Energy Conversion and Management 106 (2015) 530–542

Contents lists available at ScienceDirect

Energy Conversion and Management

journal homepage: www.elsevier.com/locate/enconman

Benchmarking energy performance of residential buildings using two-stage multifactor data envelopment analysis with degree-day based simple-normalization approach

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ARTICLE INFO

Article history:
Received 3 July 2015
Accepted 28 September 2015

Keywords:
Benchmarking
Building energy performance
Simple-normalization
Data envelopment analysis
Retrofitting

ABSTRACT

Being able to identify detailed meta factors of energy performance is essential for creating effective residential energy-retrofitting strategies. Compared to other benchmarking methods, nonparametric multifactor DEA (data envelopment analysis) is capable of discriminating scale factors from management factors to reveal more details to better guide retrofitting practices. A two-stage DEA energy benchmarking method is proposed in this paper. This method includes (1) first-stage meta DEA which integrates the common degree day metrics for neutralizing noise energy effects of exogenous climatic variables; and (2) second-stage Tobit regression for further detailed efficiency analysis. A case study involving 3-year longitudinal panel data of 189 residential buildings indicated the proposed method has advantages over existing methods in terms of its efficiency in data processing and results interpretation. The results of the case study also demonstrated high consistency with existing linear regression based DEA.

1. Introduction

Benchmarking energy performance of existing residential buildings is essential in developing successful energy retrofitting strategies. One challenge in benchmarking is to deal with numerous factors affecting the performance. These factors may include building orientation, building size, occupants' behavior, local climate, and building envelope condition [1–5]. Adopting appropriate methods and acquiring sufficient data to isolate these factors from each other is the key for this type of benchmarking research [4]. As a result, complex quantitative benchmarking frameworks have been developed to provide guidance for residential energy retrofitting activities [1,3,6].

Data-driven approaches, which derive reference values through constructed models based on historical data, have been utilized [1–3,7]. Compared to simulation approaches [7], data driven approaches have the advantage of being able to evaluate a large number of residential buildings considering multiple parameters, such as building characteristics, weather conditions and occupants' activities. Nonparametric DEA (data envelopment analysis) estimating the relative-to-best efficiency of buildings relative to an efficiency frontier which consists of the most efficient buildings, is emerging as one of the leading quantitative multifactor energy benchmarking methods [2,8–12]. DEA requires no prior functional assumptions on inherent relationships between multiple inputs (e.g. energy) and outputs (e.g. the served floor area), and can discriminate different influential factors (e.g. management, building size) which is important for an effective retrofitting [13,14].

In DEA, each individual building is generally treated as one DMU (decision making unit). When a temporal analysis is included, each individual building in a specific period can be viewed as one DMU [8,12,15]. Energy efficiency factors of existing buildings can be categorized into two groups [2]: (1) scale factors, such as building size, number of occupants; and (2) management factors, such as occupants' activities, maintenance policies, envelope insulation, COP (coefficient of performance) of heating and cooling systems. Accordingly, three types of efficiency measures can be established [2,10,11]: (1) scale efficiency, measuring the effects of scale factors; (2) management efficiency, measuring the consequences of management factors; and (3) overall efficiency, evaluating the overall performance due to all the influencing factors. In building retrofitting, these numerical efficiency values can produce two practical benefits for decision makers. First, when budget is

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http://dx.doi.org/10.1016/j.enconman.2015.09.072
0196-8904/

Nomenclature

Abbreviations

DEA	data envelopment analysis
DMU	decision making unit
MLR	multiple linear regression
EUI	energy use intensity
DEU	degree day normalized energy usage
CCR	Charnes, Cooper and Rhodes
BCC	Banker, Charnes and Cooper
CDD	cooling degree day
HDD	heating degree day
TDD	total degree day
BA	building age
FA	floor area
CO	count of occupants
NBA	number of bathrooms
AC	air conditioning
BT	basement type
BC	building condition
SD	standard deviation
COV	coefficient of variance
DRS	decreasing returns to scale
IRS	increasing returns to scale
VIF	variance inflation factor

Symbols in degree day method

T_{Max}, T_{Min}	maximum and minimum outdoor temperature
T_{Base}	base of indoor temperature setting

Symbols in Tobit regression

y_i	observed efficiency score for the ith sample
y_i^*	latent uncensored variable for the ith sample in Tobit regression
x_{ik}	value of the kth predictor for the ith sample
β_k	regression parameter of the kth predictor
ξ_i	error term

Symbols in data cloud method

$R^{(i)}, R^{(i)}_{\min}$	ratio and minimum ratio of the volume with i samples deleted over that without deletion
$V^{(i)}, V$	volumes of data clouds with and without the deletion of i building samples

Symbols in data envelopment analysis

η	its optimal solution being efficiency rating
x_{ik}, x_{ij}	the ith input values of the kth and jth building samples
y_{ok}, y_{oj}	the oth output values of the kth and jth building samples
i, o, j	the ith input variable, the oth output variable and the jth building sample
δ_j	weighting coefficient of the jth sample
η_{CCR}	solution of CCR model, overall efficiency
η_{BCC}	solution of BCC model, management efficiency

Symbols in multiple linear regression

E	energy use variable
u	constant intercept in regression
x_H	the Hth energy predictor in regression
w_H	regression coefficient for the Hth predictor

Symbols in Spearman correlation

ρ	Spearman correlation coefficient
x_i, y_i	converted ranks of raw variables X_i and Y_i
n	total number of paired efficiency scores

Symbols in computing variance inflation factors

VIF_i	variance inflation factor for predictor x_i
R_i^2	coefficient of determination for the regression when x_i is dependent variable

limited, it can provide detailed quantitative information on both energy performance and saving potential for prioritizing buildings. In addition, the detailed causes of buildings' energy inefficiency enable more focused retrofitting solutions to be developed. For example, DEA is able to answer whether the inefficiency of a building is due to inappropriate energy system or poor management [2]. The amount of energy saved through retrofitting can also be estimated.

In DEA process, the effects of pertinent climatic parameters must be considered [4]. While earlier work [16] treated climate variables as internal direct outputs in DEA in order to exclusively examine the climate control efficiency of public buildings, most recent literatures [2,6–8,11,12,15] tended to consider climate as an uncontrollable external operating environment of building structures. They generally normalized climate's effects before DEA to focus on building structure systems themselves. This approach appears more meaningful within the context of building energy retrofitting where the building structure pertinent factors, rather than uncontrollable climatic factors, are to be identified for retrofitting.

Two main approaches, i.e. MLR (multiple linear regression) [2] and clustering technique [7] were used previously to address the noise from climate variables prior to DEA modeling. Lee and Lee [2] adopted MLR based DEA which adjusted energy consumption with particular climate condition by obtaining regression coefficients from the established linear equations. In regression, the response variable is energy consumption and the explanatory variables are building related characteristics. The adjusted energy was then used for the sequential DEA analysis. While very useful, this approach is heavily contingent upon sufficient data sets [7]. Later, Lee and Kung [7] proposed to use classification based approach. The investigated buildings were first classified into separate classes based on their climate conditions using the clustering technique. The buildings within the same class were assigned with identical climate parameters and then analyzed separately at class-level against different frontiers associated with different classes. This approach is particularly valuable for a segmented DEA benchmarking (i.e., the buildings are evaluated separately compared to different efficiency frontiers of different classes). Yet, this approach may not be easy for a complete unified analysis (i.e., all the buildings are benchmarked at once against the same inter-temporal efficiency frontier) which could be desired in many cases [2,8,12].

On the other hand, simple normalization approach [3] was adopted for addressing the specific impact of individual energy influencers in building energy benchmarking [1,4,6]. In this approach, the impacts of building energy factors are evaluated based on a normalized energy performance indicator (often the ratio of total energy use over one or two particular factors) [1,3,17,18]. Two commonly used normalization metrics are: (1) EUI (energy usage intensity), normalizing the impact of