Energy Demand Analysis for Office Building Using Simulation Model and Statistical Method

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Abstract

This research is focused on the development of a reliable energy demand model for a case study using a comprehensive dual approach including: (1) engineering load calculation and simulation model via software and (2) statistical analysis. The simulated model is capable to cover the analysis of the cooling and thermal loads for a studied building. Concerning the building operation perspective, the statistical models were provided using the real measured data and multivariable regression analysis. For evaluating the performance of the developed statistical models, the authors have calibrated the models with the real measured data and then the impact of relevant variables has been evaluated through statistical tests and sensitivity analysis.

According to the results of this study, the rated power for the cooling system and the capacity of the thermal system are 75.8 (kW) and 147.7 (kW), respectively. Based on the results of the statistical models, the measured and modelled data have been correlated with a strong coefficient of determination.

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The accuracy of models has been examined by calculating the statistical error indices with a suitable finding. Thus, the proposed models can be considered as an accurate findings for the energy performance analysis and demand forecasting objectives.

Keywords: Building energy demand, simulation model, engineering model, multivariate regression, statistical analysis.

List of Notations and Abbreviations

A	Area (ft^2 or m^2)	Q_{C1}	Cooling load to overcome radiant load from exterior windows (BTU/hr)
AF	Storing factor	Q_{C2}	Cooling load to overcome conductive load from exterior windows (BTU/hr)
BF	Shortcut factor	Q_{C3}	Cooling load to overcome radiative and conductive heat from external walls (BTU/hr)
CDD	Cooling degree day	Q_{C4}	Cooling load to overcome conductive heat from interior walls, windows and doors (BTU/hr)
CF	Correction factor	Q_{C5}	Sensible cooling load of rooms air conditioning (BTU/hr)
COP	Coefficient of performance	Q_{C6}	Cooling load to overcome sensible heat from inhabitants, lighting system, electric motors and home appliances (BTU/hr)
CV (RMSE)	Coefficient of variation of Root Mean Square Error	Q_{C7}	Effective latent cooling load of rooms (BTU/hr)

E	East	Q_{C8}	Sensible cooling load for the rest of the outdoor air (BTU/hr)
E	Equivalent	Q_{C9}	Latent cooling load for the rest of the outdoor air (BTU/hr)
F	Convective heat transfer coefficient (W/m^2.K)	Ql_{app}	Latent cooling load to overcome heat from electric motors and home appliances (BTU/hr)
HDD	Heating degree day	Q_{light}	Cooling load to overcome heat released from the lighting system (BTU/hr)
h_{fg}	Latent heat for water vapor (BTU/lb)	q_{lp}	Latent cooling load per person (BTU/hr)
In	Inner (room)	q_{sp}	Sensible cooling load per person (BTU/hr)
I	Integer	Q_T	Total thermal load (BTU/hr or kW)
K	Conductive heat transfer coefficient (W/m.K)	Q_{T1}	Thermal load to overcome heat loss from walls, doors, windows, roof and ceiling (BTU/hr)
kW	Kilowatt	Q_{T2}	Thermal load to overcome heat loss related to air penetration (BTU/hr)
kWh	Kilowatt-hour	Q_{T3}	Thermal load of domestic hot water (BTU/hr)
L	Length of a seam (ft)	R	Room
L	Total number of samples	R^2	Coefficient of determination
M	Measured data point	RMSE	Root Mean Square Error
M&V	Measurement and Verification	S	Simulated data point

MAE	Mean Absolute Error	T	Temperature (°F or °C)
MJ	Mega Joule	U	Overall heat transfer coefficient (BTU/hr.ft^2.F or W/m^2.K)
MSE	Mean Square Error	V	Required air for air conditioning of rooms (CFM)
N	Number of inhabitants or maximum integer	V_{T3}	Volume of domestic hot water (GHP)
NMBE	Normalized Mean Bias Error	V	Specific volume of outdoor air (ft^3/lb)
NME	Normalized Mean Error	W	West
O	Outer (environment)	X	Thickness (cm)
Q	Amount of permeable air per unit length of a seam (CFH)	ΔT	Temperature difference (°F or °C)
$\ddot{Q}$	Acquired heat from the sun radiation (BTU/hr.ft^2)	ΔW	Difference between indoor and outdoor air humidity ratio (Grain/lb)
Q_{app}	Cooling load to overcome heat from electric motors and home appliances (BTU/hr)	v	The amount of air needed per floor area (CFM/ft^2)
Q_C	Total cooling load (BTU/hr or kW)		

1 Introduction

Over one-third of the global energy consumption is the share of the building sector. Thus, reducing the energy demand of buildings is essential with the aim of tackling climate issues [1, 2]. Climate change has got a major impact by increasing the energy demand for both heating and cooling systems in buildings [3]. Office buildings have been classified among the energy-intensive non-residential buildings. The annual energy consumption of an office varies in a wide range depending on the weather conditions, location, construction, type of energy systems, lighting installations, type of equipment and operating schedules [4]. The energy consumption analysis of buildings through the mathematical models is a complicated subject considering the interactions among the building physics with the energy systems and weather conditions. The dynamic behaviour of the weather condition and its impact on the building energy demand requires the use of computer-assisted analysis in the operation phase [5]. Some important weather condition parameters are including the local air temperature, relative humidity, wind velocity, and radiative fluxes. Several studies have shown that climate change has affected the energy demand in buildings [6, 7]. Some researchers have outlined that the building energy demand is affected by the ambient temperature changes [8–11].

Several methodologies for estimation of the energy consumption have been developed based on the statistics and simulations [3]. Papa et al. [13] proposed a normalized energy use index based on the temperature function. In their work, they discussed the influence of the weather variables and they concluded that the ambient temperature is the most important factor in the energy consumption in buildings [5]. Despite the continuous progress in the building performance simulation, the discrepancies between the simulation results and the measured data in actual buildings remained an issue. Thus, improving the match between the simulated and measured performance becomes of the high importance for the broader practical use. The statistical technique is the most recognized way to check if a model is calibrated between the simulation results and measured data [1, 12, 13]. The prediction model in the field of building energy demand has been employed through linear regression or statistical models. These methods are being used to correlate the building energy consumption with the influencing variables in a simple way. In certain simplified models, linear regression has been used to correlate energy consumption with the climatic variables [14–16]. The results of the statistical analysis are usually a reliable reference to a wide application of technology. In the study of the energy consumption in buildings, an example of some statistical methods which have been used for predicting the energy demand in the building sector are including the analysis of variance, correlation analysis and regression analysis [17–21]. Wen et al. [22] forecasted the load demand of residential buildings using a deep learning model. Fan et al. [23] investigated the transfer learning-based method for short-term building energy predictions using statistical analysis. Taylor et al. [24] provided a multi-scale calibration approach for the process-oriented building energy demand models. Ferrari et al. [25] reviewed the methods for estimating the building energy demand at the district level. Finck and Zeiler [26] developed a predictive economic model for residential building demand. An unadjusted measured energy use data analysis, a weather normalized method, the change point regression analysis and the calibrated building energy simulation have been applied as four analysis methods to verify the energy performance and the efficiency of a building [27]. According to the results of another research, the simulation model requires a comprehensive data set such as the utility billing data, general building information, building use and occupancy schedules, power ratings of equipment and appliances, and their operational schedules. The EnergyPlus has been used for the simulation of building energy performance. The developed models have been verified with the energy consumption data from the utility [28]. Ghadamian et al. [29] provided an analytical solution for energy modelling of double skin façades building. Ghadimi et al. [30] provided a numerical analysis and parametric study of the thermal behaviour in multiple-skin façades. According to this study, a designer should be aware that a multiple-skin façade does not necessarily improve the energy efficiency of their designs. Ghadimi et al. [31] developed an analytical model for free and forced convection in airflow windows using numerical simulation of heat transfer. Shakouri et al. [32] have developed a quasi-dynamic model for analysing the energy performance of the building integrated photovoltaic thermal (BIPV) façade for the Middle Eastern climate case.

By comparing the previous studies, the research team has identified that there is a research gap to provide a comprehensive method and case study to cover the aim of measurement and verification of the building energy performance using an integrated approach including measured data, simulation and engineering models as well as the statistical model. Besides, the integrated approach on the measurement and verification (M&V) methods to determine the baseline for the building energy performance has been applied in this research. This research goes one step further through the methodology. The proposed method for building demand analysis in this research is a dual-based approach that includes: (1) engineering load calculation and simulation model via software and (2) statistical analysis. This research aims to investigate the influence of the heating and cooling degree days on the energy demand of the office building with the Middle Eastern climate condition. The goal is to explore the multivariate linear regression analysis which can be adopted for the operational phase of the building. Figure 1 provides the research steps for energy demand analysis for this study which includes: (1) the data processing, (2) engineering-based load calculation and simulation in DesignBuilder, (3) regression-based model developments through statistical analysis, and (4) model validation and sensitivity analysis.

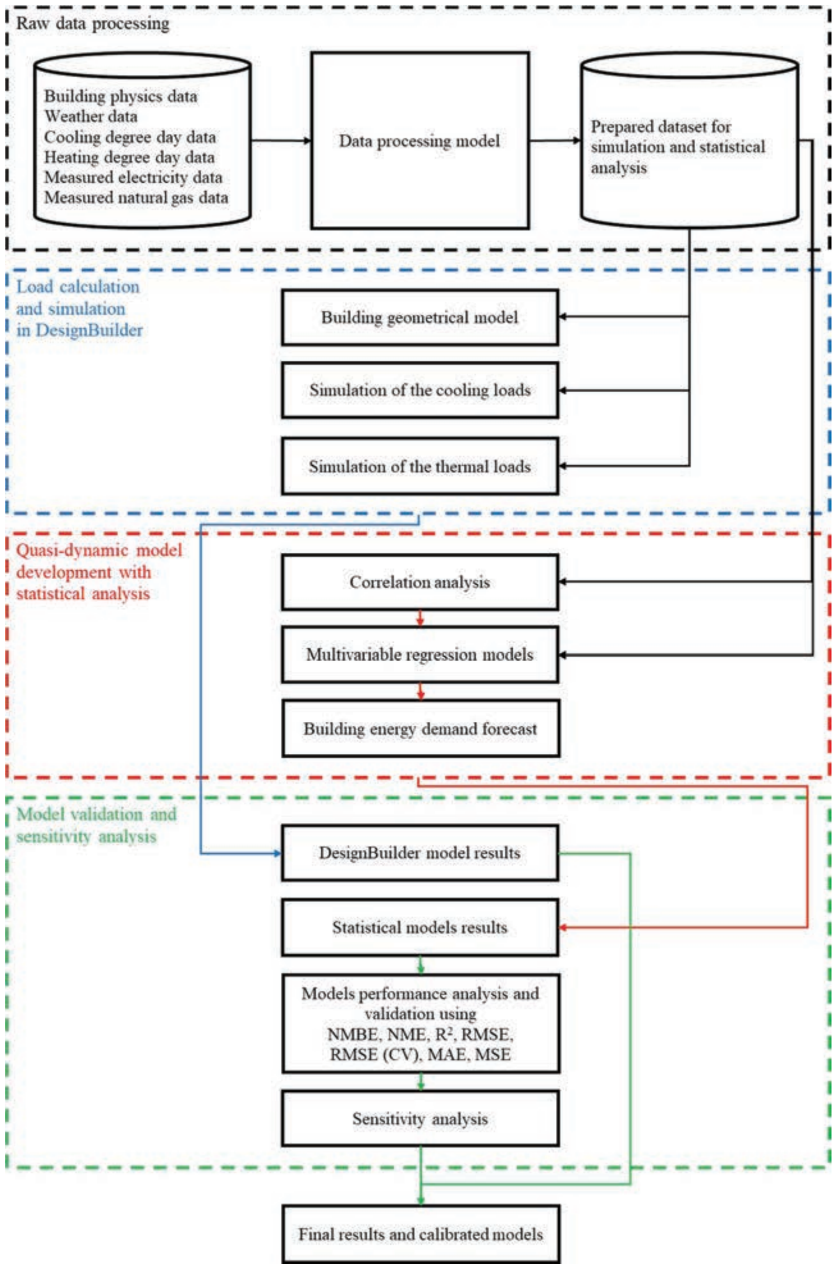

Figure 1 Research steps for energy demand analysis.

A comprehensive analysis of the application of solar energy including the photovoltaic technology on the building performance has been investigated in some researches [33–38]. There are several methods to analyse the impact of employing renewable energy on the building energy demand. For example, data analytics, quasi-dynamic performance analysis, multi-objective energy-exergy-economy-environmental analysis, life cycle analysis, etc. The scope of this study is not to cover the application of the renewable energy on the building performance as it has been covered in the previous studies. As there is an available practical research gas for quantification of the energy saving measurements and verification based on the energy demand models, authors have focused on this specific topic within this research to develop a stepwise approach for filling the gap. Although the proposed methodology is applicable for the cases with the input energy from the grid or utility companies, it can also be applicable for the cases with the application of the on-site renewable energy generation including the solar photovoltaic technology. However, sample complementary analytical methods for the application of on-site photovoltaic systems have been described in other researches [32–34].

The results would be useful for demand prediction. This paper also presents a method for the estimation of daily energy consumption based on utility bills. In order to provide a reliable output, the authors have proceeded with their work on the calibrated simulation model in the software. Compared to the previous studies, this research provides more accurate energy demand models. The applied methods and provided models can be used as a benchmark for further works. Moreover, this study has contributed to both engineering and statistical analysis. This novel approach may lead to a better interpretation of results by linking the building physics and energy consumption patterns to the mathematical models. From the structural view, this paper starts with a brief explanation of the cooling and thermal load calculations. Then the method has been presented and followed by the results and discussion. Finally, the most important findings and observations have been concluded.

2 Materials and Methods

The approach of this research is to identify the energy demand through various forecasting methods including estimation of the thermal and cooling loads by engineering approach in the DesignBuilder model and the statistical model using the real measured data from the utility meters. The advantage of this study is the provided reliable results with limited errors for the energy demand prediction models. The results would be interesting from the perspective of the measurement and verification (M&V) of energy saving. This will be useful in the case of installing the energy efficiency measures for reducing the cooling and thermal loads. Several types of data must be gathered for the data processing of this research. The most important required data types are including: (1) Building physics and geometrical data; (2) Weather-related data and cooling degree days as well as the heating degree days; (3) Measured electricity and natural gas consumption.

After gathering the required data, they must be processed and then the required dataset for the simulation and development of the statistical models have been categorized. In order to cover the aim of the research for the load calculations and simulation of the energy systems and the building response regarding the variation on the weather conditions, the studied building has been simulated within the DesignBuilder software environment.

To cover this purpose, the associated data for building physics and geometry have been provided and by assuming the required data for the cooling and heating systems and by using the provided formulation steps in the upcoming section, the cooling loads and thermal loads have been estimated. The studied building is located in latitude and longitude of 35.76° and 51.45°, in Tehran, the capital city of Iran with Middle Eastern climate conditions. It consists of five floors with ten units and the total controlled area for the heating, cooling, ventilation and air conditioning is 1621 (m^2). Figure 2 demonstrates a three-dimensional model of the simulated building in the DesignBuilder software. There are two typical plan views including a plan for the ground floor with a controlled area of 313 (m^2) and a plan for 1st to 4th floors with a controlled area of 327 (m^2) for each. The studied building is an office and the weekly working routine is from Sunday to Thursday. The official weekends are Friday and Saturday. The daily working routine time starts at 8:00 am and ends by 4:30 pm. The total number of daily inhabitants is 67 persons.

The owner of the studied building has the willingness to invest in the energy efficiency measures concerning thermal and cooling loads reduction. Therefore, a research team has surveyed to identify the baseline energy performance of the building. To estimate the cooling and thermal loads, the below formulas have been applied. Equations (1) to (4) have been used for calculation of the cooling load to overcome the radiant load from the exterior windows, conductive load from the exterior windows, radiative and conductive heat from the external walls as well as conductive heat from the interior walls, windows and doors.

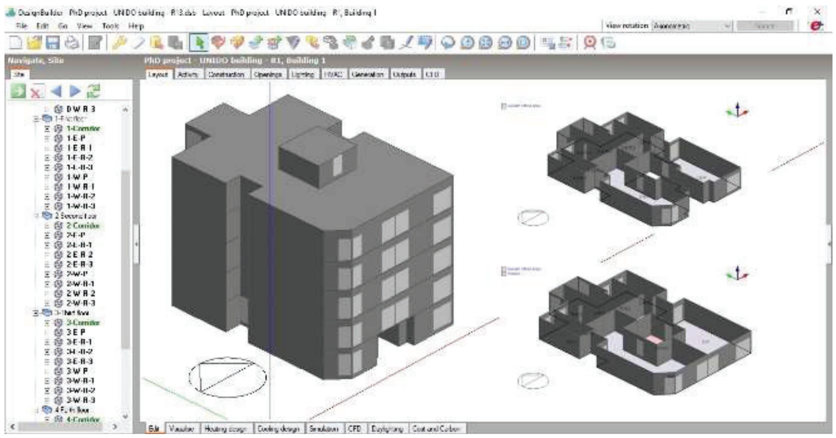

Figure 2 Three-dimensional model for the studied case in the DesignBuilder (left) with a typical 3D plan for the ground floor (right-top) and 1st to 4th floors (right-bottom).

Equations (5) to (9) have been applied for calculation of the sensible cooling load of rooms air conditioning, cooling load to overcome the sensible heat from inhabitants, lighting system, electric motors and home appliances, the effective latent cooling load of rooms, the sensible cooling load for the rest of the outdoor air as well as the latent cooling load for the rest of the outdoor air. The total cooling load can be estimated using Equation (10). Equations (11) to (13) provide formulas for calculation of the thermal load to overcome heat loss from walls, doors, windows, roof and ceiling, thermal load to overcome heat loss related to the air penetration as well as the thermal load of the domestic hot water. The total thermal load can be calculated using Equation (14).

$$Q_{C1} = \sum_{i=1}^{n} \ddot{Q}_i \times CF_{C1} \times AF_i \times A_i \tag{1}$$

$$Q_{C2} = \sum_{i=1}^{n} A_i \times U_i \times (T_o - T_{in}) \tag{2}$$

$$Q_{C3} = \sum_{i=1}^{n} A_i \times U_i \times (\Delta T_e)_i \tag{3}$$

$$Q_{C4} = \sum_{i=1}^{n} A_i \times U_i \times \Delta T_i \tag{4}$$

$$Q_{C5} = \sum_{i=1}^{n} 1.08 \times \upsilon_i \times A_i \times (T_o - T_{in}) \times BF \quad (5)$$

$$Q_{C6} = \sum_{i=1}^{n} \Big((n \times q_{sp})_i + (Q_{light})_i + (Q_{app})_i\Big) \quad (6)$$

$$Q_{C7} = \sum_{i=1}^{n} \left((V_i \times \Delta W \times BF \times \frac{60 \times h_{fg}}{7000 \times \upsilon}) + (n \times q_{lp})_i + (Q_{l_{app}})_i\right) \quad (7)$$

$$Q_{C8} = \sum_{i=1}^{n} 1.08 \times \upsilon_i \times A_i \times (T_o - T_{in}) \times (1 - BF) \quad (8)$$

$$Q_{C9} = \sum_{i=1}^{n} \left(V_i \times \Delta W \times \frac{60 \times h_{fg}}{7000 \times \upsilon}\right) \times (1 - BF) \quad (9)$$

$$Q_C = (Q_{C1} + Q_{C2} + Q_{C3} + Q_{C4} + Q_{C5} + Q_{C6} + Q_{C7} + Q_{C8}) \times 1.05 \quad (10)$$

$$Q_{T1} = \sum_{i=1}^{n} A_i \times \frac{1}{\frac{1}{f_{in}} + \frac{X_1}{K_1} + \frac{X_2}{K_2} + \cdots + \frac{1}{f_o}} \times (T_{in} - T_o)_i \quad (11)$$

$$Q_{T2} = \sum_{i=1}^{n} L_i \times q_i \times 0.0749 \times 0.241 \times (T_{in} - T_o)_i \times CF_{T2} \quad (12)$$

$$Q_{T3} = V_{T3} \times 8.33 \times (T_2 - T_1) \quad (13)$$

$$Q_T = (Q_{T1} + Q_{T2} + Q_{T3}) \times 1.05 \quad (14)$$

In order to cover the purpose of this study on the development of the energy demand models using statistical analysis, there are two types of methods that have been applied including correlation analysis and multivariable regression analysis. The models have been generated using the real data based on the 365 days of the studied one year and the data is provided according to the available metering system in the boundary of the studied building. The results of this analysis can be considered as the energy demand forecast models for the building. The potential significant variables which have been examined for developing the regression-based electricity and natural gas consumption models are including cooling degree day (CDD) and the heating degree day (HDD). Besides, a type of weekdays has an impact on the analysis

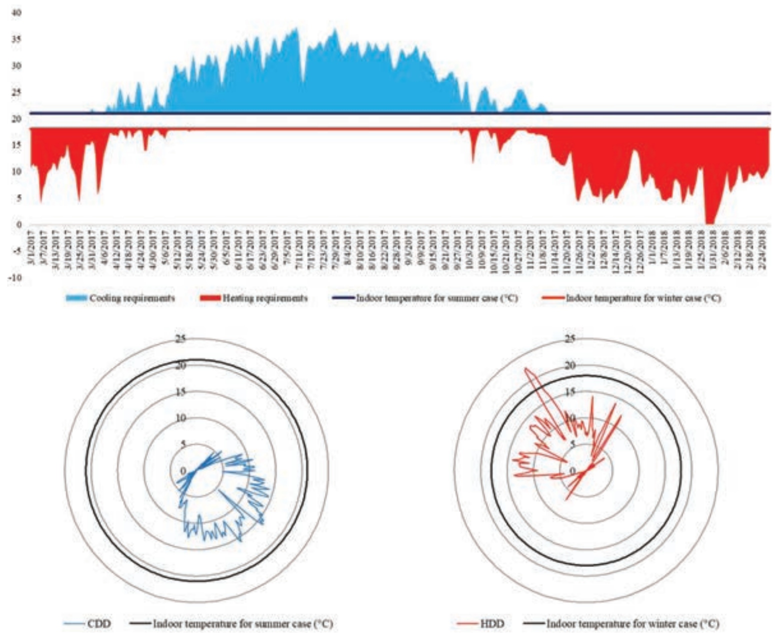

Figure 3 HDD and CDD for a common heating and cooling balance point during the studied one year.

as the pattern of energy consumption is dependent on the working days or weekends. The data for the CDD and HDD have been gathered from the nearest metrological station for the period of the study [39].

Figure 3 displays a comparison between the outdoor and summer and winter cases design temperatures with the cooling and heating requirements based on the CDD and HDD for one year. The assumed indoor design temperature for the summer case is 21 degrees Celsius. The assumed indoor design temperature for the winter case is 18 degrees. Because there are some electrical heaters in the building, it seems both CDD and HDD have an impact on the variation of daily electricity consumption. For the case of natural gas consumption in the summer case, there would be no consumption during the weekend or national holidays. Thus, for a statistical model of thermal energy consumption, it would be mandatory to consider this fact. To quantify this effect, a coefficient for the different days of a week has been defined. The statistical energy demand forecasting models have been generated using the measured daily data and the gathered data for CDD and HDD as well as the coefficient for a type of days in the week. The applied method is a multivariate regression.

Table 1 provides data related to the heat transfer coefficients in different crusts. Table 2 describes the thickness of the material used in different crusts of the building. The key assumptions and input data for the calculation of the cooling load have been provided in Table 3. The key assumptions and input data for the calculation of the thermal load and natural gas consumption have been provided in Table 4.

To cover the aim of the research, the provided regression models have been evaluated through statistical indices. The selected statistical indices for checking the accuracy of the models are including: Normalized Mean Bias Error (NMBE); Normalized Mean Error (NME); Coefficient of determination (R^2); Root Mean Square Error (RMSE); Coefficient of variation of Root Mean Square Error (CV (RMSE)); Mean Absolute Error (MAE); and Mean Square Error (MSE). The NMBE measures the sum of errors between the measured and modelled data. It expresses the mean difference between the measured and modelled data points. NMBE and NME have been calculated using Equations (15) and (16).

The calculation of NME is like the calculation of NMBE. The coefficient of determination (R^2) is the proportion of the variance in the measured data which has been explained by the model. R^2 ranges from 0 to 1, where the value 1 indicates that the regression line fits the data. Thus, the larger the value R^2, the smaller the error variance of the modelled and measured data. R^2 has been calculated by Equation (17). The RMSE represents the square root of the quadratic mean of differences between the modelled and measured values. RMSE has been calculated using Equation (18). Calculation of the CV (RMSE) is based on the RMSE but extends the RMSE by offsetting errors between the measured and modelled data. The CV (RMSE) has been calculated by Equation (19). The Mean Absolute Error (MAE) represents the direct deviation between the modelled and measured values. MAE has been calculated through Equation (20). The Mean Square Error (MSE) calculates the variance between the target of a model and forecast and has been calculated using Equation (21) [1, 14, 26]. These statistical indices have been calculated for both electricity and natural gas consumption models. The next section provides the results and discussion related to the analysed models. The final step for reviewing the accuracy of the developed models and assessing the validity of the generated models is sensitivity analysis. All the processed data and the provided information have been evaluated using the sensitivity analysis and the final results have been provided in the results and discussion section.

Table 1 Description of the heat transfer coefficients for each crust

Exterior Walls (South – North)		Exterior Walls (East – West)	
f_{in} (W/m^2.K)	1.072	f_{in} (W/m^2.K)	1.072
f_o (W/m^2.K)	0.294	f_o (W/m^2.K)	0.294
K_1 (W/m.K)	0.5	K_1 (W/m.K)	0.5
K_2 (W/m.K)	0.2	K_2 (W/m.K)	0.2
K_3 (W/m.K)	1.15	K_3 (W/m.K)	1.15
K_4 (W/m.K)	2.4	U (W/m^2.K)	0.186
U (W/m^2.K)	0.1857	Internal Walls	
Corridor Walls		f_{in} (W/m^2.K)	1.072
f_{in} (W/m^2.K)	1.072	f_o (W/m^2.K)	1.072
f_o (W/m^2.K)	0.294	K_1 (W/m.K)	0.5
K_1 (W/m.K)	0.5	K_2 (W/m.K)	0.09
K_2 (W/m.K)	0.09	K_3 (W/m.K)	0.5
K_3 (W/m.K)	0.5	U (W/m^2.K)	0.329
U (W/m^2.K)	0.1817	Ground, 1st, 2nd, 3rd Floors Ceiling	
Ground Floor Bottom		f_{in} (W/m^2.K)	1.072
f_{in} (W/m^2.K)	1.072	f_o (W/m^2.K)	1.072
f_o (W/m^2.K)	0.294	K_1 (W/m.K)	0.65
K_1 (W/m.K)	0.65	K_2 (W/m.K)	0.5
K_2 (W/m.K)	0.5	K_3 (W/m.K)	1.75
K_3 (W/m.K)	1.75	K_4 (W/m.K)	0.31
K_4 (W/m.K)	0.31	K_5 (W/m.K)	0.26
K_5 (W/m.K)	0.26	K_6 (W/m.K)	0.5
K_6 (W/m.K)	0.5	U (W/m^2.K)	0.338
U (W/m^2.K)	0.184	Windows (Glass)	
4th Floor Roof		U (W/m^2.K)	1.954
f_{in} (W/m^2.K)	1.072	Patio Door (Glass)	
f_o (W/m^2.K)	0.294	U (W/m^2.K)	1.954
K_1 (W/m.K)	0.5	Gate Door (Metal)	
K_2 (W/m.K)	1.75	U (W/m^2.K)	1.989
K_3 (W/m.K)	0.31	Room Door (Wood)	
K_4 (W/m.K)	0.26	U (W/m^2.K)	0.778
K_5 (W/m.K)	1.15	Bath Door (Wood)	
U (W/m^2.K)	0.197	U (W/m^2.K)	0.778

$$\mathrm{NMBE} = \frac{\sum_{i=1}^{L}(m_i - s_i)}{\sum_{i=1}^{L}(m_i)} \tag{15}$$

$$\mathrm{NME} = \frac{\sum_{i=1}^{L}|m_i - s_i|}{\sum_{i=1}^{L}(m_i)} \tag{16}$$

$$R^2 = \left(\frac{L\sum_{i=1}^{L} m_i s_i - \sum_{i=1}^{L} m_i \sum_{i=1}^{L} s_i}{\sqrt{(L\sum_{i=1}^{L} m_i^2 - (\sum_{i=1}^{L} m_i)^2)\cdot(L\sum_{i=1}^{L} s_i^2 - (\sum_{i=1}^{L} s_i)^2))}}\right)^2 \tag{17}$$

$$\mathrm{CV(RMSE)} = \frac{\sqrt{\sum_{i=1}^{L}(m_i - s_i)^2/L}}{\bar{m}} \tag{18}$$

$$\mathrm{MAE} = \frac{1}{L}\sum_{i=1}^{L}|m_i - s_i| \tag{19}$$

$$\mathrm{MSE} = \frac{1}{L}\sum_{i=1}^{L}(m_i - s_i)^2 \tag{20}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{L}\sum_{i=1}^{L}(m_i - s_i)^2} \tag{21}$$

$$\mathrm{MAPE} = 100 \times \frac{1}{L}\sum_{i=1}^{L}|m_i - s_i| \tag{22}$$

Table 2 Description of the material layers and thickness for each crust

Southern and northern exterior walls (Gypsum, solid brick, lined sand and stone)		Ground floor bottom (Ceramic, gypsum, ordinary concrete, concrete with light aggregates, clay block and gypsum)	
X_1 (cm)	1.5	X_1 (cm)	1
X_2 (cm)	20	X_2 (cm)	1.5
X_3 (cm)	1.5	X_3 (cm)	10
X_4 (cm)	2	X_4 (cm)	6
Corridor walls (Gypsum, solid brick and gypsum)		X_5 (cm)	20
X_1 (cm)	1.5	X_6 (cm)	1.5
X_2 (cm)	10	Ground, 1st, 2nd, 3rd floors ceiling (Ceramic, gypsum, ordinary concrete, concrete with light aggregates, clay block and gypsum)	
X_3 (cm)	1.5		
Eastern and western exterior walls (Gypsum, solid brick and lined sand)			
X_1 (cm)	1.5	X_1 (cm)	1
X_2 (cm)	20	X_2 (cm)	1.5
X_3 (cm)	1.5	X_3 (cm)	10
4th floor roof (Gypsum, ordinary concrete, concrete with light aggregate, clay block and sandy asphalt)		X_4 (cm)	6
		X_5 (cm)	20
X_1 (cm)	1.5	X_6 (cm)	1.5
X_2 (cm)	20	Internal walls (Gypsum, solid brick and gypsum)	
X_3 (cm)	6	X_1 (cm)	1.5
X_4 (cm)	10	X_2 (cm)	10
X_5 (cm)	2.5	X_3 (cm)	1.5

Table 3 Key assumptions and input data for calculation of the cooling load

Parameter (Unit)	Value
Acquired heat from the sun radiation for patio windows door for each of east units (BTU/hr.ft^2)	13
Acquired heat from the sun radiation for patio windows door for each of west units (BTU/hr.ft^2)	144.6
Acquired heat from the sun radiation of living room and middle room for each unit, east room of east units and west room of west units (BTU/hr. ft^2)	13
Acquired heat from the sun radiation of the south window of the living room for each unit (BTU/hr.ft^2)	20.9
Area of corridor wall for each of 1st to 3rd floor units (ft^2)	326.8
Area of corridor wall for each of 4th floor units (ft^2)	339.1
Area of corridor wall for each of ground floor units (ft^2)	414.7
Area of main entrance door for each unit (ft^2)	28.4
Area of north window of the living room for each unit, east room of east units and west room of west units (ft^2)	38.3
Area of north window of middle room for each unit (ft^2)	43.4
Area of patio windows doors for each unit (ft^2)	50.7
Area of the south smaller window of the living room for each unit (ft^2)	61.2
Area of the south bigger window of the living room for each unit (ft^2)	107.1
Assumed corridor temperature (F)	94
Assumed design ambient temperature (F)	100
Assumed design inlet temperature (F)	78
Cooling load to overcome heat from electric motors and home appliances for each unit (BTU/hr)	19950
Cooling load to overcome heat released from lighting system for each of 1st to 4th floor units (BTU/hr)	14123
Cooling load to overcome heat released from lighting system for each of ground floor units (BTU/hr)	13642
Correction factor	0.686
Difference between indoor and outdoor air humidity ratio (Grain/lb)	74
Latent cooling load to overcome heat from electric motors and home appliances for each unit (BTU/hr)	6750
Latent cooling load of inhabitants for each living, east and west room (BTU/hr)	470
Latent cooling load of inhabitants for each middle room (BTU/hr)	235
Latent heat for water vapour (Btu/lb)	1036.7
Sensible cooling load of inhabitants for each living, east and west room (BTU/hr)	430
Sensible cooling load of inhabitants for each middle room (BTU/hr)	215
Shortcut factor	0.25
Specific volume of outdoor air (ft^3/lb)	147
Storing factor for patio windows door for each east unit	0.23
Storing factor for patio windows door for each west unit	0.61

(*Continued*)

Table 3 Continued

Storing factor of the living and middle room for each unit, east room of east units and west room of west units	0.96
Storing factor of the south window of the living room for each unit	0.67
The required amount of air to ventilate the bathroom for each unit (CFM)	14.8
The required amount of air to ventilate each east room of east units or west room of west units (CFM)	49.1
The required amount of air to ventilate each living room of 1st to 4th floor units (CFM)	416.3
The required amount of air to ventilate each living room of the ground floor units (CFM)	397.5
The required amount of air to ventilate the middle room of each unit (CFM)	35.4
The required amount of air to ventilate each west room of east units or east room of west units (CFM)	38.2

Table 4 Key assumptions and input data for calculation of the thermal load and natural gas consumption

Parameter (Unit)	Value
Amount of natural gas consumption for central heating system burner (Nm^3/hr)	15.85
Amount of natural gas consumption for each gas oven (Nm^3/hr)	0.7
Amount of natural gas consumption for each small gas heater (Nm^3/hr)	0.3
Area of entrance door for each unit (ft^2)	28.4
Area of patio windows doors for each unit (ft^2)	50.7
Conversion factor from [(BTU (th))/(hr.ft.F)] to [W/(m.K)]	1.73
Conversion factor from [(BTU (th))/hr] to [kW]	0.0003
Correction factor for air density	0.97
Demand factor for bathrooms, toilets and pantry sinks	0.3
Direction factor for east	1.1
Direction factor for north	1.1
Direction factor for south	1
Direction factor for west	1.05
Efficiency of the central heating system	0.85
Elevation factor for 1st floor	1.025
Elevation factor for 2nd floor	1.075
Elevation factor for 3rd floor	1.1
Elevation factor for 4th floor	1.15
Elevation factor for ground floor	1
Low heat value of natural gas (MJ/Nm^3)	37.68
Minimum temperature for surfaces with contact to the indoor environment in winter case (F)	46
Minimum temperature for surfaces with contact to the outdoor environment in winter case (F)	13

(*Continued*)

Table 4 Continued

Parameter (Unit)	Value
Number of bathrooms and toilets	30
Number of pantry sink	10
Pre-power on factor	1.15
Total area of the ceiling for ground floor units (ft^2)	3369.1
Total area of corridor walls for 1st to 4th floor units (ft^2)	678.1
Total area of corridor walls for ground floor units (ft^2)	829.4
Total area of east side outdoor walls for 1st to 4th floor units (ft^2)	699.1
Total area of east side outdoor walls for ground floor units (ft^2)	1083.9
Total area of north side outdoor walls for 1st to 4th floor units (ft^2)	351.1
Total area of north side outdoor walls for ground floor units (ft^2)	370.8
Total area of north side windows for 1st to 4th floor units (ft^2)	163.3
Total area of north side windows for ground floor units (ft^2)	239.8
Total area of roof for 4th floor units (ft^2)	3519.8
Total area of southside outdoor walls for 1st to 4th floor units (ft^2)	540.4
Total area of southside outdoor walls for ground floor units (ft^2)	428.8
Total area of southside windows for 1st to 4th floor units (ft^2)	214.3
Total area of southside windows for ground floor units (ft^2)	122.4
Total area of west side outdoor walls for 1st to 4th floor units (ft^2)	699.1
Total area of west side outdoor walls for ground floor units (ft^2)	263
Total number of gas ovens in the entire building	10
Total number of small gas heaters in the entire building	10
Unit consumption of bathrooms and toilets (GPH)	8
Unit consumption of pantry sinks (GPH)	20
Volume amount of permeable air from each entrance door (CFM)	2165
Volume amount of permeable air from each north side window of each living, east and west room (CFM)	863.9
Volume amount of permeable air from each north side window of each middle room (CFM)	904.6
Volume amount of permeable air from each patio window door (CFM)	1242.8
Volume amount of permeable air from each southside window for each ground floor unit (CFM)	802.7
Volume amount of permeable air from each south side window of the living room for each 1st to 4th floor unit (CFM)	1727.7

3 Results and Discussion

The results for the design and operational phases of the studied building using the engineering load calculation and simulation software as well as the statistical models have been presented in three main parts including the results from the simulation in DesignBuilder, the results of the statistical model development and the results from the sensitivity analysis and model validation.

3.1 Results of the Engineering Load Calculation and DesignBuilder Simulation Model

Figure 4 displays the air temperature, the greatest operating temperature and the outside dry-bulb temperature at the time of the peak cooling according to the design criteria. The data provided in Figure 4 are for the different zones of the building according to the results of the analysis. Figure 5 displays the cooling load for each zone according to the results of the simulation model in the DesignBuilder. The total amount of the cooling load is 189.4 (kW). Considering the coefficient of performance (COP) for the cooling system

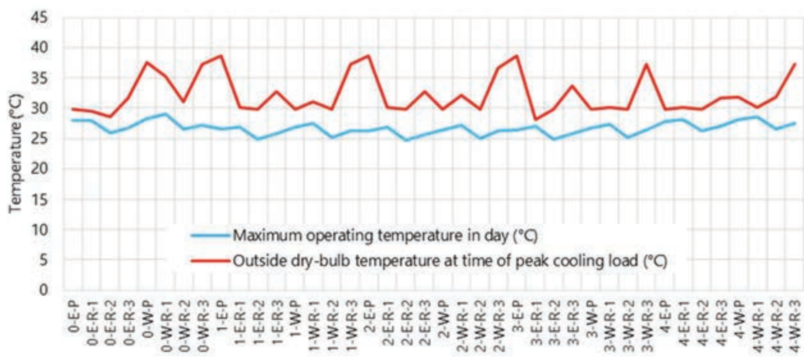

Figure 4 Cooling load mode temperatures in different zones.

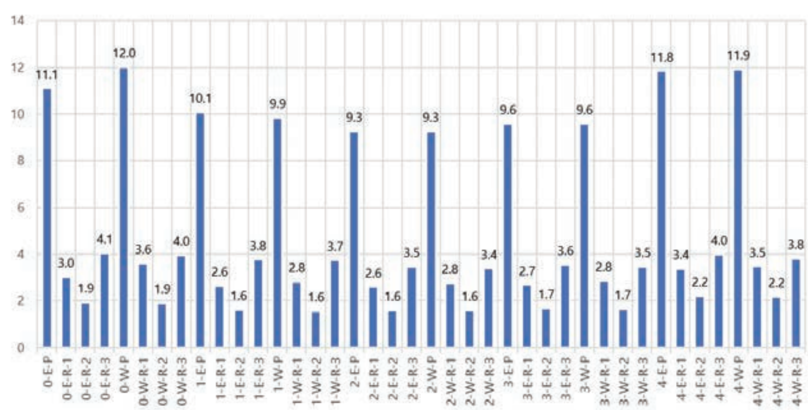

Figure 5 Breakdown of the cooling load for each zone of the studied building (kW).

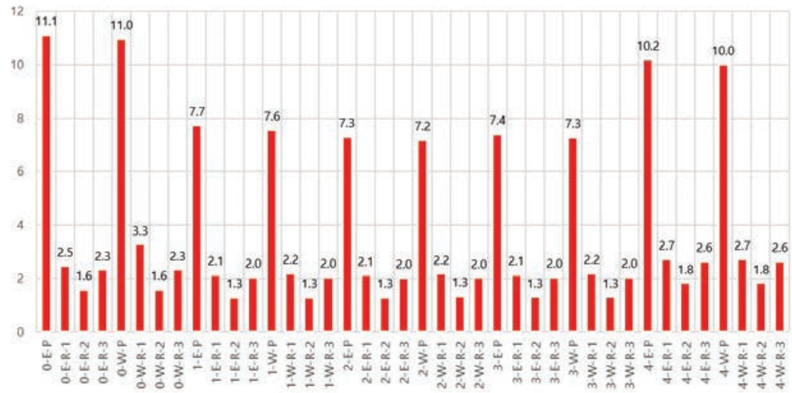

Figure 6 Breakdown of the thermal load for each zone of the studied building (kW).

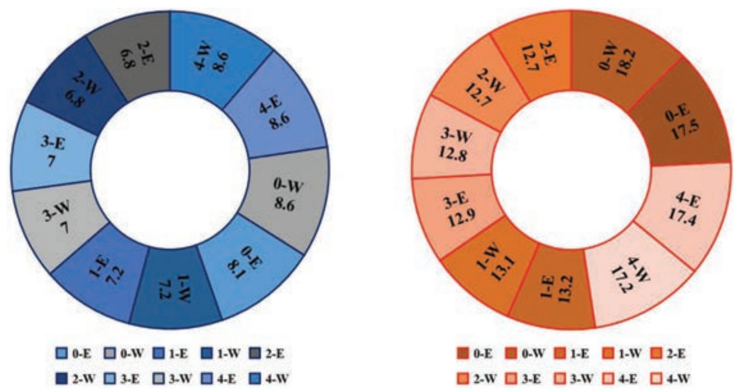

Figure 7 The cooling system rated power (left) and the heating system design capacity (right) for each unit (kW).

is equal to 2.5, the required electric power for the cooling system can be identified. The amount of cooling and thermal loads for the ground and 4th floors are higher because of the availability of a parking space and the free space on the roof. Figure 6 illustrates the thermal load for each zone based on the results of the simulation model in the DesignBuilder. The indoor design temperate in the winter case has been assumed as 18 degrees Celsius. The cooling load rated power based on the greatest cooling demand for each unit and the heating system capacity for each unit are shown in Figure 7. The cooling system rated power for the entire building is 75.8 (kW). The amount of the thermal system capacity for the entire building is 147.7 (kW). Figure 8 illustrates the simulation input/outputs based on hourly profiles

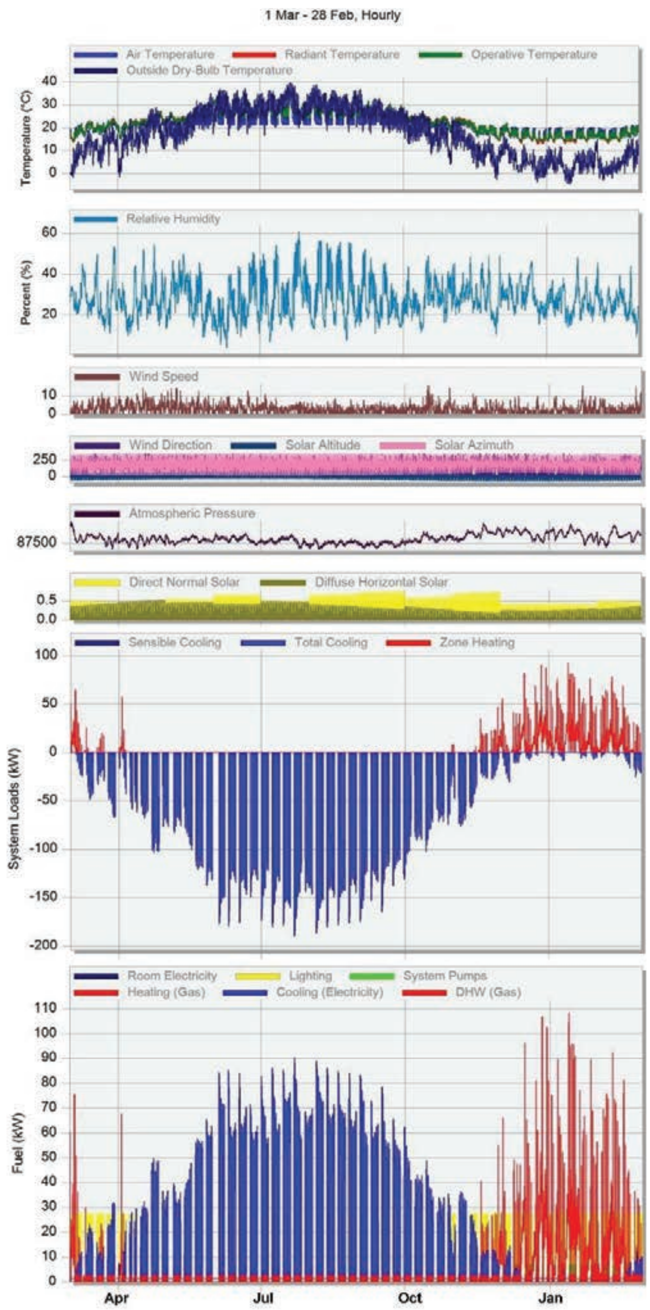

Figure 8 Simulation inputs/outputs for energy consumption analysis using DesignBuilder.

using the DesignBuilder software. Several climate related parameters have been considered as inputs for the simulation are including: air temperature, dry-bulb temperature, relative humidity, wind speed, solar irradiation, For the case of energy systems, the real situation of the building has been considered within the simulation process. As there is no renewable energy system within the scope of studied building, energy systems are consuming natural gas and grid electricity which are provided by the utility company. The energy systems with their energy source within the simulated building are including: central heating (natural gas), local cooling systems (electricity), domestic hot water (natural gas), system pumps (electricity), lighting (electricity) and room electrical users. According to the provided profiles, the demand for the heating system and domestic hot water as well as the cooling system are the most significant part of the annual energy consumption.

3.2 Results of the Energy Demand Model Development Using Statistical Analysis

Figure 9 illustrates the daily modelled electricity consumption compared to the measured data. The amount of electricity consumption has been increased from around 250 to 350 (kWh/day) from May to October 2017. The reason for this change is the application of the cooling system during this period. The grey bars in Figure 9 shows the values for the measured electricity consumption. The black trend shows the values for the modelled electricity consumption. A multivariate regression model for the annual electricity consumption has been provided in Equation (23). Figure 10 displays the daily modelled thermal energy consumption compared to the measured data.

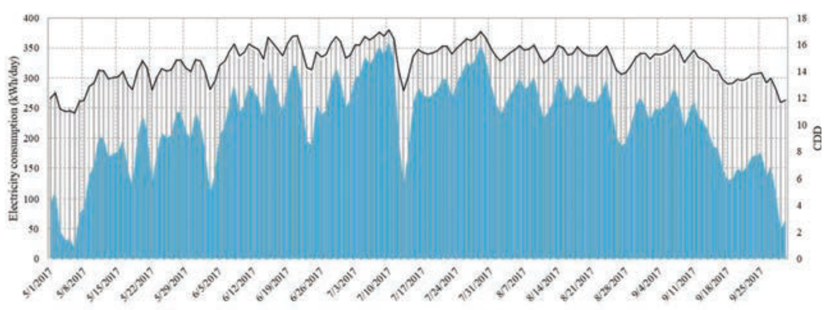

Figure 9 The trend for the daily measured and modelled electricity consumption of the entire building (kWh/day) versus cooling degree day (CDD).

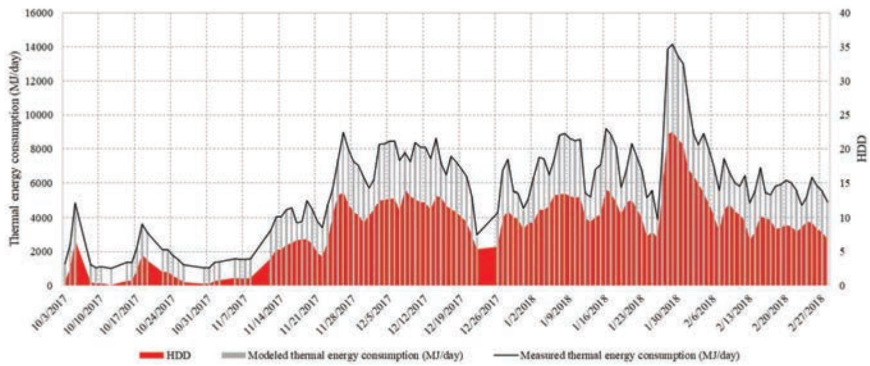

Figure 10 The trend for the daily measured and modelled thermal energy consumption of the entire building (MJ/day) versus heating degree day (HDD).

Because of the more usage of the central heating system to compensate for the cold temperatures, the natural gas consumption has been increased during the periods of March-April 2017 and November 2017 to February 2018. The grey bars prove the values of the measured thermal energy consumption and the black trend explains the values of the modelled daily thermal energy consumption. A multivariate regression model for the annual thermal energy consumption has been provided in Equations (24).

$$\text{Annual electricity consumption} = \sum_{i=1}^{n}((9.16 \times \mathrm{CDD_i}) + (3.93 \times \mathrm{HDD_i}) + (n \times 232.07)) \quad (23)$$

$$\text{Annual thermal energy consumption} = \sum_{i=1}^{n}((563.29 \times \mathrm{HDD_i}) + (1258.51 \times \text{Type of day}_i) - (n \times 297.28)) \quad (24)$$

A difference between the modelled and the measured energy consumption is negligible in accordance with Figures 9 and 10. This result is useful for the application of the energy efficiency measures and the M&V process for energy performance contracting. The results of the statistical analysis for the prediction models of the electricity and natural gas consumption have

Table 5 Results of the statistical analysis for electricity and natural gas demand models

Statistical Indicator	Result of Analysis for Electrical Energy Demand Model	Result of Analysis for Natural Gas Energy Demand Model
NMBE	0.00783	1.05883E-15
NME	0.01635	0.00493
R^2	0.9699	0.9997
RMSE	5.76048	43.2728
CV (RMSE)	0.01975	0.008428
MAE	4.8	25.3
MSE	33.18	1872.53

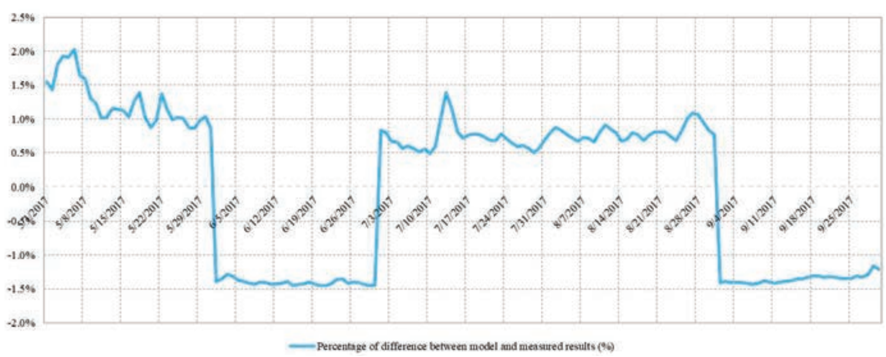

Figure 11 Percentage of the difference between the modelled and measured electricity consumption.

been provided in Table 5. Figure 11 shows the difference between the daily modelled and measured electricity consumption for the selected period of the year. The greatest amount of daily difference is 2%. This means that the model has been matched to the measured data. Figure 12 illustrates the difference between the daily modelled and measured natural gas energy consumption for the selected period of the year. The greatest amount of daily difference is 4.5%. Figures 13 and 14 show the normal distribution of measured data, normal distribution and the Pareto chart for the difference between the modelled and measured electricity consumption and natural gas energy consumption for one year. Over 78.9% of the differences for the electricity have been distributed between the first four bars including (0.8%, 1.6%], [−3.2%, −2.4%], (−2.4%, −1.6%] and (0.0%, 0.8%]. Besides, 75.7% of the distributed differences for the natural gas belongs to the bars including (−0.4%, 0.3%] and (1.0%, 1.8%].

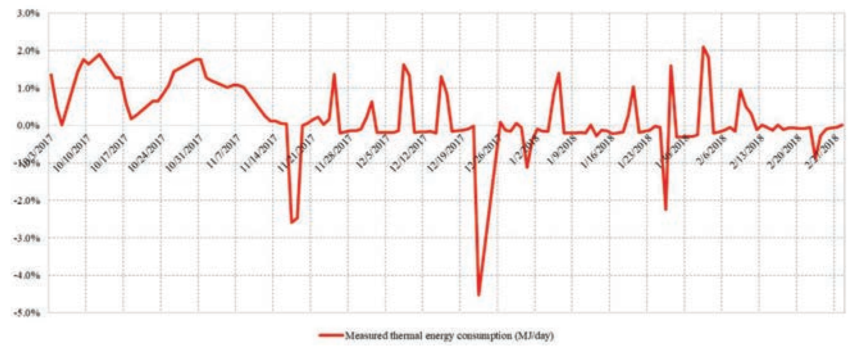

Figure 12 Percentage of the difference between the modelled and measured thermal energy consumption.

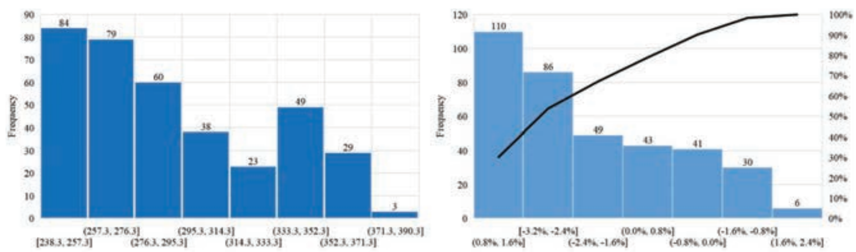

Figure 13 Normal distribution of measured data for electricity consumption (left), normal distribution and Pareto chart for the percentage of the difference between the modelled and measured electricity consumption (right).

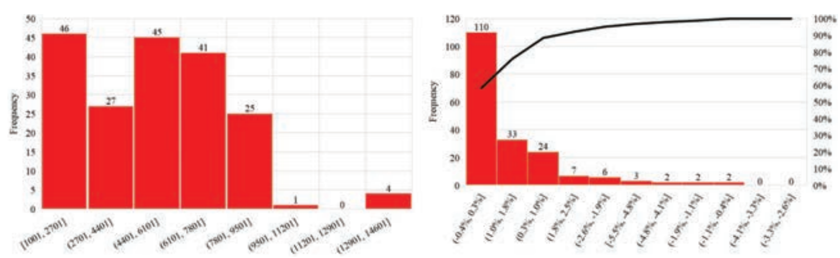

Figure 14 Normal distribution of measured data for thermal energy consumption (left), normal distribution and Pareto chart for the percentage of the difference between the modelled and measured thermal energy consumption (right).

The result showed that the model for the thermal energy consumption is more accurate than the model for electricity consumption. Besides, both methods including the simulation model in the DesignBuilder and the statistical model will provide reliable information for the energy demand prediction.

The contribution to the results of this research can be considered in two pathways. On one hand, the cooling and thermal loads have been provided by the DesignBuilder with an engineering approach. On the other hand, a validated statistical model has been proposed compared to the measured data for a real case. The results showed that for any kind of control, monitoring or retrofit energy efficiency solution, it would be viable to focus on the cooling and heating loads.

Yet, it is obvious that the statistical models have enough advantages for the prediction of the daily energy demand. One of the most important applications of such models will be for the measurement and verification of the building energy performance. Because all the statistical tests provide the proper values, the provided models for the natural gas and electricity consumption are recommended. According to the normal distribution and the Pareto analysis for the percentage of the difference between the modelled and measured electricity and thermal energy consumption, most samples have been fitted with a limited amount of error.

Finally, the authors have merged the daily measured electricity and thermal energy consumption of the studied building for one year in order to review the results of the modelling in an integrated energy consumption trend model. To cover this purpose, the energy content of the electrical energy and thermal energy has been converted to the primary energy and for the case of the electricity, the conversion factor of 0.27 has been considered as the reference factor for the power grid network and power plants efficiency.

3.3 Sensitivity Analysis and Validation of the Energy Demand Model

Figure 15 shows the total primary energy consumption based on the measured and modelled data in comparison to the trends of the cooling degree days and heating degree days. As the share of natural gas consumption is higher than the share of electricity consumption, the trend of the total primary energy consumption has promising values in cold season months. As the most important affecting variable on the natural gas consumption is the HDD, the trends for primary energy consumption and HDD have the same behaviour. The variation of the total primary energy consumption in the hot season is dependent on CDD and this can be recognized from the summer case in Figure 15. Figure 16 illustrates the comparison between the accumulated monthly measured and modelled total primary energy consumption for the studied case. According to the bar charts of this figure, it is obvious that the

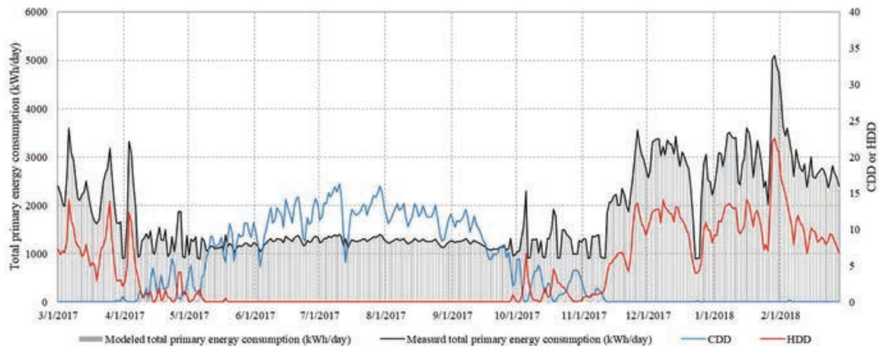

Figure 15 Daily total primary energy consumption based on the measured and modelled data in comparison to the trends of CDD and HDD.

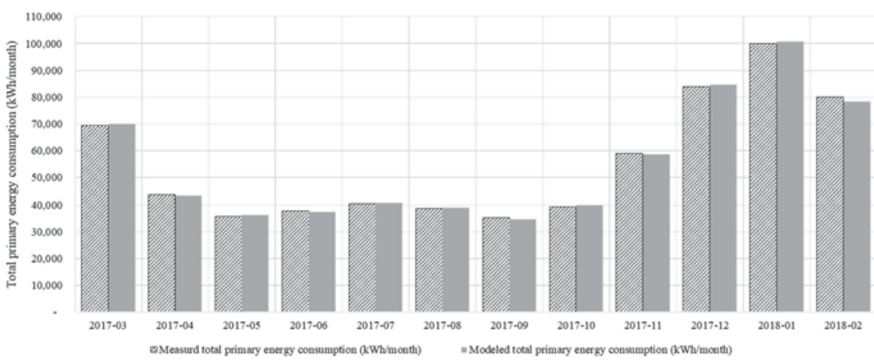

Figure 16 Comparison between the measured and modelled total primary energy consumption for the studied case.

provided models are reliable. The total annual primary energy consumption of the studied building is 663,780 (kWh/yr).

As it was mentioned in the introduction section, the total controlled area for the heating, cooling, ventilation and air conditioning is 1621 (m^2). Therefore, the value for the energy performance indicator of the studied building is 409.5 ($kWh/m^2.yr$). This energy performance value is higher than the values in the local standards. In case the building owner has an interest to invest in energy efficiency, the provided models can be considered as a reliable baseline for examining performance improvement. The impact of any retrofit measure with the target to reduce the energy consumption for cooling and heating system can be tracked using these models with a limited level of error.

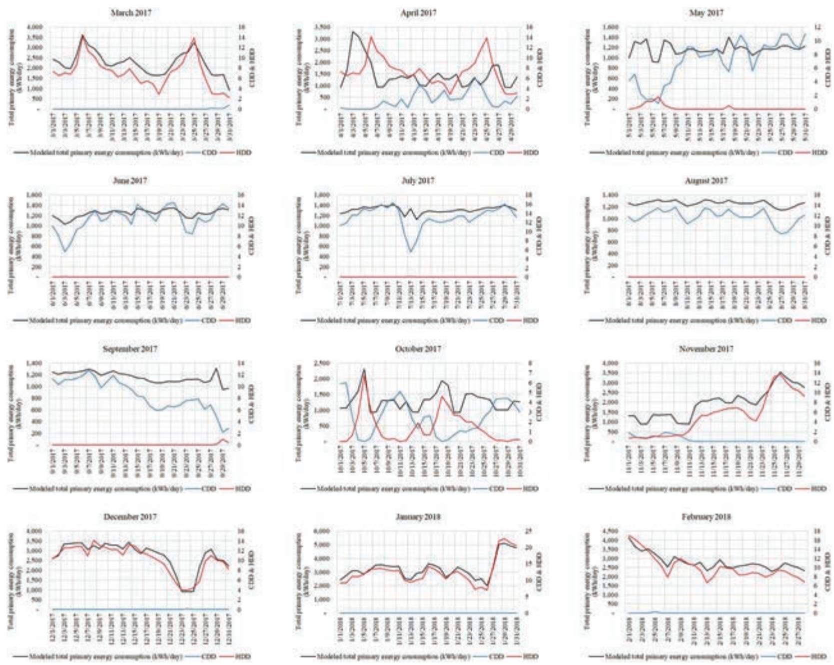

Figure 17 Modelled daily total primary energy consumption, CDD and HDD.

Figure 17 presents the monthly trends for daily modelled total primary energy in comparison to the trends of CDD and HDD for one year. The group of figures in Figure 17 have been provided to support the results of Figure 16 on monthly basis. In accordance with the sensitivity analysis related to this figure, it is recognizable that the variation of the total primary energy consumption is mostly dependent on CDD in June to September and it is dependent on HDD in months November, December, January, February and March. Figures 18 and 19 illustrate the scatter diagrams for the modelled daily total primary energy consumption versus HDD and CDD, respectively. The outcomes from these two figures are similar to the findings of Figure 17.

As one of the relevant variables on the variation of energy consumption is the type of days in the week, the trends for the total primary energy consumption on a daily basis have been provided in Figure 20. The variation of the total primary energy consumption based on the developed models is understandable based on the types of the days in a week which are including working days and weekdays.

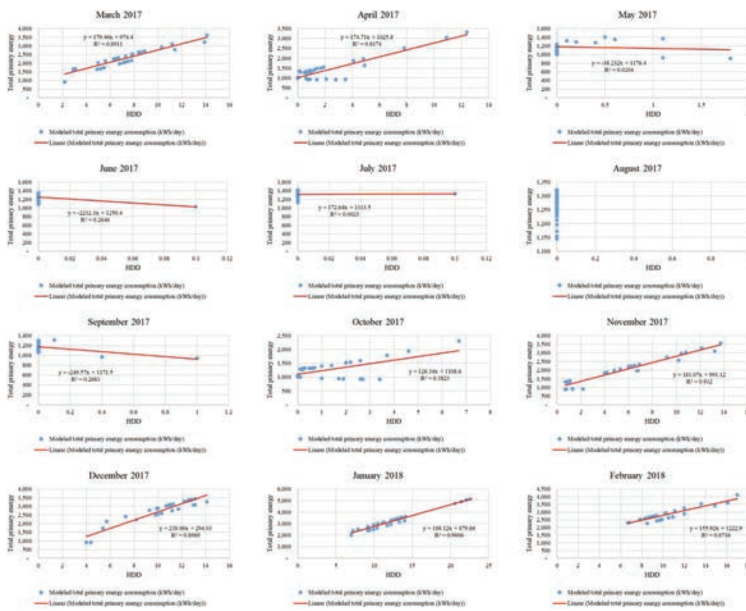

Figure 18 Modelled daily total primary energy consumption versus HDD.

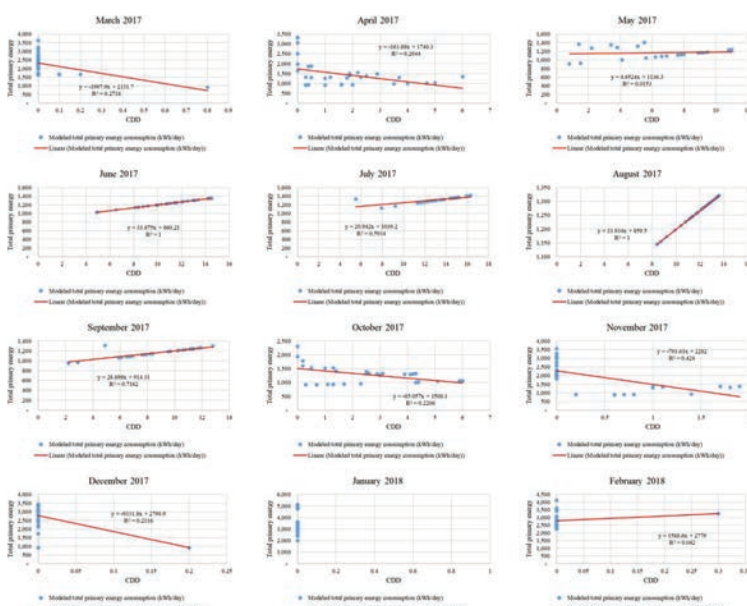

Figure 19 Modelled daily total primary energy consumption versus CDD.

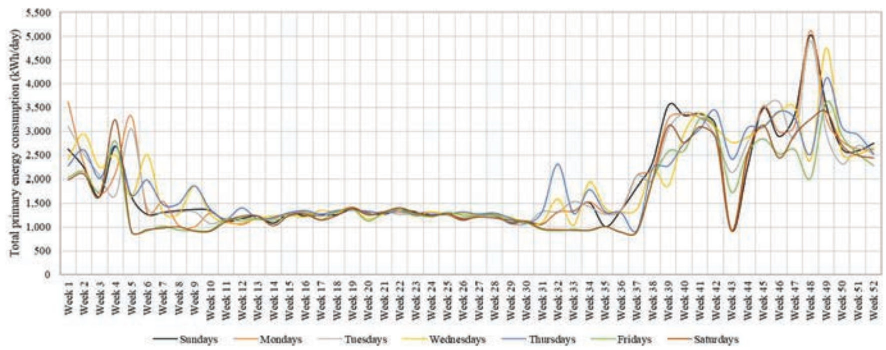

Figure 20 Modelled daily total primary energy consumption based on 52 weeks.

4 Conclusions

The energy demand prediction is one of the useful methods to forecast the required energy in the building sector. The goal of this paper is to provide an integrated approach to the demand forecasting on the design and operational phases for the office building. The applied approach has been covered using a dual approach including: (1) engineering load calculation and simulation model in the DesignBuilder and (2) statistical analysis using multivariate regression model which can be used for the measurement and verification of the building energy performance. The results of the load calculation and the developed model in the DesignBuilder explains that the cooling system rated power and the capacity of the thermal system for the entire building are 75.8 (kW) and 147.7 (kW).

According to the analysis, electricity consumption can be modelled with the variation of the cooling degree days and heating degree days. The quantitative results for the modelling of the thermal energy consumption showed that the heating degree days and the type of day in a week are the significant variables. Several statistical indices have been selected for checking the accuracy of the models for the electricity and natural gas consumption of the studied building. The provided models have been examined using the statistical test and indices and by analysing the results both demand predictions have been validated. A multivariate regression model test results confirmed that the measured data correlated with a reliable output. For instance, the value for the coefficient of determination (R2) of the analysis for electrical energy consumption and natural gas prediction models are 0.9699 and 0.9997, respectively.

According to the results, the statistical model has enough advantages for the prediction of the daily and annual energy demand. Thereafter, the impact of three identified relevant variables on the energy demand models has been reviewed using sensitivity analysis. According to the findings of the sensitivity analysis, it is provable that the selected relevant variables including HDD, CDD and type of day have an impact on the total primary energy consumption for the studied building. The results of this study showed that the provided regression models are useful for the measurement and verification of the building energy performance. The outputs are highly recommended for energy demand prediction. The developed models can be used as a baseline for the agreement between the building owner and the energy efficiency service providers on the desired energy efficiency measures for the cooling and thermal load reduction.

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