Building Energy Use Prediction Owing to Climate Change: A Case Study of a University Campus

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ABSTRACT

Global warming is expected to increase of 1.5°C between 2030 and 2052. This may lead to an increase in building energy consumption. With the changing climate, cities, communities, and university campuses need a more dynamic forecasting model to predict their future energy demands to mitigate risks. Although many building energy prediction models have been developed, only a few have focused on climate change and its impacts. This paper discusses the development of a regression-based forecasting model for a university campus energy use under changing climate. The forecasting model development follows a four-step process: (1) data frame setting, (2) descriptive statistics, (3) statistical regression modeling, and (4) validation and prediction. The independent numeric variables used as inputs are building characteristics (gross square feet, lighting power density, equipment power density; U factor of roof, wall, and windows; building age; years after building renovation; and window-to-wall ratio) and weather data (temperature and humidity). The outputs are electricity and chilled water for 2054. Prior to modeling, matrix plots and histograms are used to identify correlations between variables. This step is followed by normalization of independent variables to check their impact. Finally, multiple linear regression model for electricity and Lasso regression models for chilled water estimations are developed. For the purpose of predicting energy consumption owing to climate change, we used weather data that represents 2054. The equipment power density was the most important factor for electricity consumption and temperature was the most important one for chilled water consumption. The prediction models give an insight of which factors remain essential and applicable to campus building policy to prevent wasting energy in buildings, as a result of climate change.

CCS CONCEPTS

• Applied computing • IT architectures • Computer-aided design

KEYWORDS

Building Energy Use, Regression Analysis, Climate Change, University Campus, Statistical Prediction

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1 Introduction

Building energy use in the U.S. is 40% of the total energy consumption and is expected to increase significantly due to climate change. According to the North American Regional Climate Change Assessment Program (NARCCAP), the average earth temperature may increase between 1.44°F to 2.16°F, which is likely to reach 2.7°F, between 2030 and 2052. U.S. Southeast region has captured an increase in temperature averaging approximately 2°F in the last 50 years during summer seasons [1]. According to the U.S. Environmental Protection Agency (EPA) [2], within the next 70 years, the annual number of days above 95°F will increase significantly, i.e., from the current 15 days per year to 40-90 days per year. Additionally, the Intergovernmental Panel on Climate Change [3] reported a 1.8°F increase above pre-industrial levels that has occurred owing to human activities. With 1.8°F global warming, the cooling demand in buildings is approximately expected to rise by at least 5% and up to 20%. On the other hand, the heating demand in buildings is expected to decrease by about 3-15%. Net expenditure in annual heating and cooling is expected to increase by 2.8% and cost $7.4 billion (in 1990 dollars) with a 1.8°F warming by the end of the 21st century. This would affect the world not only financially, but also leading to significant pollution owing to excessive energy production. Therefore, in managing building energy use, we need to consider weather factors into urban size and topography accordingly.

U.S. colleges and universities use an average of 18.9 kilowatt-hours (kWh) of electricity and 17 cubic feet (ft^2) of natural gas per square feet annually, while typical U.S. higher-education buildings sized around 50,000 ft^2 consuming more than $100,000 worth of energy each year based on Friendly Power [4]. As university campuses include various building types, (i.e. libraries, offices, laboratories, hospital/infirmary, and housing), they can be useful in testing to characterize and understand the energy consumption of a group of "mixed-use" buildings. Essentially, a college or university campus runs as an independent district with a certain size. Thus, university campuses are good examples of urban energy consumption. Also, comparing to other national-level organizations, they can be pioneer green societies, as they can make immediate decisions and policies.

All the building energy standards use historical weather data for standard development, not future weather data. Kim (2018) considered energy use over long-term climate change for use in life cycle assessment (LCA) applications with nine typical Florida residential houses [5]. Energy prediction scenarios are developed with coldest, median, and hottest climate data via eQuest. This study developed scenarios from individual buildings and the sample size was too small to generalize. Fathi and Srinivasan (2019) expanded the sample size and targeted university campus instead of residential buildings [6,7]. Principal Component Analysis (PCA) and Autoregressive Integrated Moving Average (ARIMA) techniques were selected for energy prediction with climate change. As, few input variables were used for the Machine Learning (ML) approach, it does not explain the consequences and relationship between variables and outcome.

According to Godoy-Shimizu (2018), building height was considered in several studies to estimate the performance of theoretical built forms [8]. A survey of the literature showed no previous studies used both building height and the number of stories at the same time, and the renovation age was never used. Even though Capozzolia et al. (2015) considered both building height and number of stories (#Stories) to predict heating energy consumption in schools, they had too low correlation coefficient ($0.1<\rho<0.2$) to include them in the MLR model [9].

This paper discusses the prediction of 48 university campus building energy consumption. This paper developed regression-based forecasting models for a Philadelphia-based university campus energy use under climate change.

2 Methodology

The forecasting model development process follows four-steps namely: (1) set data frame, (2) conduct descriptive statistics, (3) develop regression models, and (4) validation and prediction (Figure 1).

2.1 Step 1: Set Data Frame

In this step, three separate datasets, i.e. spatial variables, energy consumption, and environmental variables were merged to form one complete dataset (Figure 2). After combining hourly energy consumption data, hourly datasets were aggregated daily and divided seasonally.

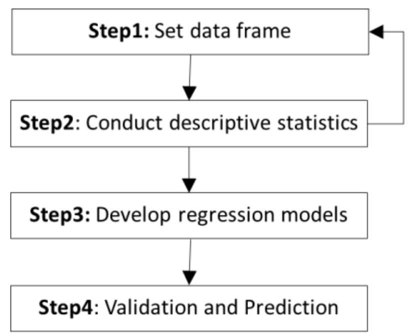


Figure 1: Research methodology flow chart

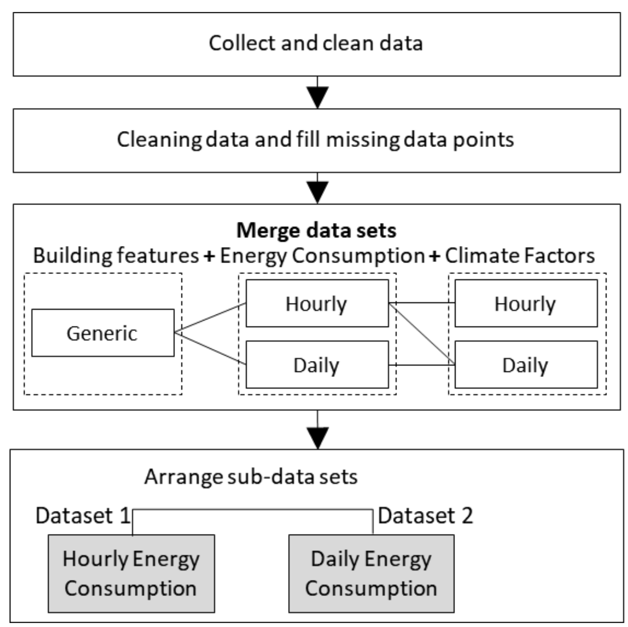


Figure 2: Step 1. set data frame

2.1.1 Spatial Variables. Spatial variables comprise of building thermo-physical properties and other power densities, which are also known as building characteristics. Spatial variables before conversion included the number of stories (#Stories), built year, the renovation ages, U-factor of roof (U-Roof, Btu/hr°F.ft^2), U-Wall (Btu/hr°F.ft^2), U-Windows (Btu/hr°F.ft^2), WWR, lighting power density (LPD, W/ft^2), and equipment power density (EPD, W/ft2). Building age (Bldg.age) was calculated from the construction year and building age since the latest renovation year (Renov.) was calculated for independent variables.

Primary data consisted of 194 buildings; however, only 46 buildings had all spatial variables. Some missing data was also obtained, including the number of floors, building height, WWR, and Gross Square Footage (GSF). For two buildings that did not have complete building characteristics, the missing data were added to create a full set of 48 buildings.

2.1.2 Energy Consumption Variables. The hourly energy consumption data were obtained from the University Physical Plant Division, which included electricity (ELC) and chilled water consumption (CHW) for 14 months from 6/30/2015 8 PM to 8/14/2016 7 PM. GSF is highly related to several variables, such as U-factors, EPD, or LPD. Therefore, GSF was included as a denominator of dependent variable by dividing energy consumption data in kBtu with GSF. Forty-eight buildings had one year of energy consumption information, and 21 out of 48 buildings were identified with electricity and chilled water consumption. In this analysis, this commonly used performance metric is assumed to be a constant with varying building size. Using building area and space functional use category as predictors of annual energy consumption may not capture all the variations, but it does accommodate many other aspects such as occupancy patterns, building equipment, and building size [10,11].

2.1.3 Environmental Variables. The environmental variables are weather factors. Regression prediction models require historical weather data and future weather data. The historical weather data was obtained from a university-based weather station for the City of Philadelphia, PA., which is an open source database that can be accessed through R via Weather Underground.

The historical weather data was obtained through open source from the nonprofit energy weather research organization, named Slipstream Group [12]. They developed the climate scenarios as a representative location for each ASHRAE climate zones with their proprietary algorithm. The mentioned algorithm uses raw climate data for future weather from the NARCCAP. Three future climate scenarios--coldest, median, and hottest for each climate zone were accessible. Future climate scenarios for PA were unavailable; however, those scenarios for Chicago, Illinois were available to represent a year of 2054 to estimate operational energy consumption under long-term climate change. PA and Chicago are both in the climate zone 5 and moist (A) category [13]. The hottest weather scenario of Chicago was chosen because it was the only one matching the PA one, based on the fact that average dry bulb temperature is supposed to increase in the median or hottest future scenarios.

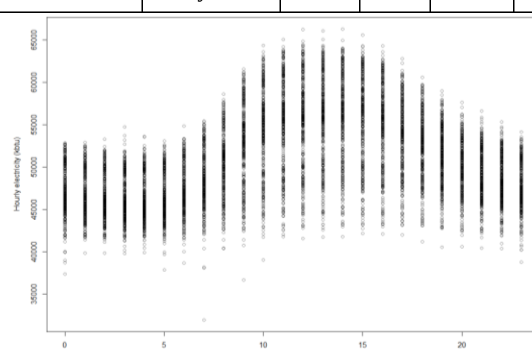
In order to choose the climate factors, common factors are selected among 15 historical weather variables and 11 future weather variables. There are four climate variables in common: temperature, humidity, pressure, and wind speed. Fathi and Srinivasan (2019) used temperature, radiation, and humidity as climate factors [7]. Ibrahim and Daut et al. (2012) also revealed a strong linear relationship between solar radiation and surface temperature [14]. However, radiation information for 2015 and 2016 in PA was not available.

In addition, pressure and wind speed are relatively insignificant factors in building energy simulation. Initially, 15 historical weather variables were used in training regression models. However, only temperature (°F) and humidity (%) were selected in order to apply to the future prediction and to gain meaningful results. The detailed process of selecting environmental variables are illustrated in section 3.1.

2.1.4 Temporal Variables. Temporal factors included year, month, day, and hour. Boiron et al. (2012) used month, day of the week, and hour to develop a regression model [15]. This can be effective to observing behavior pattern at residential building, but it does not reflect change over time despite slight improvements in R^2 of campus data (Table 1). Figure 8 showed that only electricity has an hourly consumption pattern as a cycle of the day particularly owing to occupancy rather than weather. For peak demand analysis, electricity consumption should be considered hourly, but chilled water can be done daily because there is no hourly consumption pattern (Figures 3-4). Moreover, environmental variables' change, building ages, and building ages after renovation are reflected by time. Therefore, this study excluded temporal variables for regression analysis.

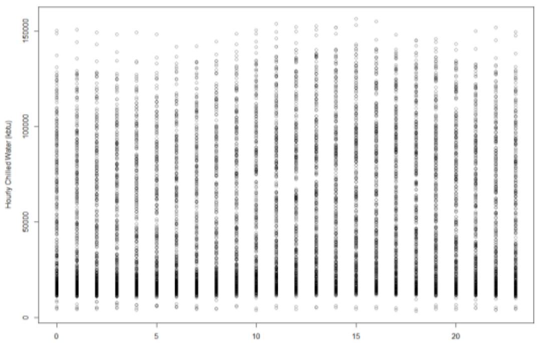
Table 1: Significance of temporal variables at different levels.

Energy Type	Temporal Resolution	Year	Day	Hour	R^2
ELC	Hourly	Y	Y	Y	0.003
	Daily	N	N	-	NA
CHW	Hourly	Y	Y	Y	0.005
	Daily	Y	N	-	0.008



X-axis: Hour (0-23), Y-axis: Electricity Energy Consumption (kBtu)

Figure 3: Hourly energy consumption patterns of ELC.



X-axis: Hour (0-23), Y-axis: Energy consumption (kBtu)

Figure 4: Hourly energy consumption patterns of CHW.

2.2 Step 2: Descriptive Analysis

Prior to statistical modeling, scatter plots and correlation-coefficient matrix plots were examined to check the relationship of all variables. Additionally, central tendency (mean, mode, median), measures of variability (range, interquartile range), variance and standard deviation, box plot, density plot, skewness, and kurtosis were checked to understand the energy consumption and relevant factors. When two datasets were merged, summaries of descriptive statistics were checked. Technical issues in merging can easily occur as the temporal variable which is not numeric.

2.3 Step 3: Regression Models

2.3.1 Checking Temporal Resolution Levels. To verify which resolution of the environmental variables is better between hour and day, regression analysis was conducted to compare them. Hourly climate factors have single point of hourly information, and daily climate factors have minimum, average, and maximum values.

2.*3.2 Developing Regression Model.* Least Absolute Shrinkage and Selection Operator (LASSO) models were developed for predicting energy consumption [16]. Lasso approach is chosen to solve the collinearity problem and to adjust the model with lambda to fit testing data by giving penalty to the training data. All variables are reviewed with p-value in the summary table, and variables which have a p-value less than 0.05 were eliminated (Figure 5). After checking all significant variables, this study used the package `leaps` in R to evaluate all the best-subset models via residual sum of squares (RSS), Mallow's Cp (Cp), Bayesian Information criterion (BIC), and Adjusted R-square (R^2). Smaller RSS, Cp, and BIC is better, and higher adjusted R^2 is better.

Three approaches were used to derive the regression model based on Akaike Information Criterion (AIC) which estimates the quality of the regression model: forward, backward, and stepwise. All three-direction regression methodologies are used to find the reduced model from the full model, which means having the least variables with the lowest AIC and high adjusted R-squared.

For the linear regression model, next step is a Variance Inflation Factor (VIF) test for checking multicollinearity. If the VIF of a variable exceeds 10, which will occur if multiple correlation coefficient for j-th variable R_j2 exceeds 0.90, that variable is said to be highly collinear, and it should be removed from the model. This step is followed by transformation and normalization. Transformation of the regression models is necessary when they violate the assumption test. The Adjusted R^2 was estimated to select best models for each energy source for forecasting.

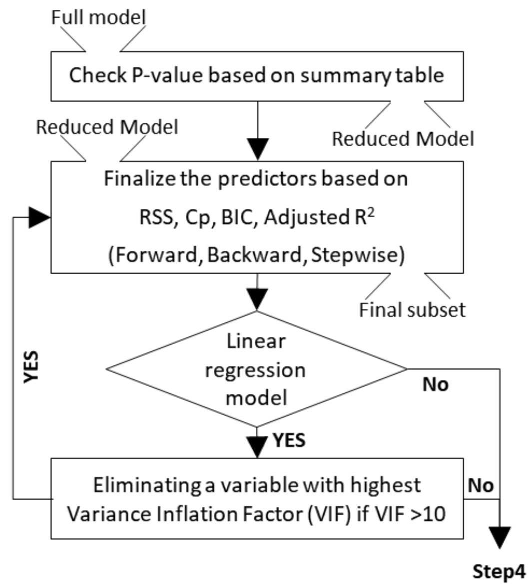


Figure 5: Step 3. develop linear regression model.

Z-score standardization was conducted to evaluate the importance of the variables with unitless [17]. Even though Z-score standardization is used for linear regression models, we can understand the impact of the independent variables by measuring without bias of units (equation 1).

$$(X\text{-mean of } X)/\text{standard deviation} \quad (1)$$

2.4 Step4: Validation and Prediction

Validation to monitor model accuracy is an essential process to check the reliability of data analysis (Figure 6). 10-fold cross validation of Lasso regression models was conducted for performance evaluation. Relative importance of predictors was checked with 95% bootstrap confidence intervals. In addition, future energy consumption in 2054 were calculated by using three regression models developed individually. This future energy consumption values are the daily average consumption of 21 buildings.

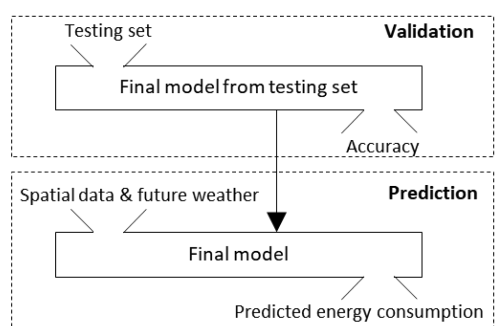


Figure 6: Step 4. validation and prediction.

3 Results and Observations

3.1 Variable Selection

3.1.1 Data Descriptive Analysis. Even though a micro-level of the weather data is "hour," using daily environmental variables led to a better explanation of the regression models. The first possibility is that hourly climate data fluctuate significantly so that it can provide more accurate prediction in the short term. Otherwise, it is difficult to normalize the fluctuation by eliminating the noises in the data. Therefore, daily weather variables are used for future energy prediction.

Data descriptive analysis consisted of three parts: Pearson linear correlation coefficient, data distribution, and peak energy demand.

3.1.1.1 Pearson Linear Correlation Coefficient. The Pearson linear correlation coefficient is a measure of the strength of the linear relationship between two variables. Multicollinearity is checked using the coefficient correlation matrix. There are strong or very strong correlations among maximum temperature, average temperature, minimum temperature, Heating Degree Days (HDD), and Cooling Degree Days (CDD). Therefore, the average temperature is used as a representation of temperature related data. Average weather variables replaced all maximum weather factors and minimum weather factors to eliminate the multicollinearity. Initially, both building height and the number of stories were considered to learn the relationship between variables and energy consumption. Even though they were both significant in the regression models and their interaction was also significant, they have a solid relation (ρ: 0.90). Also, VIF value of height was higher than 10 when both were included in the regression model. Therefore, height is eliminated in all regression models because of identically independently distribution.

3.1.1.2 Data Distribution. To observe the distribution, density plots (Figure 7) and boxplots (Figure 8) were used. These plots indicate energy consumption data are right skewed, which means these data are not normality distributed. Many outliers are observed in chilled water, but not for the electricity in boxplots.

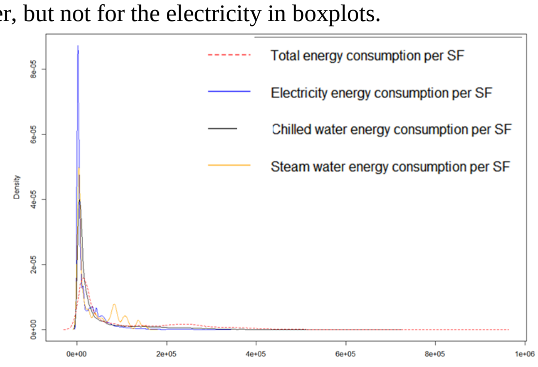


Figure 7: Density plots of energy consumption/sf

3.1.2 Relation among variables. According to Helena Bülow-Hübe (2001), as the energy efficiency of buildings increase, U-Window must decrease in order to decrease the annual heating demand, since the heating season is shortened, and useful solar gains become smaller [18].

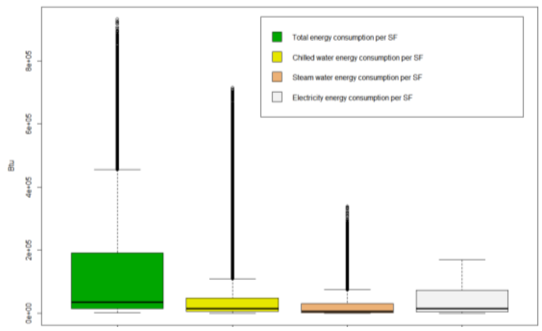


Figure 8: Box plots of energy consumption.

A junction of different materials in the building leads to lose the energy and to cause depreciation of the building quality faster. For example, windows create junctions to the wall, and they have less insulation ability comparing to the wall in most cases. Therefore, the U-Window and WWR are critical factors for building energy consumption.

Based on the slope of building age and the slope of renovation year, the influence of construction year on electricity is more critical comparing to chilled water in terms of energy consumption by building aging. In addition to the Pearson linear correlation coefficient, two-dimensional and three-dimensional plots are examined to understand relationships among variables. The 3D plots show that the chilled water consumption increases when the temperature is higher. The temperature is not related to electricity considered both building age and renovation age.

3.2 Analysis of Regression Model

Table 2 shows variables that are significant in the MLR model. More variables show significance to the dependent variable in hourly models, but their R^2 were lower than daily models.

Table 2: Significant Explanatory Variables

Data resolution		Hour	Day	Hour	Day
Energy source		ELC	ELC	CHW	CHW
Spatial variables	X_{1U_Wall}	0	0	0	0
	$X_{2\ U\_Window}$	0	0	0	0
	$X_{3U\text{-}Roof}$	0	0	0	0
	X_{4WWR}	0	0	0	0
	$X_{5Height/\#Stories}$	0	0	0	0
	$X_{6Bldg.Age}$	0	0	0	0
	$X_{7Renov.}$	0	0	0	0
	X_{8EPD}	0	0	0	0
	X_{9LPD}	0	0	0	0
Environmental variables	$X_{10Temp.}$	0	X	0	0
	$X_{11Humid.}$	0	X	0	0
	X_{12HDD}	0	X	0	0(X/0)
	X_{13CDD}	0	X	0	X(0/X)

0 represents that it is a significant variable
X represents that it is an insignificant variable
(A/ B) A is in Summer and B is in Winter season

3.2.1 Electricity Consumption. Previous research showed that climate change contributed to increased electric consumption. However, that research was not related to a campus setting. Most of the campuses used district energy systems, i.e. centralized chilled water plants instead of individual chillers in buildings. Electricity supply and demand are also becoming weather-dependent across the United Kingdom [19]. Another study found that annual consumption in the eastern China residential sector rose by 9.2%. This was within the context of a 1 °C rise in annual global mean surface temperature [20]. On one hand, residential electricity demand is very responsive to temperature fluctuations while on the other hand, industrial electricity demand is the least responsive to temperature fluctuations.

Interation terms improved regression models, but they were excluded for the better interpretation with less complexity. In the case of this study, R^2 value is 0.8429 with both interaction terms: U-Window * WWR, and the number of stories and building height (Table 3).

Table 3: R^2 of MLR by the presence of interaction terms.

Interaction term	Presence of variable		
#Story * Bldg. height	O	X	O
U-Window * WWR	X	O	O
R^2	0.70	0.83	0.84

Forward, backward regression and stepwise regression showed the different results, so forward regression is used for final model. Backward regression and stepwise regression results were used as a reference. Variables can be selected by adding a variable which may render variables already in the model non-significant in the forward regression methodology. Only the variable that was added at the last step has been tested for significance. All other variables are tested when they entered the model. Therefore, the final model for electricity consumption is chosen according to backward and stepwise regression.

Figure 9 showed that having all variables in the regression model was valid. However, interaction terms and building age after the latest renovation were removed after Lasso approach. Therefore, final model has eight variables (Table 4). RMSE were inspected for training set and testing (validation) set with 10-fold cross validation (Figure 9). RMSE decreased as the number of variables increased.

Electricity is used for cooling to control the indoor temperature in residential buildings and most of commercial buildings, so electricity demand will increase as temperature increases. However, in the case of this project, chilled water is used for cooling and, therefore, the regression result showed that temperature is not related to electricity. Thus, environmental variables are not related to electricity consumption when it is not used for cooling.

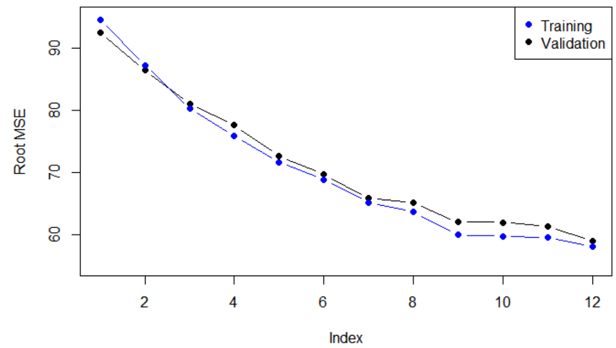


Figure 9: RMSE of training and validation data sets to choose best subset for ELC.

The relative importance for each predictor were analyzed by using “relaimpo” function in r. As a result of this analysis, EPD was the most important variable contributing to the electricity consumption (Figure 10). Building height and building age followed EPD as important predictors to explain electricity consumption.

Table 4: Coefficient of Regression models for ELC.

ELC	Variables	Lasso	Z-score normalization	Relative importance
	Intercept	189.12	215.61	
Spatial variables	X_{1U_Wall}		14.53	6
	$X_{2\ U\_Window}$		-36.29	5
	$X_{3U\text{-}Roof}$		27.30	4
	X_{4WWR}		-17.14	6
	$X_{5Height}$	0.27	24.35	2
	$X_{6Bldg.Age}$		-34.12	3
	$X_{7Renov.}$		68.21	9
	X_{8EPD}	1.76	67.59	1
	X_{9LPD}		8.19	8
	$X_{10.\ Temp}$			11
	$X_{11Humid.}$			10

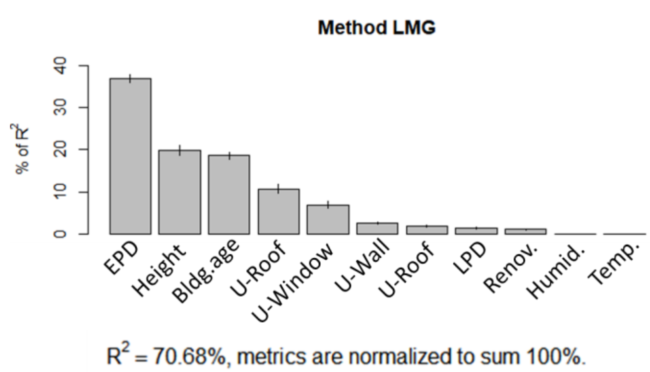


Figure 10: Relative importance for electricity with 95% bootstrap confidence intervals.

3.2.3 Chilled Water Consumption. For chilled water consumption, we followed the same process without VIF check because the regression model for chilled water was non-linear. RMSE were inspected for training set and testing (validation) set with 10-fold cross validation (Figure 11). RMSE of validation were higher than training, but RMSE plot showed that decreased as the number of variables increased likewise electricity. The lowest RMSE from cross-validation was 192.82 with 0.6214 of adjusted R-squared when the number of variables is 16 with two interaction terms and quadratic terms. However, interaction terms were removed for interpretation of individual variable in final model to predict chilled water (Table 5).

As a result of relative importance analysis, temperature was the most important variable contributing to chilled water consumption (Figure 12). U factor of window and roof came after temperature as important predictors to explain electricity consumption, but temperature took accounts most of part comparing the rest of predictors.

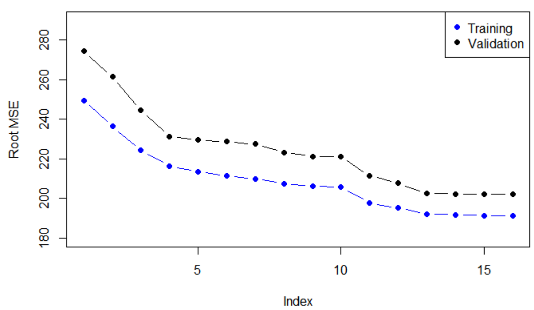


Figure 11: RMSE of training and validation data sets to choose best subset for CHW

Table 5: Coefficient of Regression models for CHW.

CHW	Variables	Lasso	Z-score normalization	Relative importance
	Intercept	732.89	107.29	
Spatial variables	X_1^2 U_Wall	-2158.45	67.28	11
	X_1 U_Wall	2287.33	-44.70	
	X_2 U_Window	-213.77	-72.40	2
	X_3U-Roof	335.93	90.70	3
	X_4WWR	351.22	51.23	9
	X_5#Stories	10.53	47.89	8
	X_6^2Bldg.Age	0.04	43.30	5
	X_6Bldg.Age	-7.03	-51.74	
	X_7Renov.	2.71	68.21	10
	X_8EPD	-7.71	-34.26	4
	X_9LPD	75.28	42.52	6
Env.	X_{10}^2 Temp	0.25	59.34	1
	X_{10}. Temp	-14.92	176.97	
	X_{11}Humid.	94.29	12.74	7

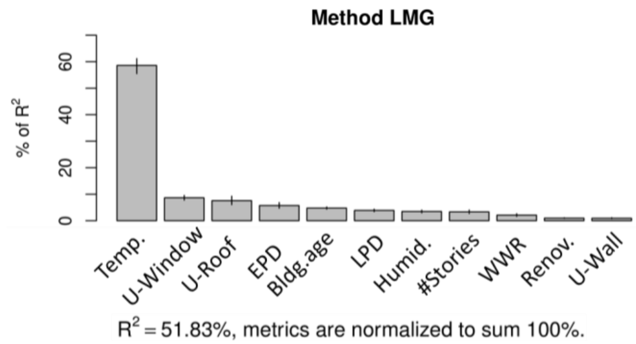


Figure 12: Relative importance for CHW with 95% bootstrap confidence intervals.

Derived regression models were used to estimate energy consumption in 2016 and 2054 (Table 6). According to the prediction result from regression models, chilled water consumption will increase more than twice in 2054 as temperature increases due to global warming. Electricity consumption will slightly decrease in 2054.

Table 6: Prediction via regression models

	ELC (linear)	CHW (Poly)
Mean of the predicted value in 2015-2016	214.08	582.96
Mean of the predicted value in 2054	197.30	1263.41

4 Conclusion

This paper introduced the main approaches and methodologies used to estimate urban building energy consumption. It focused on regression analysis narrowed to the bottom-up approaches. The regression model in energy prediction is still a robust model approach. The process of developing statistical regression models enables us to understand the relationship between each variable and energy consumptions. However, regression models are suitable to predict energy consumption in the long term because the sensitivity level highly depends on the input variables.

According to the regression analysis, chilled water consumption increases, as temperature increases when we applied the future weather scenario in 2054 to the regression model. Both the number of stories and building height are significant variables in the regression models, but building height is removed because of the high VIF values, which indicated high multicollinearity. The slopes of building height are positive and the slope of the number of stories are negative for all energy sources in spite of positive relationship between them. Since other energy modeling approaches do not need to consider collinearity, they can be used and observed in detail.

This study identified that EPD was the most important variable contributing to the electricity consumption and temperature is the most important variable for chilled water consumption. In addition, the renovation year affects chilled water consumption as well as construction year in terms of building aging.

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