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Energy Use Intensity Estimation Method Based on Façade Features

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Abstract

In the U.S., over 72% of the total generated power is consumed by commercial and residential buildings. Among a building's envelope, system, and control, which significantly influence the building's energy performance, façade is a major parametric element that accounts for 70% of its energy performance. Compared with the internal mechanical system and operation schedule, façade features information is relatively easy to obtain from the visual aspects of a building. By adopting several key façade attributes, a customized energy use intensity baseline model can be generated by considering building design features. Therefore, instead of using traditional and complicated simulation methods, a mathematical model can be established to estimate EUI baselines based on sufficient existing building practices data. In a national building performance survey, data such as CBECS and building energy usage are collected for a large database to provide performance guidance for new or renovation building projects. Unfortunately, averaged performance data are too aggregated and generic to identify specific conditions for each building category in a specific climate condition. 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. Data about building façade features, including orientation, façade area, window-to-wall ratio, volume, surface-to-volume ratio, etc., were collected along with energy use public disclosure. A prediction model, based on this dataset, was established to estimate building energy use intensity as a function of façade features. This prediction approach will provide a more realistic EUI estimation tool for calculating an energy use baseline and will enable real-time energy usage monitoring and management of each target building.

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Keywords: Energy Use Intensity; Façade Features; Regression Model;

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1. Introduction

In 2010, the U.S. consumed 97.8 quads of energy, which accounted 19% of global energy consumption [1]. In the United States, the buildings sector, including both residential and commercial buildings, represented about 41% of primary energy consumption. Among different building energy uses, 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 [2]. To reduce energy demand a good building façade design is greatly significant by determining the optimum façade features according to local climate.

Energy Use Intensity (EUI) presents a building's energy use in terms of its function, size and 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 [3] to evaluate building energy performance and energy saving potential. Annual EUI could also be used as the baseline indicator for building owners and designers to set a comparable energy reduction goal for the following years. In addition, demands from urban planners and building designers require a new method to predict building energy use by using a simple way at the early design stage, which could use easily accessible information like building façade features.

Benchmarking indicates tracking and recording each building's energy use to establish a baseline of energy performance. By using an equitable metric to compare each building energy use with its past performance as well as equivalent and similar buildings, building owners and managers will be capable of knowing their building energy use more deeply and the potential of improving efficiency and making the most cost effective decision. Over 35,000 buildings used U.S. Environmental Protection Agency's (EPA's) ENERGY STAR Portfolio Manager to benchmark energy use [4].

Architecture 2030 [5] was established to promote energy reduction by changing buildings into a solution of global energy crisis. This action adopts the Commercial Buildings Energy Consumption Survey (CBECS) 2003 data, which provides national and regional medians as the baseline. CBECS is a national building sample survey [6] that collects information on the stock of U.S. commercial buildings, including their energy-related building characteristics and energy usage data. Figure 1 presents an example of national median reference EUI of selected building types. 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, which can hardly represent the specific physical condition of each building and other building characteristics, since it doesn't consider any individual building feature. Besides, the average value from certain census division, climate zone or HDD/CDD (heating degree day/cooling degree day) range, is too general to categorize weather condition.

Nomenclature

EUI	energy use intensity
CBECS	Commercial Buildings Energy Consumption Survey
HDD	heating degree day
CDD	cooling degree day
DC	data collection
DP	data processing
MD	model development
WWR	window-to-wall ratio
V	volume
FA	façade area
SA	site area
MLR	multiple linear regression

One of the methods is to use regression model incorporating basic visualized building façade features to estimate building energy consumption instead of using average data from survey or running simulation by using complicated software. The main objective is to develop a customized building energy use baseline estimation tool by using mathematical method, considering specific façade features and local climate condition. Compared with software simulation, the tool is simpler and quicker in terms of time cost. The model would be applicable to set a reasonable EUI reduction baseline for building performance management and improvement. In addition, the tool will analyze the impact of basic façade features on energy performance in different climate zone by sensitivity analysis, in order to provide a guideline of how façade features could influence certain building energy use in a specific climate condition. At the public level, the result could also draw more attention on the significance of building energy use disclosure from ongoing benchmarking policy. 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.

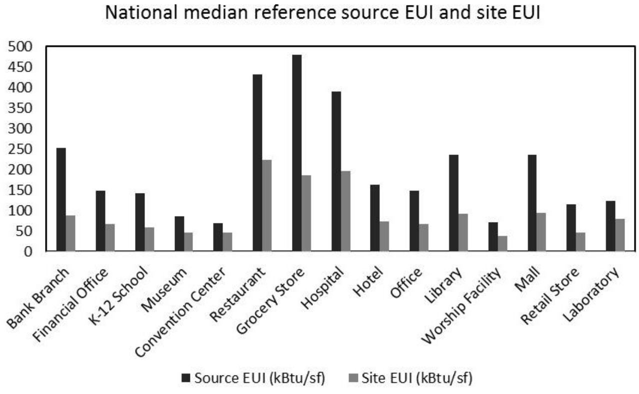

Fig. 1. National median reference EUI of selected buildings types [7].

2. Methodology

Variable regression models are developed to determine the most significant façade features which are relevant to energy aspect as well as to predict energy performance by entering a minimum number of data. Instead of using details of building information, like construction thermal properties, mechanical system, operation schedule, etc., which are used as basic input for simulation and other estimation methods, multiple linear regression and stepwise regression are 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.

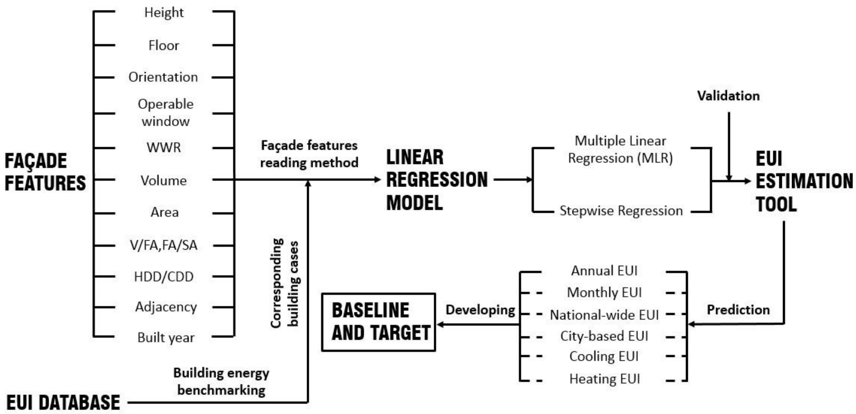

Fig. 2. Methodology

As the figure above illustrates, there are mainly three parts of the methodology: data collection (DC), data processing (DP), and model development (MD). The predicted outcome of this research is a new EUI estimation tool, which in this paper refers to the annual office EUI estimation model in New York City.

- For data collection, generally two types of data are supposed to be collected. One is real energy use data, another is corresponding façade features of the same buildings. Energy use data is presented by Energy Use Intensity (EUI) as the target metric are 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 (SketchUp, etc.) and direct information collection from design drawing or specification. Other potential factors like built year and HDD/CDD could be easily obtained from open resources.

- Data processing section is served as a 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. When it comes to monthly EUI model, simulation tool could be used to estimate monthly energy performance first. As a result, monthly data could be estimated accurately after calibrating the simulation model by real energy bill or annual EUI data.

- Finally, multiple linear regression and stepwise regression are used to develop the EUI estimation tools based on collected façade information and EUI data. In this section, the significance of each parameter and correlation between predictors and response could also be analyzed with the consideration of local code requirements, design strategies and best practices. In the end, all regression models should be validated by appropriate method, for example, cross-validation is used to validate Partial Least Square (PLS).

2.1. EUI data collection

Building energy benchmarking is used to obtain and record building energy data as baselines to compare to other properties performance. The building energy consumption and reduction potential could be reflected clearly by giving owners an opportunity to get the benchmarking data for a time period. To accomplish the task of benchmarking, it is necessary to monitor and measure utilities 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 [8], which could be used to track and evaluate energy use for commercial buildings. The benefits of using benchmarking [9] to keep track of building energy use are listed in the following figure.

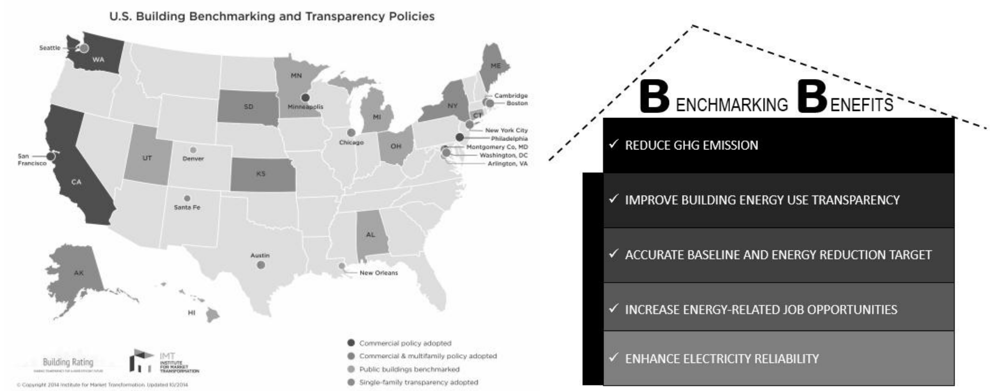

Fig. 3. (a) U.S. Building benchmarking and transparency policies. Source: [10]; (b) benchmarking benefits.

Currently, there are 9 cities in U.S. [10] which committed to implement energy benchmarking and disclosure programs for commercial buildings [11], including 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 [12], 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. It could be used to 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 available for the further regression analysis.

2.2. Façade feature definition

All building façade features used in regression model are supposed to be easily readable without knowing detailed information. Generally, unlike thermal performance, 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 assumed predictors (including height, floors, orientation, operable window, volume, window-to-wall ratio (WWR), window area, façade area, site area, floor area, volume-to-façade area ratio, volume-to-site area ratio, façade area-to-site area ratio, weather condition, surrounding context and built year) are showed in the table 1 explaining the definition of each parameter.

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. To consider other aspects of building energy use, built year as an additional predictor is used to incorporate all the requirements by code in each time period into consideration, which means 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 from urban zoning or public service information. In addition, since in urban context, adjacent building will cast shades on target buildings which in turn will influence heat gain through the façade especially glazing area, adjacency is used as another additional factor which is collected for regression analysis.

Table 1. Predictor's definition and explanation.

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

			Days	
16	Adjacent Building	If adjacent building exists to cast shading on objective building†[5]	-	Additional
17	Built Year	Year of construction complete	year	Additional

2.3. Regression

Many tools could be used to develop the regression models, like SPSS Statistics [14], MATLAB [15], etc. In this research, another statistical analysis tool, Minitab® 17 [16] is adopted for data analysis and regression model development. By using Minitab, a large amount of data can be processed [17] for basic statistical analysis, regression and correlation analysis, hypothesis tests, model validation, prediction, and graphs making, etc. All façade features, additional factors 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 and used 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:

$$\rho = a + b_1x_1 + b_2x_2 + b_3x_3 + ... + b_kx_k + \varepsilon \tag{1}$$

Where a is the constant while $b_1,\cdots, b_k$ are the regression coefficients, $x_1,\cdots, x_k$ 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 is also used to remove the least significant predictor at each step. The order of removed predictors also indicate the significance of each predictor, which in turn indicates which façade feature is the most important one in a certain area. This is also called backward elimination [18]. 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 following table 2.

Table 2. Predictor's definition and explanation.

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

[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 [13].
[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.

3. Results and discussion

3.1. Basic data analysis

All 50 raw datasets with façade features are 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.

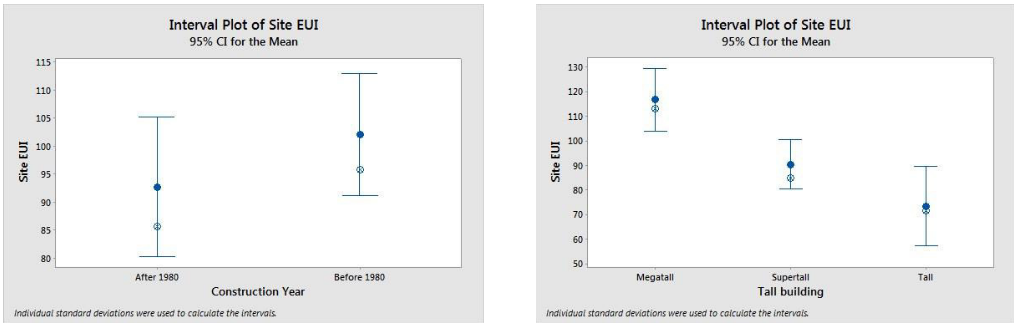

Fig. 4. (a) Interval plot of site EUI and construction year; (b) site EUI and building height.

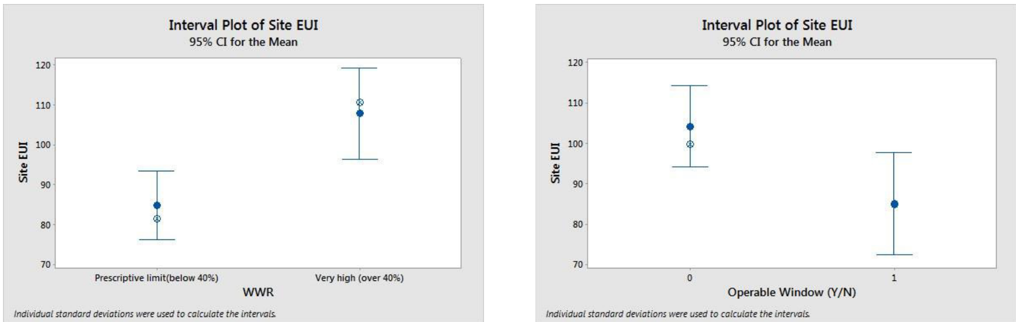

Fig. 5. (a) Interval plot of site EUI and WWR; (b) site EUI and operable window.

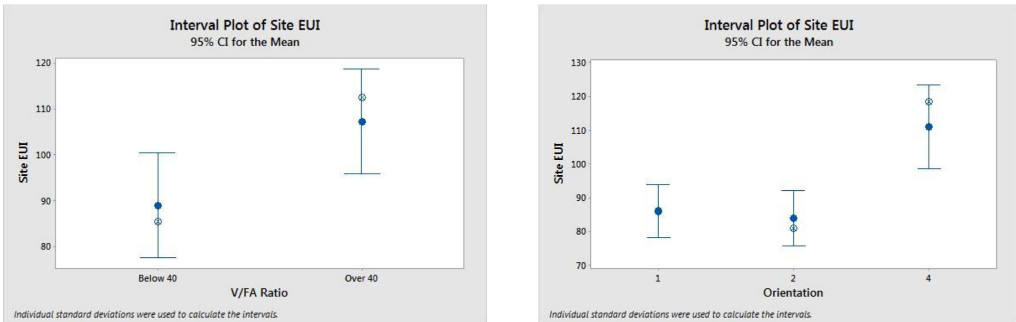

Fig. 6. (a) Interval plot of site EUI and V/FA; (b) site EUI and orientation.

Figure 4 (a) indicates the correlation between site EUI and construction year, which divides the datasets into 2 groups (before and after 1980), since the first New York state energy code was established in 1979 [19]. 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 are grouped into megatall (more than 600 ft), supertall (300 to 600 ft) and tall (165 to 300 ft) for the analysis of height [13]. Figure 4 (b) shows the significant difference of energy use for different height tall buildings. Megatall buildings consumes 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 [20] is used to divide all datasets into 2 groups and the results present 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 is 107.88 kBtu/sf compared to 84.81 kBtu/sf for lower WWR buildings. Buildings with operable windows consumes less energy since the mixed mode of natural ventilation and mechanical ventilation is more energy efficient, which is 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. V/FA ratio stands for the compactness which has significant impact on heating load. Figure 6 (a) indicates that buildings with V/FA less than 40 have the lower mean EUI of 89.03 kBtu/sf. Figure 6 (b) shows there is no significant difference of EUI between N-S orientation and NE-SW orientation while buildings with NW-SE have the highest mean EUI value of 111.01 kBtu/sf. It is because that the main façade faces south west has more heat gain through direct sun exposure.

3.2. MLR and stepwise regression results

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 is replaced by 8 different direction façade area. In MLR, all predictors are the R2 value indicates that all 25 predictors are 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 that is explained by its relationship with predictor variables, adjusted for the number of predictors in the model. 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. D-W statistic is 1.989 which is also closer to 2. All P-values of corresponding predictors are less than 0.05 while VIFs are less than 10 except south and west façade areas are slightly higher than 10. The results show 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 adds the most significant variable or removes 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 (Adj)/ R2 (pre)	77.64%	56.18%	-	88.15%	84.66%	77.72%
D-W	2.022			1.989		

Predictors	Coef	P-value	VIF	Coef	P-value	VIF
Constant	27302	0.174		-75.3	0.047	
Height	0.087	0.593	83.84	0.1553	0.000	3.85
Floors	0.06	0.979	78.14	-	-	-
Built year	-0.339	0.586	17.67	-	-	-
WWR	0.542	0.507	25.16	0.719	0.000	2.03
Orientation	26	0.033	25.61	18.77	0.000	4.53

Operable Window	-29.9	0.15	12.2	-19.65	0.000	2.11
Volume	0	0.995	605.78	-	-	-
Window Area	0.000149	0.55	100.77	-	-	-
Site Area	0.00035	0.729	54.2	-	-	-
Floor Area	-0.00007	0.031	29.78	-0.000054	0.000	8.55
V/FA	-0.84	0.809	127.38	-	-	-
V/SA	0.185	0.515	132.69	0.1352	0.001	4.52
FA/SA	-10.29	0.11	77.31	-9.47	0.000	8.61
Adjacency	-1.85	0.502	12.44	-	-	-
HDD	5.86	0.178	53879.79	0.0324	0.006	1.02
CDD	-22.7	0.181	53885.9	-	-	-
N Façade Area	-0.01101	0.201	6298.99	-	-	-
S Façade Area	0.125	0.23	1023528.62	0.001340	0.000	11.46
W Façade Area	-0.00249	0.2	598.28	-0.000634	0.009	13.83
E Façade Area	-0.0889	0.243	862326.34	-	-	-
NW Façade Area	-0.000146	0.806	49.89	-	-	-
NE Façade Area	-0.00017	0.892	553.6	-	-	-
SW Façade Area	-0.000118	0.849	148.17	-	-	-
SE Façade Area	0.000571	0.471	101.53	-	-	-

Figure 7 (a) is the histogram of standardized residual and frequency and 1 outlier may exist in the data, which needs to be proved in other analysis. Figure 7 (b) of normal probability plot shows an approximately linear pattern consistent with a normal distribution. The point in the upper-right corner is an outlier (row 33), which could be read from the plot. The plot of residuals versus the fitted values shows that the variance of the residuals are constant with a mean of zero.

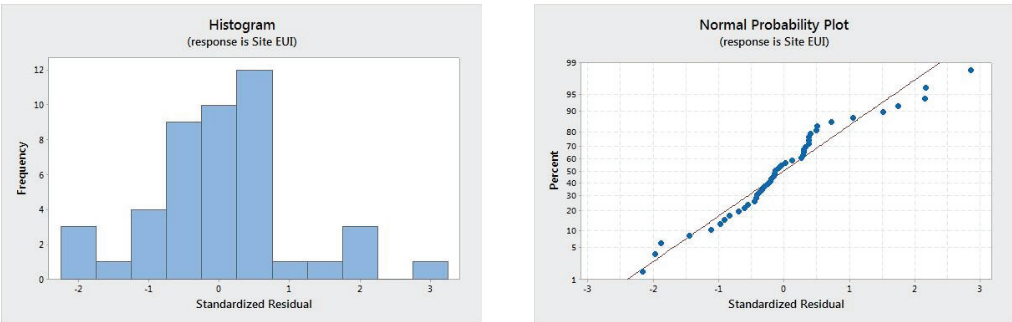

Fig. 7. (a) Standard residual and frequency plot; (b) normal probability plot.

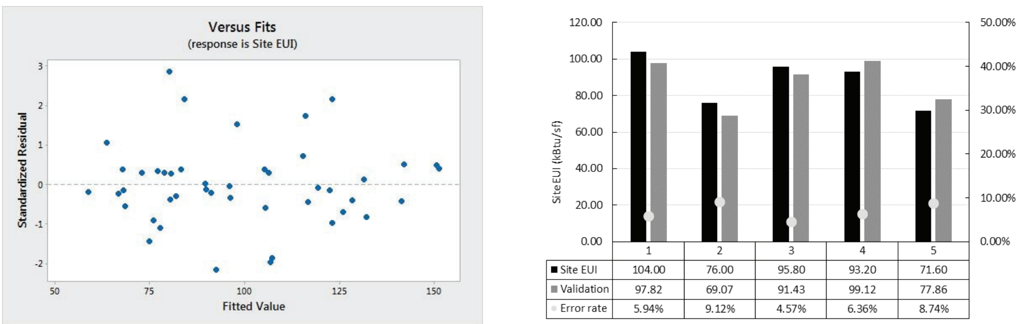

Fig. 8. (a) Standard residual and fitted value; (b) model validation and error percentage.

To validate the regression model, datasets are divided into two samples for training and validation. The samples number is 10% of original datasets for validation. In this case, 5 data from original 45 valid datasets are randomly selected as validation samples. The R2 of training samples model is 91.02% while D-W statistic is 2.04. Error rates for the 5 validation samples are 5.94%, 9.12%, 4.57%, 6.36% and 8.74%, which are at the accepted level.

4. Results and discussion

To predict building energy use and compare the accuracy, both simple multiple linear regression model and stepwise regression model are used and the results show that stepwise is more reliable to predict EUI than MLR. The comparison of estimation results and reported site EUI are illustrated in Figure 9. Compared with general national average baseline, building EUI estimated by basic façade features is more specific which considers the individual building attributes as well as local climate condition. The result is dynamic along with different features input which is better than one constant and median baseline from CBECS. In addition to assist to EUI benchmarking for improving building energy efficiency, the research potential outcomes could also 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. On the other hand, it can help building designers to estimate EUI when there is no detailed building information available for deep simulation. The reasonable energy consumption rate is achievable by inputting a minimum amount of data.

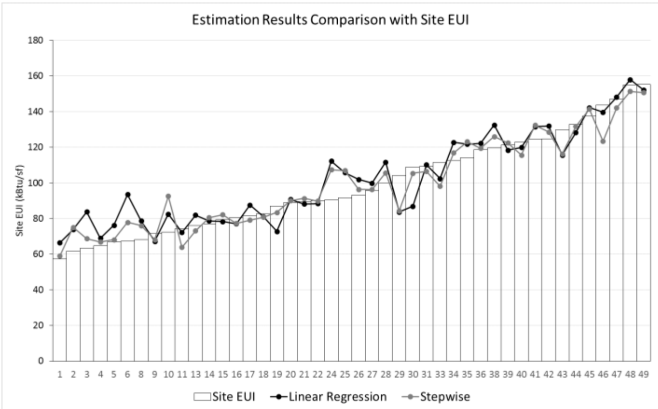

Fig. 9. Regression model results and site EUI comparison

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