Benchmarking Building Energy Performance Using Data Envelopment Analysis with Normalized Metrics---A Residential Case Study

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ABSTRACT

Data envelopment analysis (DEA) is emerging as an important benchmarking tool for building energy performance with its unique capability of discriminating scale efficiency and management efficiency. Generally, the impacts of climate factors are desired to be neutralized to obtain a climate-adjusted energy parameter when using DEA for building energy performance benchmarking. Multiple linear regression is often adopted for this neutralization. While very useful, this approach rarely considers the multicollinearity trap referring to the statistical issue that the strong correlations among explanatory variables can lead to non-robust building energy regression models. This paper presents a simple alternative normalizing approach to avoid the multicollinearity deficiency in DEA benchmarking application through neutralizing energy input with degree day and floor area. First, the annual energy consumption of each building is normalized by its floor area and local degree day to acquire the degree day normalized energy use intensity (DEUI). Second, with each building as one decision making unit, DEA model is constructed with the number of occupants and the floor area as DEA outputs and DEUI as input. Finally, DEA is calculated to obtain overall efficiency, scale efficiency and management efficiency. The energy performance of 31 one-story residential buildings is benchmarked using the developed approach based on historical data. The case study reveals that the low energy performance of the targeted buildings is mainly due to the inefficiency of management factors but further verification is desired.

INTRODUCTION

Complex factors can potentially affect the energy consumption of an existing building, including such uncontrollable scale factors as building size, number of occupants and such manageable factors like occupants' behavior, maintenance, equipment efficiency, etc. (Wang 2013;Wang and Shen 2012). This leads to the importance of discriminating the effects of these factors to take appropriate measures for effective building energy saving. Among the legion of existing models for building energy benchmarking, data envelopment analysis (DEA) which is a typical multi-factor efficiency analysis tool stands out due to its capability of discriminating scale efficiency and management efficiency. The scale efficiency is attributable to uncontrollable factors while the management efficiency is a measurement of manageable factors (Lee and Lee 2009). With each building as a decision making unit (DMU), DEA model essentially benchmarks the targeted buildings by comparing their performance with the energy frontier buildings that are identified by linear programming.

Climate is a significant energy consumption influencer, so to examine the residential energy efficiency using DEA, its influence should be neutralized. Linear regression is often used to eliminate the effects of climate factors (Lee and Lee 2009; Lee 2010). First, the linear equation between energy consumption and available influencing variables (e.g. floor area, occupants' counts, climate conditions) is established. After that, the climate-adjusted energy consumption is calculated using average climate information related to the targeted buildings. These adjusted energy values are then used as the input for the following DEA computation. While very useful, multicollinearity trap remains an issue in regression application. Multicollinearity refers to the statistical phenomenon that the strong correlations among explanatory variables make a regression model not robust (Farrar and Glauber 1967). Multicollinearity phenomenon could be common in building energy linear regression models considering that the strong correlations often exist between the adopted explanatory parameters (Wang 2013).

On the other hand, energy use intensity (EUI) is a most commonly used floor-area-normalized performance metrics of building energy (Chung 2011). Degree day is an indicator of indoor-outdoor temperature difference frequently used for energy use estimating (Lee 2010). These two parameters can then be further integrated to compose an indicator of degree day normalized EUI (DEUI) to neutralize the energy effects of two important factors: floor area and climate (Ueno 2010; Barry 2011). This further normalized indicator makes the energy comparison between different building individuals for benchmarking more reasonable.

This paper combined DEA with DEUI for analyzing residential energy efficiency. With the targeted individual building as DMU, DEUI is used as energy supply and input, and then floor area and number of bedrooms are used as outputs for the DEA model to measure the scale efficiency and management efficiency. This approach is applied to benchmarking energy efficiency of 31 buildings with real historical data.

METHODOLOGY

Data Envelopment Analysis. Data Envelopment Analysis (DEA) has been frequently taken for quantifying the relative efficiency of organizations, generally called Decision Making Units (DMUs). Its core principle is to first obtain the best practice frontier, and then calculate the relative efficiency of all DMUs with respect to it. Figure 1 shows a simple single-input single-output DEA example. To get the relative efficiency profile of the four DMUs, the efficient frontier needs to be firstly identified and then used as a benchmark for calculation. For n*th* (n=1, 2, 3, 4) DMU_n with an output of O_n and an input of I_n, the efficiency factor λ_n can be computed with the following formula:

Objective function $Max\lambda_n = (y_n * O_n)/(x_n * I_n)$

Subject to $(y_n * O_k)/(x_n * I_k) \le 1$ for $\forall k = 1,2,3,4$

Where $x_n, y_n \ge 0$ are the weighting coefficients; I_k and O_k are input and output for k*th* DMU, respectively.

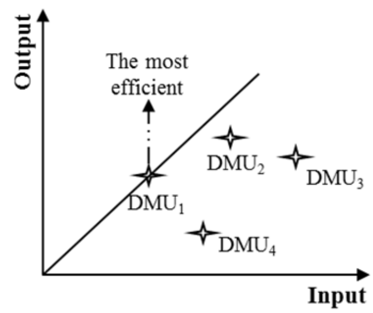

Figure 1. Single-input single-output DEA

Data Envelopment Analysis for Buildings with Normalized Metrics. The building energy system can be viewed as an input-output system. As shown in Figure 2, buildings consume energy which can be regarded as input and provide such comfort services, like heating, cooling, lighting and so forth to the building occupants. To obtain scale efficiency and management efficiency profiles, the effect of climate on energy consumption is neutralized. This neutralization is achieved by using degree day normalized EUI (DEUI) which can be defined as Btu/ (Square foot* Degree day*Year) (Ueno 2010; Barry 2011). The DEUI normalization not only considers the immediate impact of ambient temperature but also avoids the multicollinearity risk when compared to the regression method.

The input-oriented DEA approach is used because the reduction in energy input is targeted while maintaining the comfort level constant. Two basic models including constant returns to scale (CRS) model and variable returns to scale (VRS) model are adopted. Figure 3 presents a graphical example of using VRS for building energy management efficiency assessment. The floor area (Lee and Lee 2009) which indicates building size and the number of bedrooms which represents the number of occupants (Ueno 2010) are taken as DMU outputs (scale factors) and DEUI is made as DMU input. The surface is VRS frontier. The DMUs lying on the frontier present the best management efficiency. The value of management efficiency for DMU_1 is then represented by the length ratio of AB over AC. Higher ratio value indicates better efficiency.

CASE STUDY

The sample buildings' ages range from 15 to 106 years, with mean floor area of 998.0 SF and standard deviation of 239.9 SF. The mean value and standard deviation for the counts of bedrooms are 2.4 and 0.8, respectively. The samples cover three types of basement, including the slab, the partial and the full basement and two kinds of air conditioning system, i.e. central and non-central. The energy data were collected through three continuous years 2008, 2009, 2010.

Statistical dispersions differ among the three types of efficiency profile (Figure 4). In general, the investigated buildings show highest level of scale efficiency and lowest overall efficiency. It implies that these buildings are poor in building energy efficiency in terms of the overall indicator but the scales (including building size and occupants' counts) of buildings are at optimal level. Inferred from their relationships, i.e., the overall efficiency is the product of the scale efficiency and management efficiency, the poor overall efficiency may mainly be due to the poor management. The management efficiency in Figure 4 validates this inference.

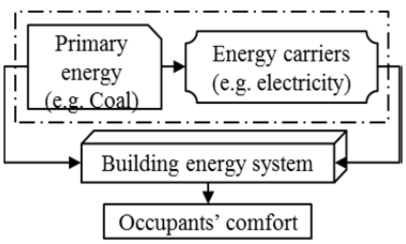

Figure 2. Building DEA

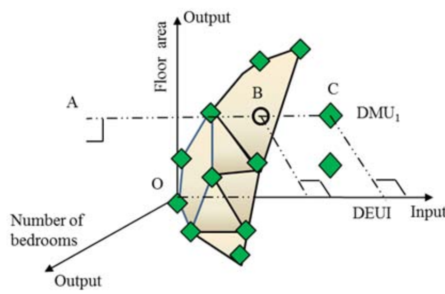

Figure 3. DEA for building energy efficiency (Lee and Lee 2009)

Figure 5 presents the cumulative distribution profiles of three efficiency categories. The mean overall efficiency value and standard deviation are 0.32 and 0.20, respectively. The coefficient of variation (COV) is an indicator of measuring variability and can be calculated as the ratio of standard deviation over the mean value. Higher values indicate larger variability. COV value for overall efficiency is 0.63, implying that large variability exists among the overall energy efficiency of buildings, i.e., the discrepancy between the better and the worse ones is significant. About 80% of the buildings have the overall efficiency below 0.50. This large proportion of building samples of poor overall efficiency presents a great potential for energy efficiency improvement through such measures as better maintenance, building envelope renovation, more economical behavior, etc.

The scale efficiency has higher mean value of 0.81 and the lower standard deviation of 0.19 than the overall efficiency. The COV is 0.23 and much less than COV of overall efficiency which means lower variability. More than half (about 68%) of the buildings show their scale efficiency above 0.81. It may indicate most of the building energy systems are suitable for the buildings in terms of building size and the number of occupants. Little energy is wasted due to the too small building size or too few occupants. From this concern, it may not be effective to reduce energy consumption by improving the building system design.

From Figure 5, the management efficiency graph appears quite even. The mean value is 0.43 while the standard deviation is 0.28. The COV for management efficiency is 0.65 which is greater than the above two COVs. It means the variability of management efficiency is the largest among that of the three types. The management efficiency discrepancy between buildings is significant. Around 77% of the residential buildings have the management efficiency less than 0.60. It may be inferred that, compared to the frontier, most of the investigated buildings are poorly managed or used, e.g. bad building condition, poor maintenance, extravagant energy use and so forth. As a result, the energy consumed by these inefficient buildings may be significantly saved by improving management factors.

Figure 6 shows the relationships between energy efficiency and DEUI. Moderate negative linear relationships are detected between overall efficiency and observed DEUI (Overall efficiency = 0.64-0.0015*DEUI), management efficiency and observed DEUI (Management efficiency = 0.80-0.0018*DEUI) with r^2 of 0.53 and 0.36, respectively. It means the buildings have higher DEUI very possibly show lower overall efficiency and management efficiency. However, almost no linear relationship exists between scale efficiency and observed DEUI (Scale efficiency= 0.83-0.000091*DEUI) with r^2 of 0.002.

Figure 4. Building energy efficiency

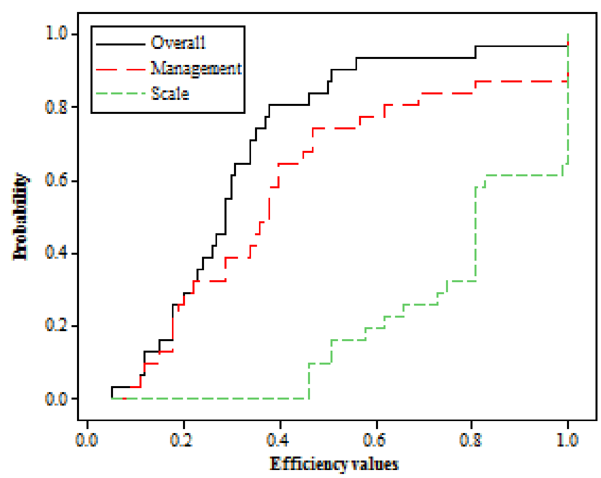

Figure 5. Cumulative distribution

The further relationships between the management efficiency, scale efficiency and overall efficiency are presented in Figure 7. No significant relationships are observed between scale efficiency and overall efficiency (Overall efficiency = 0.37-0.063*Scale efficiency) with negligible r^2 of 0.004. Significant positive correlation is detected between management efficiency and overall efficiency (Overall efficiency = 0.058+0.61*Management efficiency) with r^2 of 0.75. It means if management efficiency increases, the overall efficiency can be significantly improved. Nevertheless, the improvement in scale efficiency cannot help to promote the overall efficiency of these buildings.

Figure 8 shows the relationship between management efficiency and scale efficiency (Management efficiency =1.01-0.71*Scale efficiency) with r^2=0.24. It can be seen moderate negative correlation exists between scale efficiency and management efficiency. As the scale efficiency increases, the management efficiency decreases. It may indicate that the larger buildings in this region are subject to worse management.

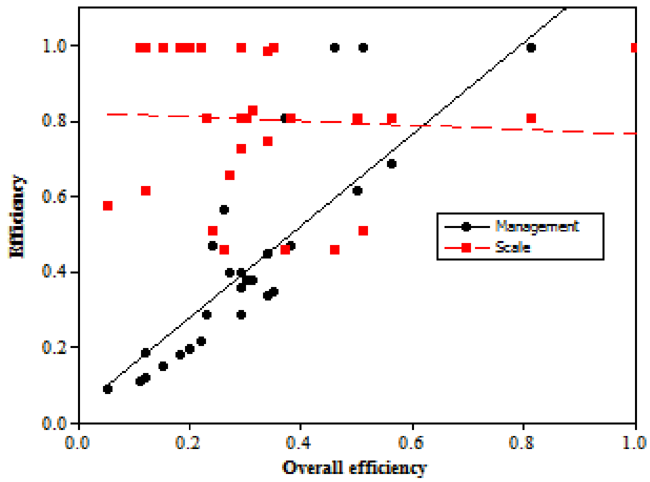

Figure 7. Impacts of scale efficiency and management efficiency on overall efficiency

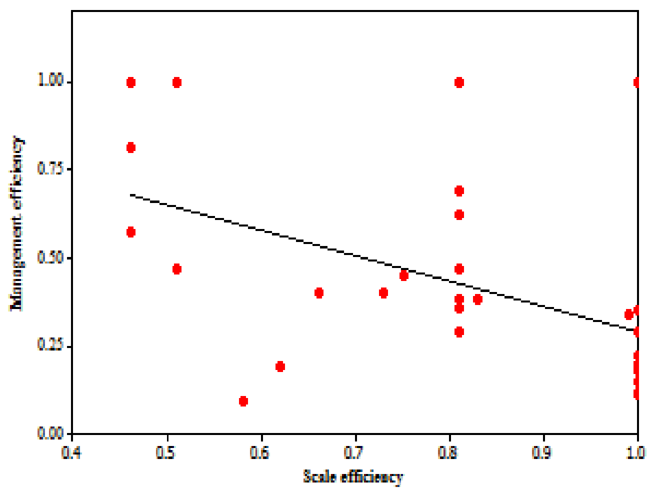

Figure 8. Relationship between management efficiency and scale efficiency

CONCLUSION

Reliable benchmarking of building energy performance is an important step towards energy saving. However, the long list of influencers for building energy consumption leads to the difficulty in its reliable benchmarking. As a typical numerical productivity efficiency benchmarking method, data envelopment analysis (DEA) has been recommended for building energy efficiency benchmarking. DEA has the unique capability of identifying the impacts of scale and management influencers which makes building energy efficiency improvement more specific. However, when using DEA for benchmarking building energy efficiency, the impacts of climate factors need to be normalized. The linear regression approach can be useful but subject to the typical multicollinearity risk.

This paper develops a degree-day normalized EUI (DEUI) based DEA approach for building energy efficiency benchmarking. It is able to normalize the variation of both indoor and outdoor temperature and simultaneously avoid the trouble of multicollinearity deficiency. First, DEUI is obtained by dividing energy use intensity by degree day counts. Second, treating each building as a decision making unit (DMU), DEUI is used as energy input and two parameters of floor area and occupants counts as outputs for DEA calculation. Lower level of overall efficiency and management efficiency and higher level of scale efficiency are observed for the case buildings. It indicates that these buildings have poor energy management but relatively optimal building layout design. The relationship study shows the improvement of overall efficiency is largely dependent on the management efficiency increase. This developed normalized DEA approach is simpler than the conventional manner but the normalization process is still limited to linear nature and its resulting accuracy needs further case validation.

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