ENERGY STAR Score Model Feature Analysis

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***Abstract*—Many methods for improving the efficiency of building energy consumption, which includes engineering approach, statistical methods, and artificial intelligent methods have been developed by researchers of related fields. This paper examines one of the energy consumption evaluation model in which has been developed by the U.S. Environmental Protection Agency (EPA) and have been used in energy performance rating of buildings. More specifically, the model has been simulated with respect to the ENERGY STAR Methodology documentation using the linear regression approach.**

Keywords: Building Energy Consumption Prediction; Building Energy Consumption Rating; ENERGY STAR; Linear Regression; Machine Learning Approach

I. Introduction

Nowadays, it has become increasingly important to optimize the efficiency of building energy consumption in order to prevent redundant waste of energy. Developing a model to accurately predict energy consumptions is an essential step to conquer such a challenge. As the energy consumption of buildings is influenced by various factors, such as local weather conditions, building operations, heating, ventilation, and air-conditioning (HVAC) systems, occupancy and their behaviors, this fact makes accurately implementing models on predicting building energy consumption very difficult.

According to the Commercial Buildings Energy Consumption Survey (CBECS) provided by U.S. Energy Information Administration (EIA), the energy consumption demand of U.S. commercial buildings experienced a slower growth rate, comparing to the growth of total buildings and total floor area, from 2003 to 2012. This reveals a fact that newer constructions were built using high energy efficiency standard, and improved building energy consumption efficiency has successfully decreased the overall energy demand. Therefore, it is necessary to evaluate buildings based on its energy consumption efficiency in order to make further improvements.

Building energy benchmarking involves various theories. One comprehensively implemented methodology is the annual energy use intensity (EUI) which aim to evaluate the unit floor area energy use intensity. Straightforward though, this idea is believed to be overly simplified. EPA, along with Natural Resources Canada (NRCan) suggested an alternative way to assess a building's energy efficiency: the Energy Star Scoring. By considering both conventional metrics such as square footage and temperature, the Energy Star Scoring takes into consideration almost every available information about the building, from the shape of the building to the type of light bulbs. They also emphasize the total source energy consumption in form of EUI as dependent the variable in order to obtain energy efficiency ratio. Details about this model itself remain confidential throughout the years, however, EPA has published technical references for Energy Star model, in which both training algorithms and datasets were discussed. The technical analysis explained how the model training is conducted with EIA 2003 micro-data, John H. Scofield in his analysis rebuilt the model, complaining that the Energy Star Scoring is insufficient. [2]

In this project, the latest 2012 micro-data published by EIA is used to build this Energy Star Scoring model, using linear regression approach and testing its function with test dataset excluded from the training set. This attempt is, obviously, simplified, yet adequate to illustrate basic idea of EPA energy benchmarking.

II. Dataset Description

A. Introduction

The dataset used in the project is obtained from the CBECS page published by EIA. All data in the dataset were collected in the year 2012 and the set is released in 2016. It contains measurements of energy consumptions of various energy source and other related characteristics for buildings located around the United States.

There is a total of 1,119 attributes, most of them are applicable in this case, indicating the geographic information of buildings, components of construction, type of heating/cooling systems, as well as the actual energy consumptions for each type of resource in appropriate units. There are a total of 6,721 records in the dataset, and each represent measurements from an unique building within the United States.

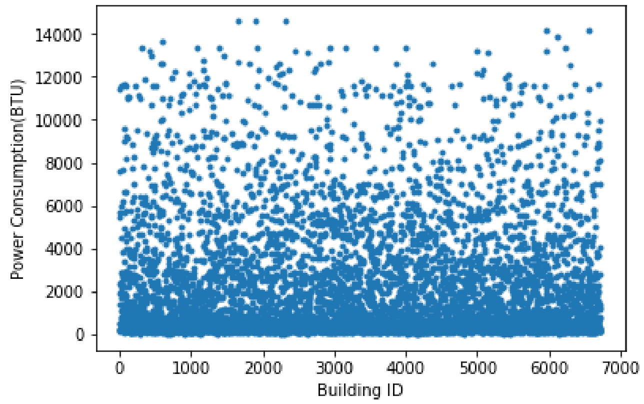

Fig. 1. Overview of the building energy consumption distribution in U.S.

	Number of buildings (thousand)	Total floorspace (million square feet)	Total Workers (thousand)	Mean square feet per building (thousand)	Mean square feet per worker[1]	Mean operating hours per week
All buildings	5,557	87,076	88,187	15.7	936	62
Principal building activity						
Education	389	12,239	10,885	31.5	1,124	53
Food sales	177	1,252	1,172	7.1	1,067	121
Food service	380	1,819	3,431	4.8	530	82
Health care	157	4,133	7,595	26.4	544	60
Inpatient	10	2,352	4,262	245.6	552	168
Outpatient	147	1,780	3,333	12.1	534	53
Lodging	158	5,722	3,066	36.2	1,861	165
Mercantile	602	11,391	9,117	18.9	1,250	64
Retail (other than mall)	438	5,437	4,023	12.4	1,352	62
Enclosed and strip malls	164	5,954	5,093	36.3	1,169	69
Office	1,012	16,007	33,785	15.8	474	55
Public assembly	352	5,531	3,103	15.7	1,710	56
Public order and safety	84	1,434	1,854	17.1	753	113
Religious worship	412	4,559	1,940	11.1	2,296	31
Service	619	4,587	4,031	7.4	1,075	56
Warehouse and storage	796	13,130	6,362	16.5	1,851	67
Other	125	2,015	1,611	16.1	1,201	61
Vacant	296	3,257	236	11.0	3,309	8

Fig. 2. Dataset Summarization: total and mean of floorspace, number of workers, and hours of operation, 2012

B. Data Imputation

The building records in the dataset are significantly varied, many metrics that are not applicable to all buildings and were remained blank. Therefore, imputation of metrics is conducted. All missing data points are replaced by the mean value of their attribute in this analysis (except when "missing" actually means a kind of state such as "Free standing", missing means not).

III. Overview of the ENERGY STAR Methodology

The ENERGY STAR rating system uses 1-100 scale to evaluate the performance of each building. A larger score indicates the better overall performance of the building in term of energy utilizations. The rating system categorized office buildings by principle building activities, such as bank/financial institutions, hotels, schools, retail stores, etc. The energy performance is rated by the source of energy consumption, including primary energy consumption as well as energy used in generation and transmissions. [1]

To develop the model, records of a large number of buildings of various principle building activities are collected. For each building, suitable independent variables for the regression were selected in order to meet the criteria of building operation normalization. These characteristics are able to describe the physical operation of buildings, such as heating/cooling requirement, square footage, number of occupants, number of refrigeration units, etc. Technology factors, such as market conditions were not taken into considerations.

The dependent variable is the source energy used intensity (source EUI), defined as the total source energy divided by the gross floor area of the building. Once the regression variable is identified, the regression coefficients can be determined and use to predict the source energy use intensity for this type of building. If the actual usage of source energy is lower than the prediction, then it is said to be more energy efficient than its peers within the same group, and vice verse.

Then, dividing the actual source EUI of each observation by the predicted source EUI generates the energy efficiency ratio or EER. Note that the actual source energy is typically not measured directly, but rather estimated from energy source purchases. For each group of building types, the EER is sorted in ascending order and combined with the building weight (as each observation represents a different number of buildings), and a cumulative EER distribution of this particular building type can be generated.

IV. Approach and Result

The scoring system is differentiated by buildings, in this project, buildings were divided into 20 groups according to their principle activities. EPA offers a suggestion of what attribute should be included in each kind of building model. This could be problematic since data attribute categories change from 2004 data to 2012 data, some categories are ambiguous or not identical (K-12 school and Educational). It requires much more efforts and professional skills to properly find needed attributes. EPA also keeps updating the attributes and their weights. In this studying, this has to be simplified by including all attributes in all models after imputation.

A. Algorithm

Linear regression is implemented as a model for understanding the relationship between input and output numerical variables. The input is training dataset, describes as A. Given N observations, the output and input can be written in the form of equation(1):

$$y = Ax \tag{1}$$

Where as $x \in \mathbf{R}^M$ is the parameter vector, $A \in \mathbf{R}^{N \times M}$ contains all independent characteristic of the building, and $y \in \mathbf{R}^N$ is the source EUI of observations. Then, the parameter vector x can be solved using the following relation:

$$\hat{x} = (A^T A)^{-1} A^T y \tag{2}$$

The predicted y can be solved by $y_{predicted} = A\hat{x}$. The predicted y is then divided by the actual y in order to make assessment on the energy efficiency of buildings. Extracted from the imputed dataset the the training set should exclude energy consumption attributes and unrelated attributes such as ID of the building. We then separate training set by principle activities and store them into a dictionary object. Finally, we will exclude 4 buildings from the training set. They will be used to test the models later

The Energy Star Scoring Technical Methodology suggests that only the total energy consumption is needed to be considered.[2] In this step, each building's total annual energy consumption of different energy sources (electricity, natural gas, etc.) is identified and summed up then divided by its square footage, as the total energy consumption and EUI of observations (Btu/square feet) . Similar to the training dataset, these data are separated according to their principle activities.

After obtaining the training set and EUI observation set, appropriate method in Python can be implemented and each parameter vector can be calculated using equation(2), prediction of energy consumption and EER can be calculated with equation(1). The final result of models are drawn as CDF plots using subplot method.

B. Result

The result of linear regression, 20 CDF plots for all models are shown on figure 3 and figure 4. Each plot expresses ratings on a scale of 1-to-100 according to EER. Most of them, as expected, resemble to gamma distribution. Some of these curves changes more dramatically such as the non-refrigerated warehouse while others like public service and safety are more smooth.

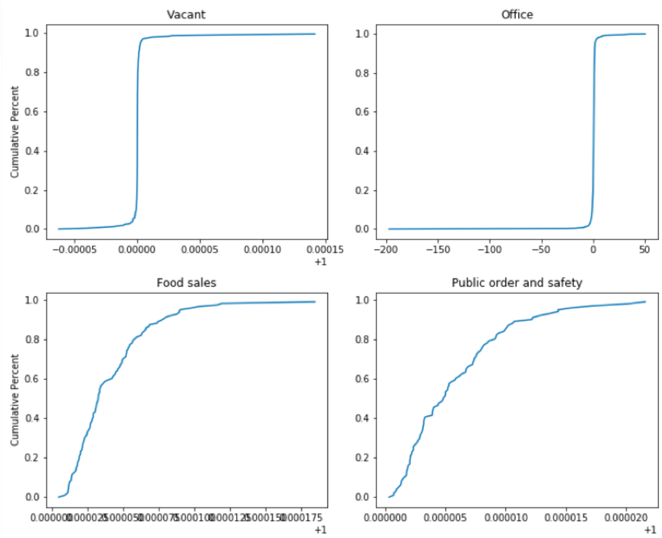

Fig. 3. Cumulative EER Distribution for vacant, office, food sale and public buildings

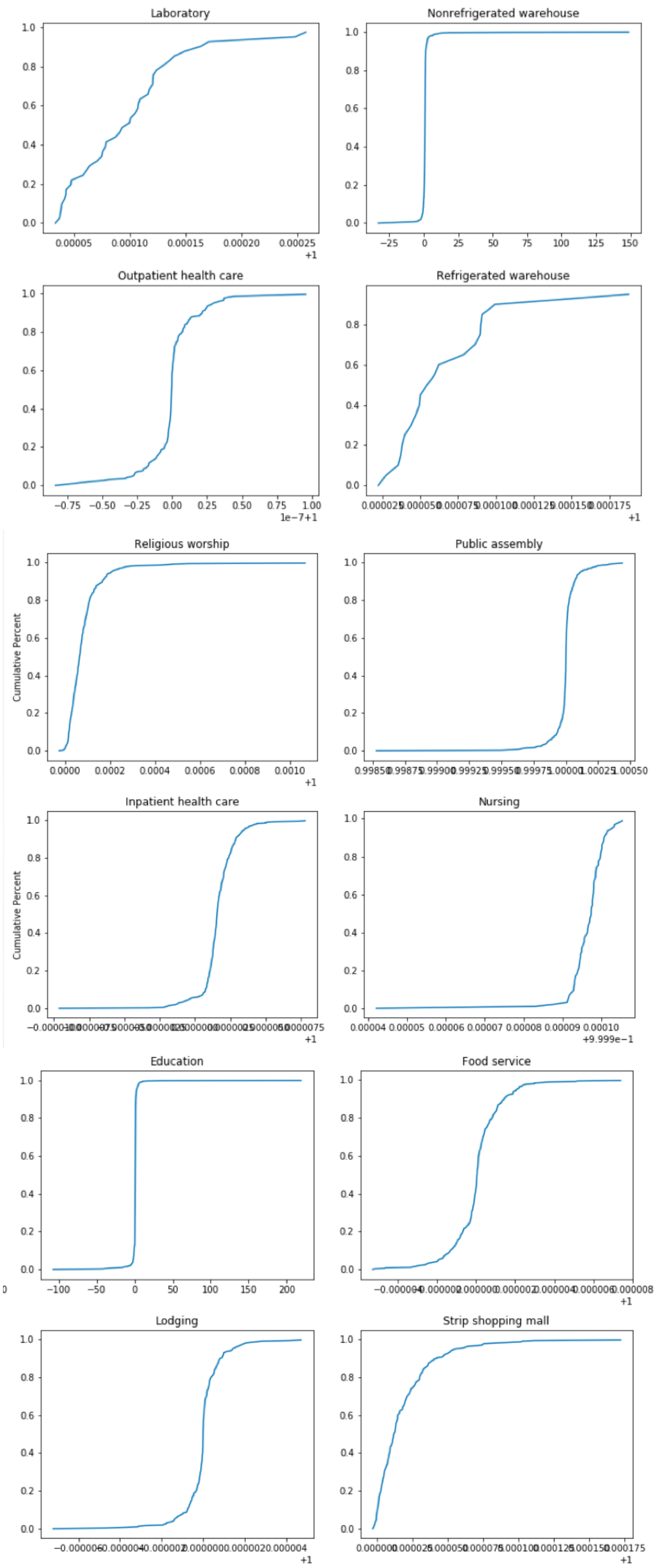

Fig. 4. Cumulative EER Distribution for lab, warehouse, health care, educational, and hospital buildings

C. Implementation

Implementations of previous determined models are performed for testing purpose. As identified in the "2012

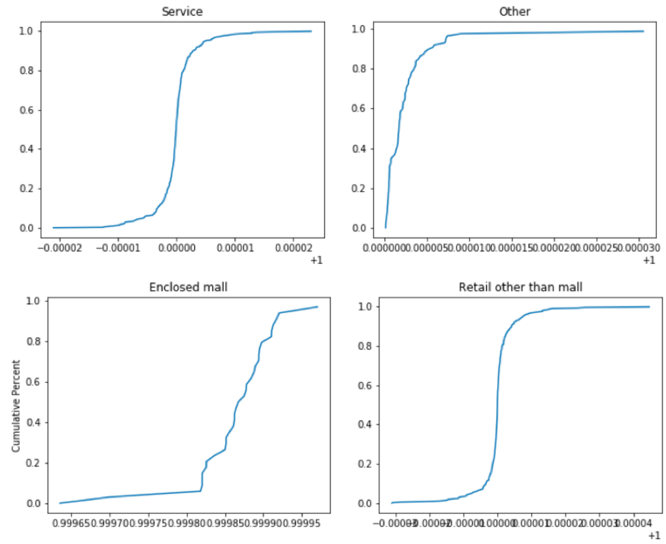

Fig. 5. Cumulative EER Distribution for service and other type buildings

TABLE I
IMPLEMENTATION EXAMPLE OF THE MODEL

Index	Building Type	EER	Ranking
0	Service	0.02	18%
4	Office	1.82	100%
24	Non-refrigerated warehouse	0.67	35%
207	Refrigerated warehouse	0.84	5%

- PUBLIC USE DATA VERSION”, 3 most comprehensive types of building are office building, service building, and warehouses [3]. 4 data samples are excluded before training the dataset: one office type, one service type, one non-refrigerated warehouse and one refrigerated warehouse. These 4 records are fitted into corresponding models in order to validate the scoring system.

Table 1 demonstrates the results obtained from the corresponding model of each selected record. Index refers to the index of each sample before been excluded from dataset. Type of building indicates the type and type of model it fits. EER refers to the energy efficiency. Ranking is the final evaluation about what percentage it locates among its peer buildings. The service building #0 get a EER value of 0.02 which is a low value from model and is ranked as 18% among its peer buildings. Building #4 has a high EER of 1.82 and is regarded as the building with highest energy efficiency. Building #24 has a EER of 0.67 and ranks 35% and #207 respectively has a EER of 0.84, ranks only 5%

The result proves that the energy benchmarking system is functional and properly worked.

V. Conclusion and Future Work

The study has successfully simulated the ENERGY STAR methodology with linear regression and tested the model of three most common building types. The result of testing suggested that models were working properly.

One possible improvement to make in the future is that instead of using all the attributes, specifications on matrices used for each model should be determined separately. Other energy consumption benchmarking system can also be used to validate the accuracy of ENERGY STAR methodology.

References

[1] ENERGY STAR Performance Ratings Technical Methodology. October 2007.

[2] Scofield, John H. Oberlin College. ENERGY STAR Building Benchmarking Scores: Good Idea, Bad Science. 2014 ACEEE Summer Study on Energy Efficiency in Buildings.

[3] Eia.gov. (2017). Energy Information Administration (EIA)- Commercial Buildings Energy Consumption Survey (CBECS). [online] Available at: https://www.eia.gov/consumption/commercial/index.php [Accessed 9 Dec. 2017].