error 0.128) demonstrating a lesser degree of clustering around the mean than would be anticipated for a normal distribution. As a rule of thumb, if the value of skewness is in a range of - 1 to + 1, the distribution can be considered as a normal distribution [20]. In our case, the skewness is within this range, therefore, the distribution is considered as a normal distribution.

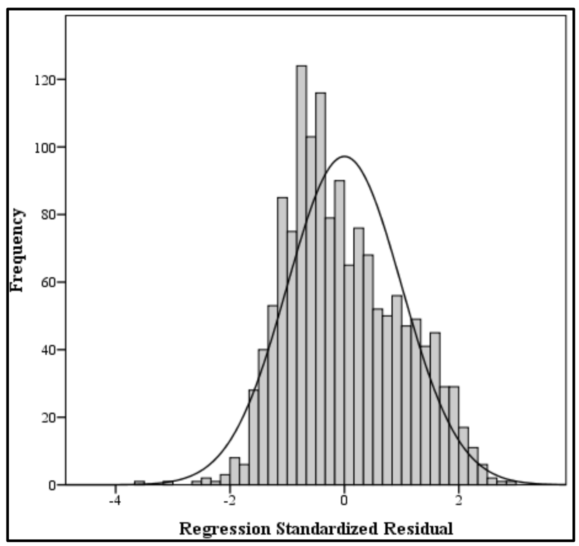

Figure 4 Histogram of regression residuals

Another way of checking the distribution of regression standardised residuals is by plotting a scatterplot of regression standardised residuals and regression standardised predicted values. This can be seen in Figure 5. We can see that the residuals are almost equally distributed.

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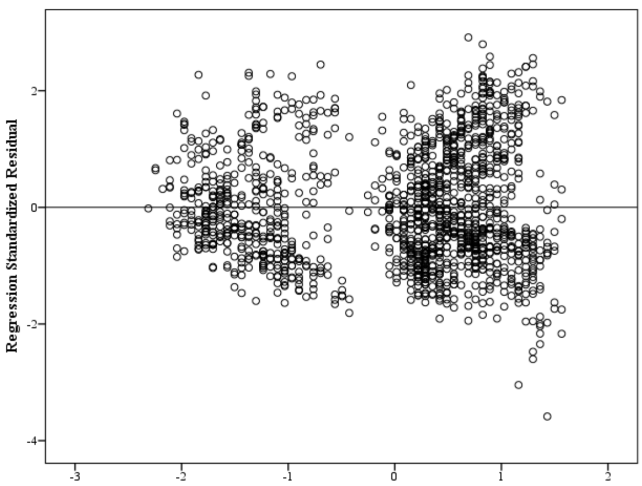

Figure 5 Scatterplot of Regression Residuals

Therefore, the recommended regression model equation for forecasting the daily electricity consumption of the Keyworth Centre building can be written as:

$$\boldsymbol{E_d = 1{,}572.016 - 4.723.T + 139.75.W_{di}} \quad (9)$$

Where:
E_d *is daily electricity consumption in Wh/m²*

Using the Eq.6 and Eq.9, we can forecast daily electricity consumption in kWh.

VII. Testing and Validation of Model

The developed modelwas tested against the actual daily electricity consumption datasets (Wh/m²) for the period 1 January 2011 to 31 December 2011 for the same building, i.e. the Keyworth Centre. It is important to mention here that this dataset was not used in the development of the models and therefore it is purely used for the testing purpose. Using the values for all independent variables for same period, daily electricity consumption was forecasted by using both models.

The evaluation criteria for the performance of both models are the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE), and the Mean Relative Error (MRE), which is employed to compare the results of forecasts. These errors are given by Eq. (10).

$$MAE(N) = \frac{1}{N}\sum_{i=1}^{N}|Y_i - Y_i^*|$$

$$RMSE(N) = \sqrt{\frac{\sum_{i=1}^{N}(Y_i - Y_i^*)^2}{N}} \quad (10)$$

$$MRE(N) = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y_i - Y_i^*}{Y_i}\right|$$

Where *Yi* is the actual value and *Yi** is the forecasted value. *N* represents the sample size.

Table 4 shows the values for these errors for the developed model. It is evident that the RMSE is 46which shows that in general, the model predicts daily electricity consumption with high accuracy.

Table 4 Error comparison of MR model

Error	MR Model
MAE (Wh/m²)	51
RMSE	46
MRE	0.019

This is further demonstrated with the help of Figures 6, 7 and 8 which show a comparison between the actual and forecasted daily electricity consumption (Wh/m²) in the form of;

a) A box plot;
b) Bar graphs of daily electricity consumption (Wh/m²); and,
c) Bar graphs of monthly electricity consumption (kWh).

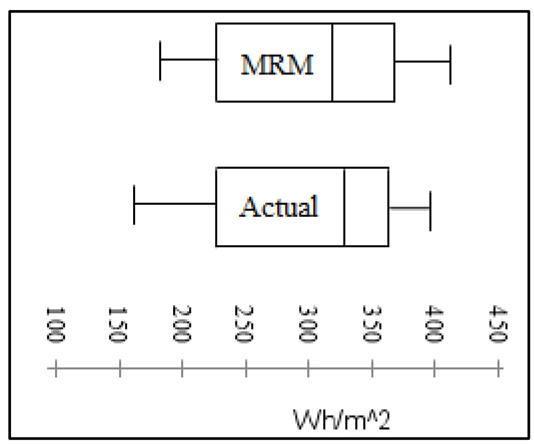

Figure6 Comparison of actual and forecasted daily electricity consumption values (Wh/m²)

Figure6 shows a box plot for actual and forecasted daily electricity consumption (Wh/m²) for the period January 2011 to December 2011. In general, the range of the actual output is bigger than the predicted output of the model. The lower andupper quartile values of the actual and model are quite close to each other while the minimum forecasted value is 22% higher than the actual minimum value.

Figure7 shows the comparison between actual and forecasted daily electricity consumption for the test data for full year in the form of bar graph. It can be seen that model's prediction is quite close to the real output.

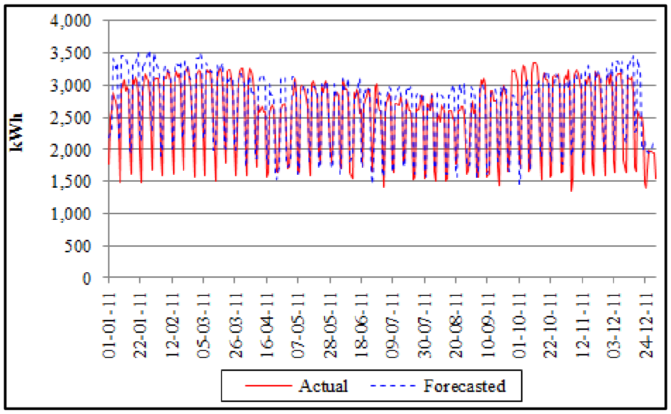

Figure 7 comparison of actual forecasted monthly electricity consumption

Figure 8 shows the actual and predicted monthly energy consumption in the form of a bar chart.

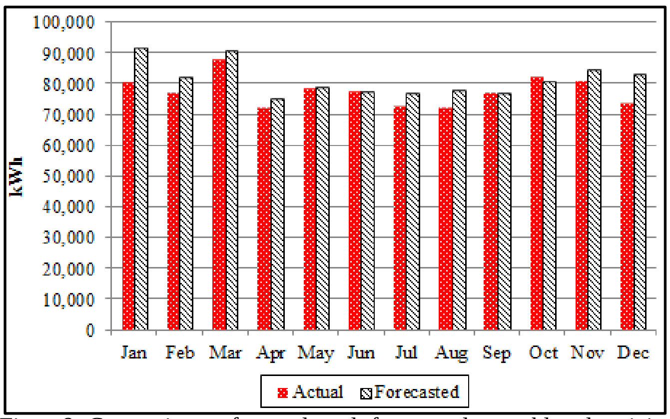

Figure8 Comparison of actual and forecasted monthly electricity consumption

VIII. Limitations of the Model

Although the model predicts the building daily electricity consumption very well, some considerations must be taken into account. Some parameters were set constant to enable the analysis, such as building opening and closing schedules, building activities and building shape. Changing these variables would require additional studies to extend the model's equations.

IX. Conclusions

In this research work, we have developed a Multiple Regression Linear Model to forecast the daily electricity consumption of an academic building of the UK Higher Education Sector. Initially five independent variables that included ambient temperature, wind speed, relative humidity, solar radiation and the weekday index were selected and analysed. It was found that wind speed is not a significant variable whereas high collinearity was observed among solar radiation, relative humidity and ambient temperature. Therefore, wind speed, relative humidity and solar radiation were removed from further analysis and the model equation was updated.

Final multiple regression model was tested against actual daily electricity consumption data for the period January 2011 to December 2011. An overall error of + 4.43% was observed.

It is believed that the analysis, forecasts and comments presented in this paper would be helpful to energy Managers, Planners and Policy makers to prepare future energy budgets with a higher degree of accuracy. Therefore, this model must first provide a good fit to the current data, and secondly, be a reliable predictor of future daily electricity consumption, provided of course that the assumptions made in this study are unaltered.

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