BUILDING PERFORMANCE ESTIMATION: FACADE VISUAL INFORMATION-DRIVEN BENCHMARK MODEL

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ABSTRACT: The goal of this paper is to investigate and determine the significant impact of building facade information (i.e., basic façade features), as well as climatic impact, on building energy performance. Compared with these easily accessible façade features, parameters including envelope thermal properties, internal systems, and operating schedules are regulated by building codes and regulations, based on different building functionalities. Such façade parameters are variables that have large potential for affecting building energy performance. These attributes were extracted to conduct a data mining process to establish a correlation between building energy consumption and relevant physics information. Stepwise regression, and artificial neural network (ANN) are techniques used in this research. A façade visual information-driven benchmark model was developed as a building energy use intensity estimation baseline. Considering its comprehensive interpretation of variable variance and better predictive ability, it was proved that it is capable and feasible to use the façade visual information as the building key performance indicator, for estimating the building energy use, which is a fast and straightforward way to predict the energy use at urban scale. Traditional energy predictions, as a very complicated and time-consuming process, require multiple details and information about a building when preparing for energy modeling. Incorporating a transformative building energy performance estimation approach may enable stakeholders to easily assess their existing building energy consumption as well as establish a viable integrated energy master plan.

KEYWORDS: Facade Features, Data-Driven Model, Benchmarking, EUI Estimation, Energy Performance

INTRODUCTION

As urban built environment is the largest contribution to world's fossil fuel consumption and greenhouse gas emissions, it is imperative to transform the irreversible climate change problems into solutions through the built environment, in paving to a carbon neutral future. In California, with the aim of minimizing the fossil fuel energy consumption, California Public Utilities Commission (CPUC) established the tangible goals that all new residential construction in California shall be zero net energy (ZNE) by 2020, and all new commercial construction shall be ZNE by 2030. Per the ZNE Action Plan, K-12 schools and community colleges are prior than other types of building at this stage to implement the ZNE retrofit. To make this change possible, major efforts shall go beyond individual buildings to urban planning by modelling the campus energy performance as well as proposing the energy use metrics for energy goals. It is concerned with the measurement and benchmarking of the whole building energy consumption. However, due to the complexity of the energy consumption structure, it is quite difficult to estimate the energy consumption precisely. In spite of the prevalent use of advanced building simulation, it is not mature for urban scale energy analysis. The critical limitations of existing simulation tools are the excessive amounts of building information required and the time-consuming process. The lack of sufficient building information will significantly restrict the utilization of a computational performance diagnostic method, hinder the effective management of energy in old or existing facilities. Therefore, under this situation, there is a high potential in developing a fast and straightforward energy estimation approach, which facilitates the energy management at the urban scale.

Building energy consumption is influenced by multiple variables including building envelope information, local climate characteristics, building principal activities and internal energy systems. Among these influential variables, building envelope, as the elegant component that helps shape the architectural aesthetics of the building, is a crucial factor in determining the energy performance (McFarquhar, 2002). In addition, façade features are more easily obtained as opposed to obtaining the detailed building system information. The goal of this research is to provide stakeholders with a simplified but reliable energy benchmark model to assess their existing building performance while motivating the establishment of performance goals. To accomplish this goal, the façade visual information-driven benchmark performance model as a function of architectural physical frames, facades, and their dynamic climate conditions was developed to facilitate energy management of a whole building or urban scale to provide a scalable and extensible tool.

1.0 BACKGROUND AND CONTEXT

The AEC industry has stepped into the prime time, revolutionizing from traditional construction to sustainable designed with concerns for high-efficiency and high cost-effectiveness. In the long term, measuring the energy performance at a community or city scale do contribute in achieving the urban sustainability targets.

1.1 Building energy use baseline and benchmarking

Creating the baseline for current energy consumption will assist both the stakeholders and the design team in evaluating the energy performance as well as understanding the energy expenditures associated with the building operation costs. It is the starting point for setting the energy efficiency improvement goals as well as providing a comparison point for assessing future efforts and trending overall performance. For instance, the 2030 Challenge established by Architecture 2030 uses the national average or median energy consumption of existing U.S. commercial buildings reported by the 2012 Commercial Building Energy Consumption Survey (CBECS) as its baseline for the target goals (Architecture 2030, 2015).

Building energy benchmarking is an approach to evaluate the building performance and establish the comprehensive energy reduction goal, which has already become a standard process across the nonresidential building markets. There are a wide variety of benchmarking tools for building energy performance. The Building Performance Database is the national largest dataset for users to perform the statistical comparison in both commercial and residential buildings across the national real estate sectors (U.S. Department of Energy, 2016). In addition, Energy Star Portfolio Manager is an interactive online energy management tool tracking energy consumption across the life cycle of the building. It is a well-established whole building benchmarking tool in the U.S (Borgstein & Lamberts, 2014). Energy use intensity (EUI) is the key metric used for energy consumption baseline. It is the building energy use as the function of the building size, normally square footage, with the unit in kWh/m^{2}yr (kBtu/sf.yr). Buildings with different internal principal activities have different EUIs, for example, hospitals have relatively higher EUI since there are large amounts of testing and inspection instruments, which consume higher electricity loads. There are different ways to predict the building EUI with different levels of accuracy. Estimating and modeling the building EUI precisely, especially in the community or urban level, is an essential process for future energy benchmarking and urban energy infrastructure planning.

1.2 Building energy performance estimation approach

There are three mainstream approaches to estimate the building EUI: national benchmarking tool, energy modeling software, and energy bill based analysis. The national or local average or median energy consumption is one approach to estimate the building EUI. Commercial Buildings Energy Consumption Survey (CBECS) is a national sample survey compiled by the U.S. Department of Energy, which collects the information on the stock of U.S. commercial buildings (U.S. Energy Information Administration, 2016). It includes the basic energy-related building characteristics as well as the building energy consumption and expenditures. CBECS provides the average EUI for buildings in geographic regions based on climate zone, building size, floor space and building principal activity. The benchmarks were developed by multivariable regression to compare buildings of different typologies, based on various characteristics (U.S. Environmental Protection Agency, 2010). It is a simple normalization which is inexpensive and easy to implement, however, it only concerns with limited building factors, which cannot normalize for the thorough building physical characteristics which may affect the building energy consumption (Borgsteina & Lamberts, 2014).

Other ways include the computer-aid energy modeling software. There are various simulation programs in the industry that are well developed for modeling the building energy consumption, for example, EnergyPlus, DesignBuilder, IES-VE, eQuest, EnergyPro, etc. With inputs of detailed building information such as building envelope assemblies' thermal properties and building systems' efficiency, the energy program will calculate the energy usage and analyze the end-use consumption. It is powerful for designers to evaluate potential savings of different design schemes or sustainable strategies at the predesign stage. However, the accuracy of the energy modeling depends on how much specific information related to envelope thermal properties, internal system performance and operation schedule, can be input to the model, as well as the similarity between the real design and the 3D model built up inside the modeling module. It is almost impossible to obtain all the detailed and accurate building information, especially for those old buildings built decades before, since some parameters may be unavailable to many organizations, for example, the detailed information of internal individual rooms (Zhao & Magoulès, 2012). For the large urban scale energy analysis, it is extremely time-consuming and cost-ineffective to perform the energy simulation building by building. The expertise level of the building energy analyst may also affect the accuracy of the modeling results. Daly and colleagues clearly state that "building energy modeling typically relies on a range of simulation assumptions and default values for certain 'hard-to-measure' building and behavioral inputs to building performance simulations". In addition, different simulation programs may result in different energy consumption, even with the same settings, since it varies with different algorithms in the modeling engine. Grawley, Hand and their research team (2008) conducted a comparison and contrast study on capabilities of different building energy performance simulation programs. Similarly, Sun (2015) conducted a result variation analysis of different simulation programs. In his research, 11 case buildings were selected to run the energy modeling by using several different prevalent software, see Figure 1. It is clearly that there are large discrepancies among different simulation program. The modeling capabilities and detail level vary with different software even if they share the same energy modeling algorithm. There is a need to further develop a simple, robust and validated model for energy prediction.

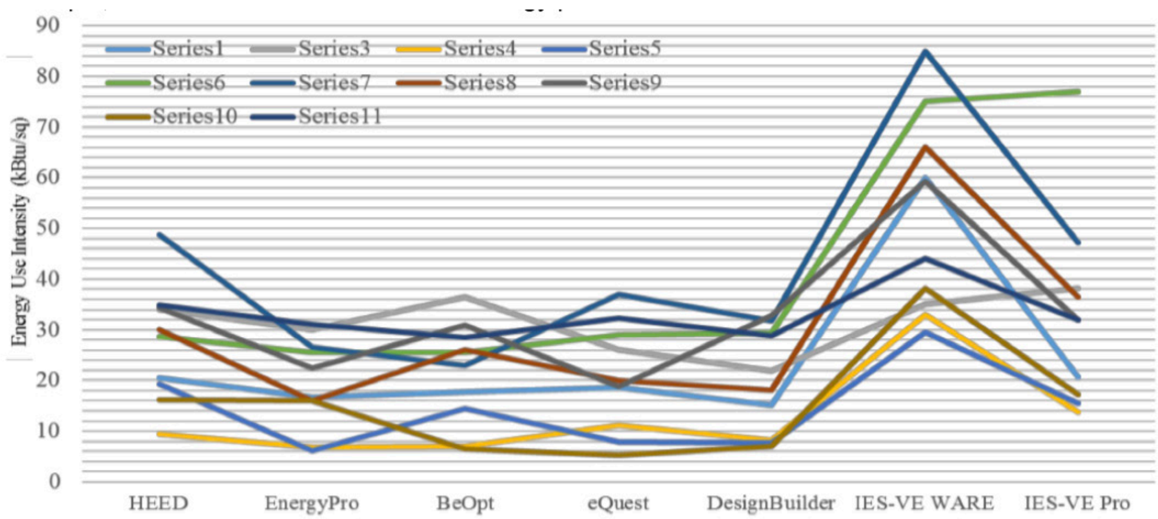

Figure 1: Comparison of predicted EUI from seven programs of one building (Source: Sun, 2015)

For energy prediction of existing facilities, the energy-bill based method is the most precise one as well as the most cost-effective. However, the monthly bills only provide the total energy usage of the whole building, thus it could not help with the multi-level assessment and diagnosis. In fact, at the urban level, it is sometimes not feasible to collect the 12-month of energy bills for all buildings. Compared with the energy bill, building sub-metering system is an approach to monitor the real-time energy consumption. However, it is not practically applied in the real industry due to the high initial investment (Piette et al, 2001). Therefore, under this situation, there is a high potential in developing a fast and accurate energy estimation approach, which facilitates the energy management at the urban scale.

1.3 Urban scale modeling approach

There are numerous researches on the urban energy models, focusing on data, algorithms, workflow and potential applications on city-wide energy supply/demand strategies, urban development planning, electrical grid stability and urban resilience (ASHRAE 2017 Winter Conference). There are several urban energy modeling tools that have been developed or at on-going research stage. Hong and his colleagues (2016) from Lawrence Berkeley National Laboratory proposed a web-based data and computing platform to facilitate the urban scale energy efficient planning. City Building Energy Saver (CityBES) is a web-based platform for urban scale energy performance modeling of a city's building stock. It employs EnergyPlus as the simulation engine for investigating the building energy use and potential savings under various energy efficient strategies. CityGML, as an XML-based open data model, was used to represent and exchange the 3D city models, and provide virtual 3D city models for advanced analysis and visualization. The MIT Sustainable Design Lab is currently developing a new generation of urban building energy models (UBEM), for estimating the citywide hourly energy demand loads down to the individual building level (MIT Sustainable Design Lab, 2017). Urban Modeling Interface (UMI) is a Rhinoceros 3D software-based tool for urban level modeling including the operational and embodied energy use, daylighting and walkability analysis (Reinhart et al., 2013). It used the EnergyPlus and Radiance as the simulation engine. It works as the plug-in for the commercial 3D computer graphics and CAD modeling software. CitySim is a new software developed by Robinson and his research team in 2009, providing the decision support for urban planner on energy and emission reduction. It was developed based on its own XML schema to represent the building information. And the developers plan to incorporate water, transportation, and urban climate modeling into CitySim in the future (Robinson et al., 2009). However, at this stage, this software is isolated for specific applications, since they are not using the open standards, such as CityGML (Hong et al., 2016).

2.0 METHODOLOGY

In this research, a data-driven performance benchmark model based on building visual façade information was proposed. It aims to provide a direct and real-time forecast of the existing building energy performance, especially for urban scale energy analysis and benchmarking, as well as to provide a fast and straightforward tool for evaluating the building envelope design decision at the project predesign and schematic design stage.

To accomplish this goal, a data-driven benchmark performance model as a function of facades, and dynamic climate conditions was developed upon the following research methodology diagram, see Figure 2. There are three main parts of methodology in this research: data collection, data mining and validation. Finally, the building performance benchmark model used to predict energy consumption were derived based on building visual façade information, basic climatic characteristics and building monthly energy consumption. The following sections gave an explicit methodology for this research and documents the overall workflow.

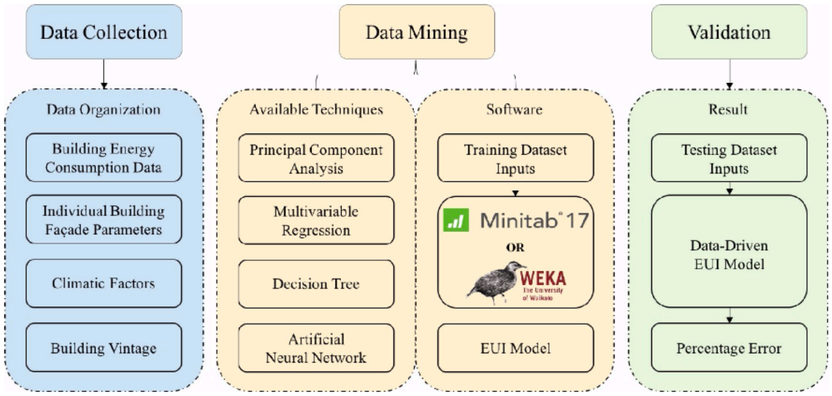

Figure 2: Methodology Workflow Diagram

2.1 Data collection

Research dataset of 32 different buildings were collected from two California colleges in different climate zones. The dataset includes the real building energy consumption data, building façade features information, climate and weather data, and building vintage. The building energy consumption dataset were collected for each building including the yearly and monthly end use consumption in heating, cooling, fan/pump, lighting and miscellaneous plugins and the total building site EUI. Instead of using the detailed building information including construction assembly thermal properties, internal system performance, operation schedule, only accessible façade features such as height, floor area, WWR and basic climate characteristics were considered.

Table 1: Façade and Climate Parameters

No.	Façade & Climate	Definition
1	Vintage	Year of construction complete
2	Height	From open air pedestrian entrance to highest occupied floor
3	Floorspace	Total floor area inside the building envelope
4	Orientation	Positing of a building with respect to the North
5	WWR	Window-to-wall ratio (total window area/total exterior wall area)
6	Volume	Inner space volume enclosed by external envelope
7	Window Area	Total glazing area
8	Façade Area	Total area of all parts of the structure's façade
9	Aspect Ratio	proportional relationship between the width and height
10	Shape Coefficient	Ratio of volume to façade area
11	Shading	any external shading device
12	Number of Floors	Total occupied stories or levels
13	FAR	Floor to Area Ratio
14	Operable Window	Window could be open or close based ventilation need4
15	South WWR	Window-to-wall ratio of south facing façade
16	West WWR	Window-to-wall ratio of west facing façade
17	North WWR	Window-to-wall ratio of north facing façade
18	East WWR	Window-to-wall ratio of east facing façade
19	Monthly CDD	Cooling degree day (the demand for energy to cool a building)
20	Monthly HDD	Heating degree day (the demand for energy to heat a building)
21	Dry-Bulb Temperature	Monthly average outdoor air temperature
22	Diurnal Temperature	Monthly average daily temperature swing range
23	Monthly Average RH	average of relative humidity

Building vintage was used to indicate the minimum requirements on building envelope and internal systems. Climate feature is one of the most significant factors in influencing the building energy performance. HDD and CDD are commonly used in calculations relating to the energy consumption for heating and cooling the building. Other climate factors including dry-bulb temperature, diurnal temperature and relative humidity were taken into consideration since they are important factors for establishing the indoor thermal comfort. Annual and monthly heating degree day and cooling degree day were collected from Degree Days.net, which is an online open source for worldwide weather data. Other weather data shown in the table were collected from the nearest weather stations from the online open source Weatherbase.com. Table 2 shows a sample dataset demonstrating the data organization of building monthly EUI and different attributes associated with façade and climate factors. All 32 groups of buildings data were organized in this format for future data mining.

Table 2: Sample Data Organization

	Month	EUI (kBtu/sf)	HDD	CDD	Dry-Bulb Temperature	Diurnal Temperature	RH	Vintage	Floorspace (sf)	WWR (%)	Height (ft)	Façade Area	Orientation	Volume	Window Area	Aspect Ratio
	Jan	3.163	275	21	58.8	16.9	68.6									
	Feb	2.857	150	131	60.1	19.9	70.8									
	Mar	3.226	147	62	61.2	18.7	71									
	Apr	3.324	93	111	63.8	18.2	67.7									
	May	3.730	70	71	64.3	15.7	71.1									
	Jun	3.824	23	225	77.7	16.7	72.7									
BLDG 1	Jul	4.131	4	339	82.3	18.1	72.2	1963	45568	20	16	65765.6	1	729088	4008	1.540
	Aug	4.094	1	313	83.1	16.7	70.8									
	Sep	3.666	12	264	80	17.1	71									
	Oct	4.026	34	169	73	23.7	69.7									
	Nov	3.101	197	79	64.9	14.3	65.8									
	Dec	3.025	324	33	60.5	12.9	67.3									
	Total	42.165	1330	1818	69.1	17.4	70.1									

*Building long axis along with North to South is marked as 1, NE-SW is 2, E-W is 3, SE-NW is 4

2.2 Data mining and validation

Until now, there are numerous researches on data-driven building energy prediction model. Possible techniques include principal component analysis, multivariable regression, decision tree and artificial neural network (ANN).

Ruch and colleagues (1993) developed a data-driven method for estimating the daily electricity consumption in a commercial building by utilizing the principal component analysis to minimize the collinearity of the performance parameters and hence derive a more stable regression equation. Kalogirou et al (1997) applied the back propagation neural networks for estimating the heating load of buildings. In 2000, they conducted a research on application of artificial neural network on energy consumption prediction for passive solar buildings without mechanical systems for heating or cooling. Later, Ma et al (2010) derived a monthly energy consumption prediction model for large scale public buildings by integrating multiple linear regression. Yu, Haghighat and their research colleagues (2016) proposed a decision tree method for building energy demand estimation, which is a flowchart-like tree structure segregating a set of data into various predefined classes.

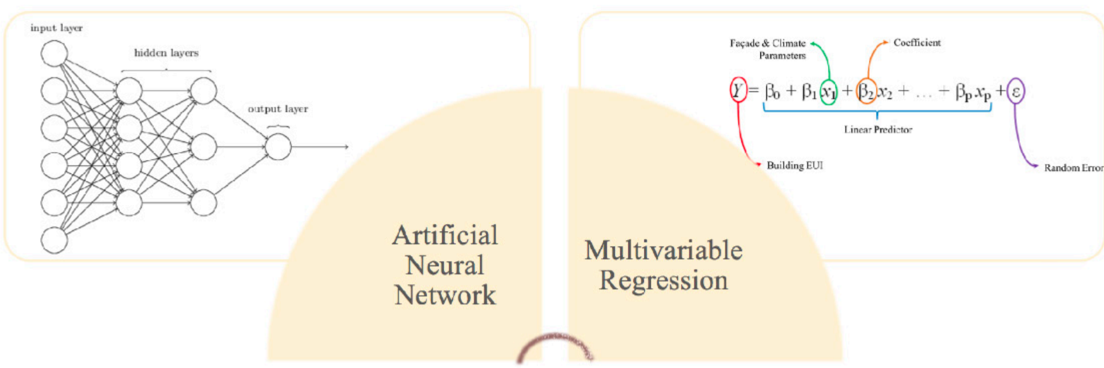

Figure 3: Possible Data Mining Techniques

In this research, two main data mining techniques were used including multivariable regression and artificial neural network to compare the result and accuracy, see Figure 3. Minitab and WEKA are two data mining tools used for multivariable regression and ANN separately. Minitab is a statistics package developed by the Pennsylvania State University. It contains a complete set of statistical tools including descriptive statistics, hypothesis tests, confidence intervals and normality tests, and could help uncover the internal relationships between variables and identify the important factors affecting the quality of the products and services (Minitab, 2016). WEKA is a collection of machine learning algorithms for data mining tasks. It can either be applied directly to a dataset or called from user's own Java code. It is a workbench contains a collection of visualization tools and algorithms and graphical user interfaces for data pre-processing, classification, regression, clustering, association rules. (WEKA The University of Waikato, 2016).

As an extension of simple linear regression, multivariable regression is a technique that estimates the relationship between several independent or predictor variables and a dependent or criterion variable (StatSoft, 2016). It is used to predict the value of a variable based on the value of two or more other variables. Stepwise regression is a dimension reduction measure to screen out the best combination of the predictor variables (façade & climate attributes) for predicting the dependent variable (EUI). Minitab stepwise regression feature can automatically outputs the most significant attributes by adding the most significant variable or removing the least significant variable during each regression steps (Minitab 17 Support, 2017). In machine learning and cognitive science, an artificial neural network (ANN) is a network inspired by biological neural networks which is the central nervous systems of animals, in particular, the brain. Artificial neural network is commonly used to estimate or approximate functions that can depend on a large number of inputs that are generally unknown.

3.0 RESULT AND DISCUSSION

The 32-building dataset with 23 façade and climate attributes were firstly analyzed in Minitab for stepwise regression. Table 3 and Table 4 summarize the result and corresponding regression coefficient of the stepwise regression. According to the Minitab stepwise regression, HDD, dry-bulb temperature, south WWR, RH and façade area are five significant independents selected for the regression model to predict the site building EUI.

Table 3: Minitab's Stepwise Regression Output & Coefficient Summary

	Step 1		Step 2		Step 3		Step 4		Step 5	
	Coef	P	Coef	P	Coef	P	Coef	P	Coef	P
Constant	0.897		-26.21		-28.49		-39.51		-43.68	
HDD	0.025429	0.000	0.027461	0.000	0.027622	0.000	0.027856	0.000	0.027869	0.000
Dry-Bulb Temperature			0.3873	0.000	0.3839	0.000	0.3537	0.000	0.3422	0.000
South WWR					0.138	0.000	0.1009	0.000	0.0932	0.000
RH							0.2159	0.000	0.3124	0.000
Façade Area									-0.000039	0.000
s		6.78355		6.10505		5.70983		5.57225		5.48038
R-sq		68.27%		74.36%		77.63%		78.75%		79.49%
R-sq(adj)		68.19%		74.24%		77.47%		78.54%		79.24%
R-sq(pred)		67.14%		73.16%		76.06%		77.14%		77.84%
Mallows' Cp		232.84		111.03		46.65		25.96		12.81

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-43.68	3.58	-12.20	0.000	
HDD	0.027869	0.000715	39.00	0.000	1.08
Dry-Bulb Temperature	0.3422	0.0358	9.56	0.000	1.12
South WWR	0.3124	0.0521	6.00	0.000	1.64
RH	-0.000039	0.00001	-3.86	0.000	1.32
Façade Area	0.0932	0.0189	4.93	0.000	1.23

Minitab's stepwise regression can automatically output the most significant models. A good prediction model should have a small S value, a high R2, adjusted R2 and predicted R2 as well as a relatively small Mallows' Cp close to the number of the predictors. As can be seen from Table 3, the HDD has the largest R2 of 68.27%, which means it is the most dominant attribute for predicting the building site EUI. The S value of 5.48 shows the average distance the observed value fall from the regression line. The final model was highlighted in red with the R2 of 79.49%, representing the overall accountability. The output shows HDD, Dry-Bulb Temperature, South WWR, RH and Façade Area are five key attributes predicting building EUI. Normally, the attribute with the accountability (R2) less than 1 can be neglected. The standard error coefficient (SE Coeff) of the RH is the lowest, which means the model is capable of predicting the coefficient for RH with greater precision. VIF refers to the variance inflation factor for describing the multicollinearity, the larger the multicollinearity, the higher variance of the regression coefficient. With the lower VIF, the less correlation between each predictor. The VIF shown in Table 4 is low as no more than 2, which means a relatively stable prediction model. However, the stepwise regression performed in Minitab shows a basic linear correlation between the building site EUI and corresponding building facade visual information and climatic factors. Artificial neural network (ANN) was also used to conduct the data mining for the original dataset and compare with the Minitab regression result for accuracy.

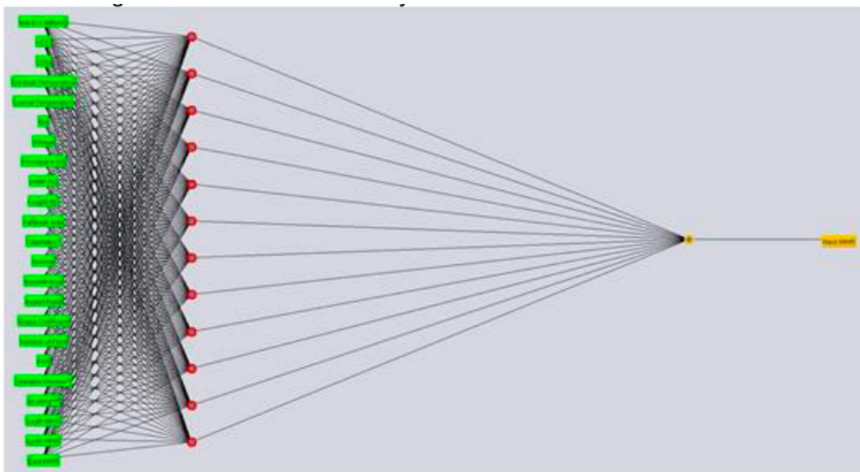

Figure 5: WEKA's ANN Output Interface & Output Summary

The algorithm of the ANN used in WEKA is the multilayer perceptron, which uses the backpropagation for classification. The dataset was divided into a large portion of training dataset for creating ANN and the remaining small portion of testing dataset for validating the accuracy. Figure 5 shows the interface of artificial neural network processed in WEKA data mining software.

Table 4: WEKA's ANN Output Summary

Correlation coefficient	0.9939
Mean absolute error	0.7325
Root mean squared error	1.4335
Relative absolute error	12.1756%
Root relative squared error	11.9319%
Total Number of Instances	416

It can be seen that the correlation coefficient is 0.9939, which implies 99.39% of the attributes in the dataset have been explained by the model. It can be considered as a perfectly correlated set of predictions. The relative absolute error shows the accuracy of the predicted model, which is within the common acceptable accuracy of 70% in the data mining field (Manaf et al., 2011).

Due to the limitations of time and resource accessibility, several research limitations, that may cause inaccuracy or error in the outcome, were addressed in this section. Limitations were mainly countered with the data collection process including the insufficient research database and inaccurate data inputs. The research database includes 32 buildings' energy consumption data, which may not be enough to establish a robust data-driven energy prediction model. Besides, all the buildings are education facilities, thus the variety of the building type is very limited, while more than half are classrooms with similar geometry. In this case, the model might be limited to a specified group of buildings and may not be applicable to other building types. In addition to building EUIs, most façade features were collected from building 3D models and some of them may require manual reading and estimate due to information inaccessibility. It is sometimes not accurate due to the subjective and cognitive influence. Building monthly EUIs were obtained based on the energy modeling program, weather files (epw.) were imported for simulation. However, climate data considered in this research were collected from the online open source, they might be inconsistent with the weather input to the energy modeling program. This may also contribute to inaccuracy of the predicted model.

4.0 CONCLUSION AND RECOMMENDATION

With more and more attention on urban sustainability, the large-scale building energy master plan with the comprehensive energy reduction strategies are essential today in meeting the energy reduction goal. To facilitate the building energy performance estimation process at the urban level, the façade visual information-driven benchmark performance model was introduced as a transformative approach to estimate energy performance. It is a fast and more accurate way to predict the energy use intensity in the schematic design stage and it will facilitate the energy consumption analysis of multiple buildings in the urban scale to establish the comprehensive energy master plan as well as establishing the EUI metrics and helping propose the feasible energy management strategy plans. For this paper, due to the limited time and sources, 32 buildings were analyzed at this stage. The research will be continuing all along with more groups of buildings for the data mining to develop a more robust benchmark performance model.

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