Method for estimating energy use intensity based on building façade

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ABSTRACT: Commercial and residential buildings are tremendous users of energy, accounting for more than 72% of electricity use in the U.S. Among the main building performance factors (i.e., enclosure, system, and control), that influence a building's energy performance, building façade features are one of the major parametric elements. The recorded Energy Use Intensity (EUI) of existing buildings performance come from relevant organizations (such as CBECS and USGBC), which contain aggregated energy performance information (based on the ranges of certain parameters), but it is difficult to identify the specific condition of each building category within a selected climate zone. In addition, the averaged performance data is too general to determine if a specific building is energy efficient or not. On the other hand, it is very time-consuming to develop a simulation model in software to each case, which also needs very detailed information about geometry, system, and operation schedule and control modes. This is because an accurate energy performance prediction mainly depends on a variety of detailed data about indoor thermal conditions, mechanical system performance, occupancy level, etc. In this research, a vision-based performance prediction model was developed to estimate building energy consumption based on simplified façade attribute information and weather conditions. Building façade features, including shading, window-to-wall ratio, orientation, surface-to-volume ratio, etc., were collected along with the energy performance records from New York City building energy benchmarking database. Based on this training dataset, a prediction model was established to estimate annual energy use. The developed estimation model adopted architectural physical attributes and their dynamic ambient environmental conditions as input variables. This prediction approach will provide a more specific baseline and goal especially in the pre-design phase, it also could asses EUI by a minimum amount of data.

KEYWORDS: EUI, Baseline Model, Regression, Façade Features

INTRODUCTION

In 2010, the U.S. consumed 97.8 quads of energy, which represented 19% of global energy consumption (Program and Efficiency 2012). The buildings sector in the United States, including residential and commercial buildings, accounted for about 41% of primary energy consumption in 2010. Space cooling, space heating and lighting are the dominant end uses, which accounted for about 52% of total energy consumed by buildings sector. Façade features, such as exterior wall type, glazing type, shading type, window-to-wall ratio, etc., have a great influence on space heating, cooling and even lighting demand (Shan 2014). A good building façade design will be greatly useful to reduce energy demand by selecting appropriate façade features according to local climate characteristics.

Energy Use Intensity (EUI) represents a building's energy use as a function of its size or other characteristics, which is calculated by dividing annual building energy consumption in one year by the total gross floor area as kBtu/sf. EUI is a very important indicator (Andrews and Krogmann 2009) to evaluate building energy performance and energy saving potential. Annual EUI could also be the baseline for building owners and designers to set a reasonable energy reduction goal for the following years.

Architecture 2030 was established to promote energy reduction by changing buildings into a solution of global energy crisis (Architecture 2030 2011). Architecture 2030 uses the Commercial Buildings Energy Consumption Survey (CBECS) 2003 data, which provides national and regional medians as the baseline. CBECS is a national sample survey ("About Commercial Buildings Energy Consumption Survey" 2012) that collects information on the stock of U.S. commercial buildings, including their energy-related building characteristics and energy usage data. Energy use intensity (EUI) baseline currently relies on a national or local energy usage average based on census division, climate zone, building size or year constructed. These factors can't represent the specific physical condition of each building, since it doesn't consider individual building features and local climate condition. The average EUI value based on certain census division, climate zone or HDD/CDD (heating degree day/cooling degree day) range, is also too general to categorize weather condition.

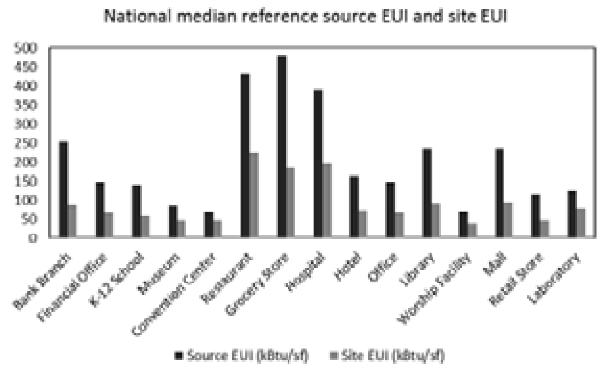

Figure 1: National median reference EUI of selected building types. Source: (Energy Star 2014)

Demands from urban planners and building designers require a new method to predict building energy use through a simple way at the beginning of design stage, which could be based on easily accessible information. Many mathematical methods were used to calculate building energy use other than computer simulation which depends on building detailed information input. Rajesh et al. (Kumar, Aggarwal, and Sharma 2013) used Artificial Neural Network (ANN) to estimate total energy use for heating and carbon emissions. The results presented the total load for a six stories building by using ANN method which collected data representing the past history and performance of the real system. Decision tree method is another approach to predict building energy use in practice. Zhun et al. (Yu et al. 2010) demonstrated that a decision tree method can predict building energy demand by 93% accuracy for training data and 92% accuracy for test data. Case-based reasoning (CBR) was used by Danielle et al. (Monfet et al. 2014) to forecast building energy demand and the model was validated by real monitored data. The advantages of using CBR include easily updating feature, simple understanding of reasoning, ability to deal with missing information and large amounts of predictors. Regression model based on basic visualized building façade features is a feasible alternative to estimate building energy consumption instead of using average data from survey or running simulation in complicated software. The main goal is to develop a customized baseline model considering specific façade features and local climate condition. Due to its simplicity and quick processing time, the model would be applicable to set a reasonable EUI reduction baseline for building performance management and improvement. In addition, the impact of basic façade features on energy performance in different climate zone could be clearly presented by sensitivity analysis in order to provide a guideline of how façade features could influence building energy use based on real energy database. The result could also draw more attention on the significance of building energy use disclosure to public from government benchmarking policy.

1.0 METHODS

Multiple regression models are developed to predict energy performance by entering a minimum number of façade data. Instead of using details of building information, like construction thermal properties, mechanical system, operation schedule, etc., multiple linear regression is adopted with easily accessible façade features, which include building height, orientation, volume, floor area, façade area, site area, window-to-wall ratio, volume-to-façade area ratio, etc.

There are mainly three parts of the methodology: data collection (DC), data processing (DP), and model development (MD) as represented in Figure 2.

1. For data collection, generally 2 types of data should be collected. One is real energy use data, another is corresponding façade feature. Energy use data is presented by Energy Use Intensity (EUI) as the target metric from building energy benchmarking and disclosure data by local government. On the other hand, façade features are collected by using different methods which contain manual estimation (visual reading and physical model rebuilding), existing building model reading (SketchUp etc.) and direct information collection from design drawing or specification.

Other potential factors like built year and HDD/CDD could also be easily obtained from open resources.

2. Data processing section is served as data preparation for the following model development. For annual EUI model development, this step could be skipped since annual EUI data is the basic data provided by different building energy resources.
3. Finally, multiple linear regression is used to develop the EUI estimation model package based on collected façade information and EUI data. In this section, the significance of each predictor and correlation between predictors and response could also be analyzed with the consideration of local code requirements, design strategies and best practices. Other regression methods would be used for comparison, which include stepwise regression. In the end, all regression models should be validated by appropriate method.

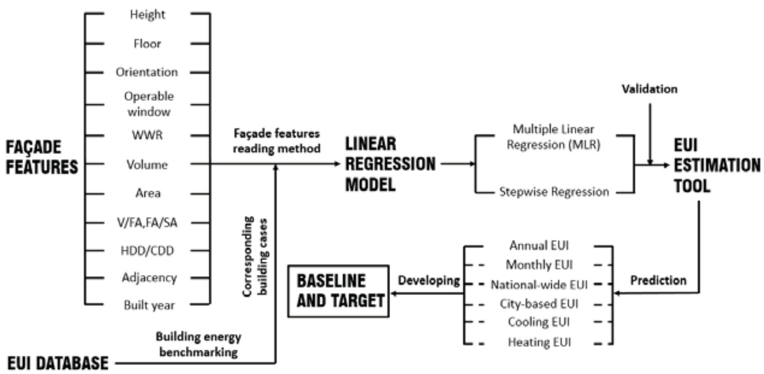

Figure 2: Methodology.

The predicted outcome of this research is a new EUI estimation package, which could provide building EUI baseline at different scale. In this paper, the annual office EUI estimation model in New York City is the expected result.

1.1. EUI data collection

Building energy benchmarking is a method to get building energy data as a baseline to compare to other properties performance. It will give owners a better understanding of how much energy their buildings exactly consume for a time period and how much energy reduction potential they can get when adopting energy efficient measures. To accomplish the task of benchmarking, the energy monitoring and recording are needed, and the data should be submitted by using a common format to be available to put into database. The most commonly used tool is Portfolio Manager developed by EPA (Energy Star 2014), which is normally used to track and evaluate energy use for commercial buildings. The benefits of using benchmarking (Milliken and Jones) to keep track of building energy use are listed in the following figure 3.

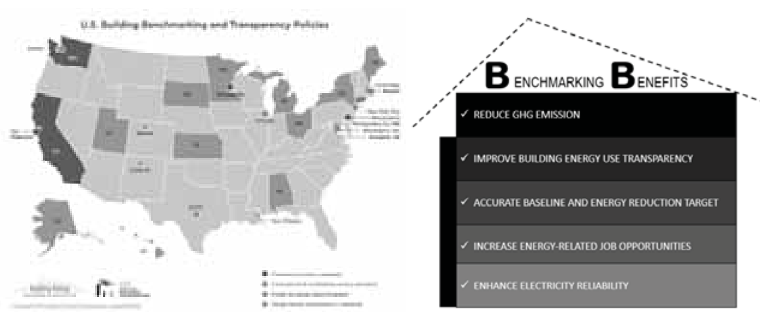

Figure 3: U.S. Building benchmarking and transparency policies. Source: (IMT 2014)

In U.S. there are 9 cities (IMT 2014) which committed to implement energy benchmarking and disclosure programs for commercial buildings (Cox, Brown, and Sun 2013), which include Seattle, San Francisco, Austin, Minneapolis, Cambridge, Boston, New York City, Philadelphia, Washington, DC, etc. In New York City, benchmarking policy of Local Law 84 (LL84), part of Greener, Greater Buildings Plan (GGBP) was adopted in 2009 (GGBP 2013), which requires all non-residential buildings with floor area over 50,000 square feet to submit and disclose their building energy and water data to the city. The results show that the median source EUI for office properties in 2010 and 2011 are 213.3 kBtu/sf and 207.3 kBtu/sf and the median Energy Star score increased from 64 to 67.

In this paper, office building energy benchmarking data in New York City are used to develop an exemplary regression model which could predict annual energy use for office buildings in New Your City. 99 office buildings in Manhattan, New York City from the benchmarking database are firstly selected. Then 28 buildings with existed SketchUp model are further sorted out in order to read the façade features easily and accurately. In most selected buildings there are 2 years of reported energy data available (24 of them have both years). In total 50 datasets with full information of both real EUI and façade features are the basis for the further regression analysis.

1.2. Façade feature definition

All building façade features could be easily readable without knowing detailed information. Generally, geometry attributes are the basic predictors. Roof or wall R-value, window U-value and SHGC, etc. are not used since the fabric information are not accessible without the permission from owner or designer. The original 17 predictors are showed in the table below which explains the definition of each parameter.

Table 1: Predictors definition and explanation.

No.	Façade feature	*Definition*
1	*Height*	From open air pedestrian entrance to highest occupied floor[1]
2	*Floors*	Total occupied stories or levels[2]
3	*Orientation*	Positing of a building with respect to the North[3]
4	*Operable window*	Window could be open or close based ventilation need[4]
5	*Volume*	Inner space volume enclosed by external envelope
6	*WWR*	Window-to-wall ratio (total window area/total exterior wall area)
7	*Window Area*	Total glazing area
8	*Façade Area*	Total area of all parts of the structure's façade
9	*Site Area*	Total site area within fixed boundaries
10	*Floor Area*	Total floor area inside the building envelope
11	*V/FA*	Ratio of volume to façade area
12	*V/SA*	Ratio of volume to site area
13	*FA/SA*	Ratio of façade area to site area
14	*HDD*	Heating degree day (the demand for energy to heat a building)
15	*CDD*	Cooling degree day (the demand for energy to cool a building)
16	*Adjacent Building*	If adjacent building exists to cast shading on objective building[5]
17	*Built Year*	Year of construction complete

Note: 1. Height is measure from the level of the lowest, significant, open-air, pedestrian entrance to the finished floor level of the highest occupied floor within the building (Council on Tall Buildings and Urban Habitat).

2. Floors refer to the total levels of a building which could be used by occupants.

3. Long axis along with North-South is quantified as 1, NE-SW is 2, E-W is 3, SE-NW is 4.

4. With operable window is quantified as 1, without operable window is quantified as 0.

5. No adjacent building is quantified as 0, while adjacent building on the north side is 1, others are clockwise defined by 2 to 8.

In this research, a basic assumption is that EUI could be estimated only based on simple façade features as well as a few other factors, like HDD/CDD which represents dynamic local weather condition. Another factor built year is used to take all the requirements by code in each time period into consideration. It assumed that after the first national/local building energy code established a building had to meet the requirements of corresponding codes or standards, including fabric thermal performance, system efficiency, ventilation rate requirements, etc. The built year is easy to obtain as a basic building information. In addition, since in urban context, adjacent building will cast shades on objective buildings which in turn will influence heat gain through the façade especially glazing area, adjacency is another factor which is collected for regression analysis.

1.3. Regression method

To develop regression model, many tools could be considered for analysis, like SPSS Statistics (IBM 2014), MATLAB (MAthWorks 2014), etc. In this research, another statistical analysis tool, Minitab® 17 (Minitab 2014) is used for data analysis and regression model development. By using Minitab, a large amount of data can be processed (Minitab 2013) for basic statistical analysis, regression and correlation analysis, hypothesis tests, model validation, prediction, and graphs making, etc. All façade features and EUI data can be input as basic training samples. The correlation between each factor and EUI could be analyzed by calculating Pearson's correlation coefficient. Then different regression models could be compared to determine the most accurate model which is sufficient to predict response values for new observations.

Rather than only using one independent variable as predictor in regression, multiple linear regression (MLR) has multiple independent variables. The same purpose as simple linear regression is to develop the relationship between response and predictors and predict the new response with a new set of predictors at an acceptable confidence level. The multiple linear regression is presented as the following form:

$$EUI = a + b_1x_1 + b_2x_2 + b_3x_3 + \cdots + b_kx_k + \varepsilon$$
(1)

Where
a is the constant while $b_1,\cdots b_k$ are the regression coefficients, $b_1,\cdots b_k$ are the significant predictors and ε is the random error.

In addition, when there are a large number of predictors to be used in regression, stepwise regression should be used to removing the least significant predictor at each step. The order of removed predictors also indicate the significance which could be analyzed to determine which predictor is the most important one in a certain area. This is also called backward elimination (Support Minitab 2014). This automatic process is useful to identify the most significant predictors. To analyze the results of regression models, multiple indicators could be calculated to evaluate the characteristics of the corresponding models. The main indicators are listed in the table 2.

Table 2: Key indicators in regression model.

No.	Indicator	*Explanation*	*Accepted Range*
1	*Pearson Correlation*	Whether 2 continuous variables are linearly related	(-1,1)/closer to 1
2	*P-value*	The probability of obtaining a test statistic	(0,1)/closer to 0
3	*VIF*	Multicollinearity (correlation between predictors)	NA
4	R^2	Pct. of response variable variation can be explained	(0,100%)/closer to 100%
5	R^2 *(adj)*	R^2 adjusted for the number of predictors in the model	(0,100%)/closer to 100%
6	R^2 *(pred)*	Models predictive ability	(0,100%)/closer to 100%
7	*Durbin-Watson*	whether the correlation between adjacent error terms is 0	(1,3)/closer to 2
8	*Error rate*	discrepancy between the estimated values	NA/closer to 0

2.0 RESULTS AND DISCUSSION

2.1. Basic data analysis

All datasets with façade features were firstly analysed by dividing into different groups. The results represent the correlation between reported site EUI with each predictor through interval plotting. The confidence interval is 95% by default which indicates 95% probability from the future experiment within this interval.

Figure 4 indicates the correlation between site EUI and construction year, which divided data into 2 groups (before and after 1980), since the first New York state energy code was established in 1979 (U.S. DOE 2014). Office buildings that were built before 1980 have higher mean value of 102.06 kBtu/sf than 92.74 kBtu/sf after 1980. Even the confidence intervals are slightly overlapped, but with more strict requirements of building performance from improved energy code, buildings consume lower energy as expected. Tall buildings were grouped into megatall (more than 600 ft), supertall (300 to 600 ft) and tall (165 to 300 ft) for the analysis of height (CTBUH 2013). Figure 5 shows the significant difference of energy use for different height tall buildings. Megatall buildings consumed the highest energy, followed by super tall and tall buildings. National median site EUI of 67.3 kBtu/sf is only in the tall building EUI range. The overall 40% of

WWR for prescriptive fenestration requirement (NYCECC 2011) was used to divide all datasets into 2 groups and the results presented that WWR is a significant factor to influence office building energy use in terms of heating and cooling load by solar heat gain. The mean value of buildings with over 40% WWR was 107.88 kBtu/sf compared to 84.81 kBtu/sf for lower WWR buildings. Buildings with operable windows consumed less energy since the mixed mode of natural ventilation and mechanical ventilation is more energy efficient, which was proved by the fact that the mean value 84.9 kBtu/sf for buildings with operable window is lower than 104.25 kBtu/sf for buildings without operable window.

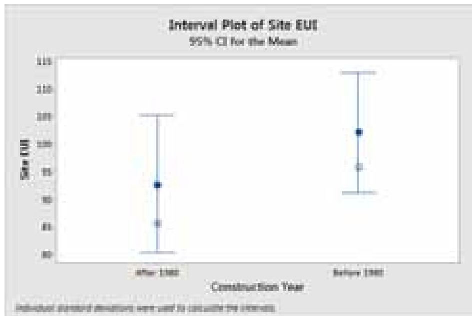

Figure 4: Site EUI (kBtu/sf) and construction year.

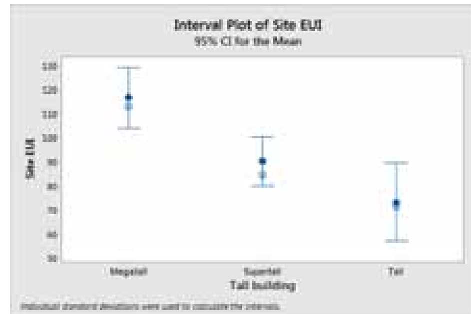

Figure 5: Site EUI (kBtu/sf) and building height.

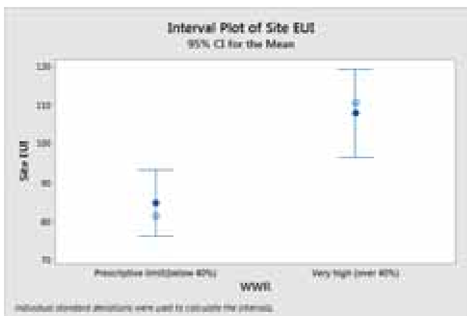

Figure 6: Site EUI (kBtu/sf) and WWR .

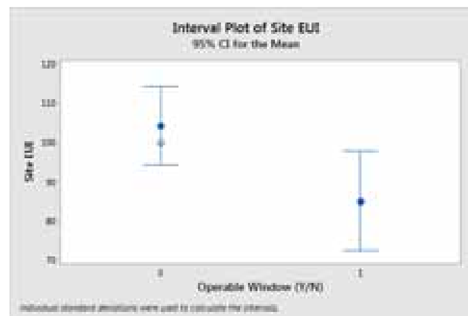

Figure 7: Site EUI (kBtu/sf) and operable window.

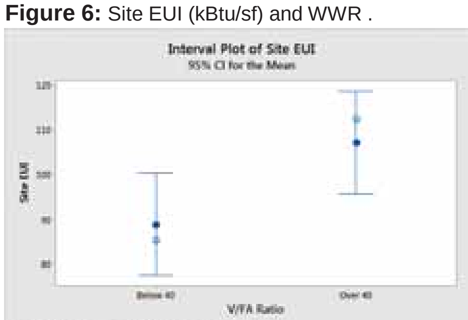

Figure 8: Site EUI (kBtu/sf) and V/FA ratio.

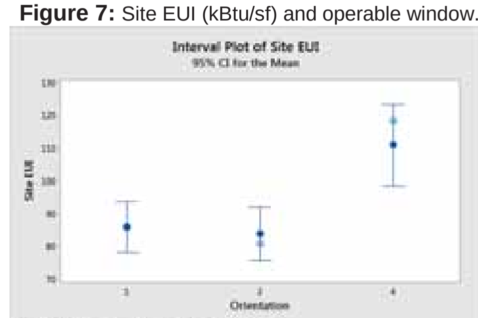

Figure 9: Site EUI (kBtu/sf) and orientation.

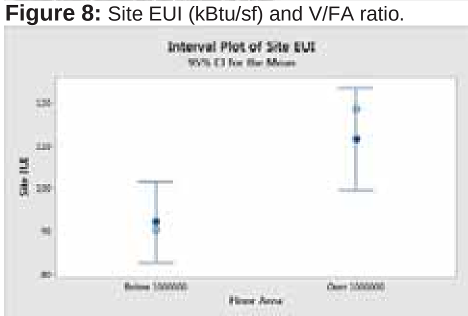

Figure 10: Site EUI (kBtu/sf) and floor area.

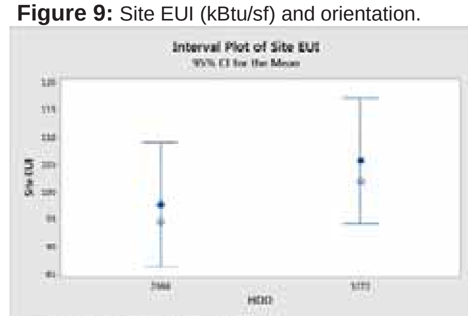

Figure 11: Site EUI (kBtu/sf) and HDD.

V/FA ratio stands for the compactness which has significant impact on heating load. Figure 8 illustrates that buildings with V/FA less than 40 had the lower mean EUI of 89.03 kBtu/sf, which means in this heating dominated area, compact buildings are not necessary consuming less energy than buildings with greater façade area. It also depends on glazing and exterior wall thermal performance and other factors. Figure 9 shows there was no significant difference of EUI between N-S orientation and NE-SW orientation while buildings with NW-SE had the highest mean EUI value of 111.01 kBtu/sf. It is because that the main façade facing south west has more heat gain through direct sun exposure. Figure 10 indicates that buildings floor area over 1000000 had significantly higher energy use than smaller area buildings. Another important predictor is heating-degree day which is extremely important for heating demand of a buildings. In total there are only 2 years energy data used in this regression research but it is clear that most buildings consumed more energy in 2011 than in 2012, which is showed in Figure 11, since the HDD of 3272 in 2011 is higher than 2988 in 2012 while other façade features didn't change within these 2 years.

2.2. MLR and stepwise regression

EUI can be predicted by the façade features through 2 methods: MLR and Stepwise Regression. The results are showed in table 3. Total façade area was replaced by 8 different direction façade area. In MLR, all 25 predictors were included in the every model. The R^2 value indicates that all predictors could explain 77.64% of the variance in EUI while the adjusted R^2 means only 56.18% of EUI variable variation can be explained by its relationship with predictor variables. D-W statistic is closer to 2, which means there is no significant autocorrelation. Only orientation and floor area are significantly related to annual EUI at an α-level of 0.05 since P-values are close to 0. VIF values for coefficients are greater than 10 which means the regression coefficients are poorly estimated due to severe multicollinearity.

By comparison, R^2 from stepwise regression means 88.15 % of the variance in EUI. The adjusted R^2 is also improved when compared to MLR. The predicted R^2 value is 77.72% which indicates the model does not appear to be overfit and has adequate predictive ability since it's close to R^2 and adjusted R^2. All P-values of corresponding predictors are less than 0.05. The results showed the advantage by using stepwise regression is not only to improve each indicators of accuracy but also to identify a useful subset of predictors. The stepwise process systematically added the most significant variable or removed the least significant variable during each step. As a result, predictors including height, WWR, orientation, operable window, floor area, V/SA ratio, HDD as well as south and west façade area are the most important factors which have greater impact on energy use for office buildings in New York City.

Table 3: MLR and stepwise regression coefficients and indicators.

Determination	*Multiple Linear Regression*		*Stepwise Regression*	
R2/ R2 (pre)	77.64%	-	88.15%	77.72
Predictors	Coef	P-value	Coef	P-value
Constant	27302	0.174	-75.3	0.047
Height	0.087	0.593	0.1553	0.000
Floors	0.06	0.979	-	-
Built year	-0.339	0.586	-	-
WWR	0.542	0.507	0.719	0.000
Orientation	26	0.033	18.77	0.000
Operable Window	-29.9	0.15	-19.65	0.000
Volume	0	0.995	-	-
Window Area	0.000149	0.55	-	-
Site Area	0.00035	0.729	-	-
Floor Area	-0.00007	0.031	-0.000054	0.000
V/FA	-0.84	0.809	-	-
V/SA	0.185	0.515	0.1352	0.001
FA/SA	-10.29	0.11	-9.47	0.000
Adjacency	-1.85	0.502	-	-
HDD	5.86	0.178	0.0324	0.006
CDD	-22.7	0.181	-	-
N Façade Area	-0.01101	0.201	-	-
S Façade Area	0.125	0.23	0.001340	0.000
W Façade Area	-0.00249	0.2	-0.000634	0.009
E Façade Area	-0.0889	0.243	-	-
NW Façade Area	-0.000146	0.806	-	-
NE Façade Area	-0.00017	0.892	-	-
SW Façade Area	-0.000118	0.849	-	-
SE Façade Area	0.000571	0.471	-	-

Figure 12 illustrates that the predicted EUI from the developed MLR and Stepwise regression models, and the average error rates are 9.03% and 6.70% respectively. Both of the results are less than 10%, which are better the static baseline from CBECS and TargetFinder. In addition, the dynamic results calculated by regression model are more meaningful and realistic as energy reduction baselines. Stepwise regression has higher predictive ability to estimate new observations, which could be used as the baseline estimation model.

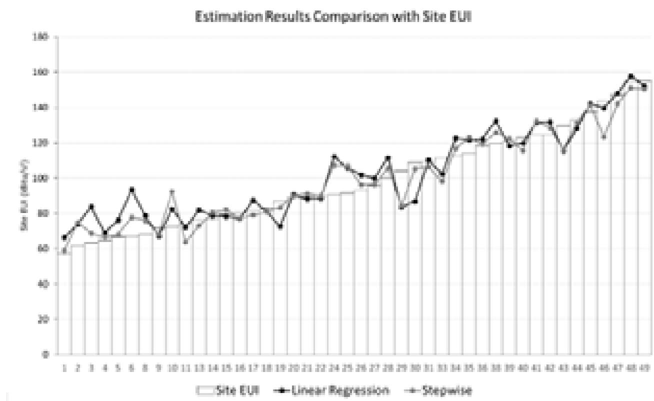

Figure 12: Estimation results and site EUI.

CONCLUSIONS

To estimate building energy use, both simple multiple linear regression model and stepwise regression model were used and the results showed that stepwise is more reliable and accurate to predict EUI than MLR. Building EUI estimated by basic façade features is more specific since it considers the individual building attributes as well as local climate condition. The result is dynamic according to different features input which is better than one constant and median baseline from CBECS as the baseline. In addition to assist to EUI benchmarking for improving building energy efficiency, the research potential outcomes could be applied for new construction to provide a more accurate baseline and energy reduction target at the predesign stage and to evaluate basic façade design decisions. While for existing buildings, it can help to estimate EUI when there is no detailed building information available for deep simulation and get a reasonably correct energy consumption rate by inputting a minimum amount of data. Customized baseline could be more acceptable for building owners to know building energy saving potential and adopt measures to improve energy efficiency, which in turn will benefit energy conservation for the whole society.

The limitation of the simplified EUI estimation model is the limited range of application and the assumption that other important factors can be incorporated into “built year”. In this paper, EUI estimation model can be only used for office buildings in New York City. More data are needed to generate more regression models for different function of buildings and different climate zones or locations. In addition, other factors also have great influence on building energy use, such as envelope thermal properties, HVAC system efficiency, lighting fixtures, even building use schedules. Regression model based on simple façade features is more useful when no detailed data are available for energy use calculation no matter by simulation or real-time monitoring, so one of the basic precondition of using regression model is assuming when building was built in a certain period it had to meet all fabric and system efficiency requirements for corresponding code or standard. The future work could also consider the extended predictors when more information are available.

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