Energy and Buildings 75 (2014) 10–22

Contents lists available at ScienceDirect

Energy and Buildings

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

Benchmarking energy performance of building envelopes through a selective residual-clustering approach using high dimensional dataset

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ARTICLE INFO

Article history:
Received 15 September 2013
Received in revised form
21 November 2013
Accepted 26 December 2013

Keywords:
Building envelope
Energy performance
Residential
Benchmarking
Principal component regression
Multicollinearity
High-dimensional variables

ABSTRACT

Benchmarking energy performance of existing residential buildings' envelopes remains a challenge due to the complex physical and non-physical interacting factors of buildings. Regression analysis with sufficient data samples can be attractive for benchmarking application due to its capability in neutralizing the effects of noise variables. However, multicollinearity effects among explanatory variables often lead to unreliable regression models, especially in cases of high-dimensional variables. Principal Component Regression can transform co-linear variables via principal component analysis to orthogonal components and simultaneously has the neutralization function of linear regression analysis of high dimensional dataset. A new benchmarking method is developed using multivariate linear regression analysis with principal component analysis to address the multicollinearity risk with high dimensional dataset. The method was applied to datasets of a real project. The results indicate that Principal Component Regression is able to address multicollinearity risk, through using fewer orthogonal principal components that are linear combinations of original variables. The benchmarking outcome using this method is validated through infrared thermography validation. The benchmarking result is superior to that of the traditional statistical rating method using average energy consumption of buildings.

1. Introduction

Retrofitting existing buildings provides a key area for achieving building energy efficiency in U.S. [1–3]. According to Holness [2], around 86% of building construction expenditures is related to existing buildings renovation. Building envelope is a significant component in most energy retrofitting projects [4]. As such, being able to conduct a reliable evaluation of building envelopes' thermal performance is critical for the success of an energy retrofitting project.

Among methods developed to evaluating building envelopes' energy efficiency, data-driven benchmarking method that quantifies energy performance of a building against the peer buildings [5], is often used due to its convenience over other methods, such like blower door test [6], infrared thermography [7], physical observation and simulation [5,8,9]. However, due to the complexity of building energy interaction and the disturbance of "noise" factors, such as building style, building layout, occupants' behavior, climate related factors and so forth [5,9–11], the reliability of this method remains a challenge. For example, the energy saving contributed by moderate climate condition or occupants' more economical behavior should not be viewed as building envelope energy efficiency improvement. As a consequence, directly comparing the summed energy consumed in different buildings cannot accurately measure building envelope energy efficiency. After the effects of "noise" factors are removed/neutralized [10], the difference among corresponding residuals can offer a practical indication of building envelope energy efficiency [11,12].

Much research effort has been put aiming at neutralizing the "noise" influencing factors through either performance metrics normalization or numerical model development and eventually improving benchmarking reliability [5,8,10,12,13]. Substituting Energy Use Intensity (EUI) (e.g. J/m^2/Year (or Btu/SF/Year)) which measures building energy consumption relative to the building size for the straightforward metric which purely measures entire building energy use (e.g. J/Year (or Btu/Year)) is a radical improvement in performance metrics though this simple floor-area-normalized EUI is still sensitive to other factors, e.g. climate condition and occupants' behavior [10,12]. Several numerical models have been used to neutralize the effects of "noise" factors and each has different virtues and limitations [5,9,12,14]. Among them, multiple linear regression analysis (MRA) is a typical approach and is frequently utilized due to its flexibility in quantifying the relationships among selected variables [8,10–12]. Arguing that neither mean

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http://dx.doi.org/10.1016/j.enbuild.2013.12.055

nor median EUI is reliable, Sharp [10] proposed using MRA model errors to benchmark buildings. Lee and Lee [8] obtained climate-adjusted building energy consumption using MRA. Chung et al. [11] developed a MRA residual-based benchmarking approach in which energy efficiency is indicated by the difference between the actual energy use and the predicted energy use. This residual benchmarking concept is further used by Chung [15].

In the case of large-scale high dimensional dataset with long list of explanatory variables, MRA has the limitation of multicollinearity, which describes the statistical phenomenon that explanatory variables in a linear regression model are significantly correlated and affects the robustness of the developed model (e.g. uncertainties of coefficients tend to be greater in the presence of multicollinearity) or even leads to wrong conclusions [16–18]. This phenomenon is common in building energy benchmarking due to the often subjectivity or as-available nature in the selection of explanatory variables [19,20]. For example, Tzikopoulos et al. [18] found the correlation coefficients between building area and building volume, degree months and sun days can be as high as 0.89 and −0.82, respectively. Climatic variables which are commonly included in benchmarking models are often related to each other [21]. On the other hand, Principal Component Analysis (PCA) [17,22], as a typical dimensionality-reduction technique, can be a valuable support to cope with this multicollinearity deficiency by representing raw highly collinear variables with reduced number of orthogonal components and has been applied in many fields for this type of purpose, e.g. dendroecology [21], health and nutrition [23], coastal engineering [24] and so forth.

Starting from the concept of using residual to measure building envelope energy efficiency, this paper constructs a selective residual-clustering based building envelope benchmarking model which adopts the residuals generated from either MRA or Principal Component Regression (PCR) which integrates the methodological strength of MRA and PCA, depending on the seriousness of multicollinearity problem. More specifically, it mainly includes four steps: (1) Variance inflation factors (VIFs) are calculated to detect multicollinearity problem. (2) Depending on the results of multicollinearity detection, MRA in the case without multicollinearity or PCR in the case with multicollinearity is performed. When PCR is required, PCA is preliminarily run to compose mutually orthogonal principal components which best represent the original high dimensional dataset. After PCA, MRA is conducted on the scoped components. Through either MRA or PCR, the corresponding residuals are obtained. (3) The obtained residuals are classified utilizing the state-of-art clustering rating scheme to rate the building samples. (4) The benchmarking results are validated by infrared thermography which is a reliable technique widely used for determining building envelope thermal property [25,26].

2. Methodology

2.1. Statistical procedure

A list of inclusive statistical methods containing PCR, PCA, MRA, Fuzzy C-Means clustering are respectively described in Appendices A.1–A.4 with their particular functions and concrete algorithms. Based on these methods, a selective residual-clustering approach for benchmarking building envelope energy performance is developed with specific components shown in Fig. 1: data preparation (Appendix A.5), building energy performance indicator choice (Appendix A.5), detection of multicollinearity problem (Appendix A.6), principal components identification (Appendix A.7), linear regression development (Appendix A.8), residuals calculation using predicted results and observed values and classification with clustering. Fig. 1 also presents the detailed implementation procedure using the developed benchmarking approach.

2.2. Field survey using infrared thermography

Infrared thermography which is dependable to locate thermal defects through hardware-based infrared observation [7,25] is adopted for evaluating the benchmarking model results. Derived from complicate physics law (e.g. Planck's radiation law), its intuitive operation is to identify thermal deficiencies by outlining the "hot" spots in planar temperature maps of existing buildings (Fig. 2). These "hot" spots often result from poor design level of building envelop insulation, general physical deterioration or unexpected thermal defects [25]. The more "hot" spots indicate more deficiencies and poorer level of thermal performance.

The total area of "hot" points is quantified through image binarization (see Fig. 2) on the color scale thermal image [27] after defining a threshold pixel level. The relative thermal performance will be indicated through the percentage of white color area representing zones of poor thermal performance to the overall area. In the case referred in Fig. 2, if threshold value is defined to be 0.5, then the resulting percentage of white area is 0.51, which means 51% of the wall area may have heat loss problem in cold season.

3. Case results

Following the procedure in Fig. 1 and the methodology presented in Section 2 and the Appendix, the proposed model is validated through the benchmarking of 480 households community in Iowa. According to the findings of previous research related to building energy investigation [3,6,8,10,11,18,19,28], the desired database should consist of local climate statistics (e.g. monthly-averaged ambient temperature), building envelope related information (e.g. building age, floor area, building condition), occupants' demography (e.g. number of occupants) and energy consumption data (e.g. heating energy, cooling energy). The monthly recorded climate and energy consumption data are required to be aggregated to be ones on a yearly basis considering the fact that building envelope deterioration tends to be slow and could be more meaningfully evaluated on a yearly basis than on a monthly one [29,30].

3.1. Variables selection

Based on the empirical procedure for selecting inclusive variables in previous literatures [10,18,19], given data availability, nine concrete variables involving building condition (BC) (e.g. Excellent, Good), building age (Age) (e.g. 60), basement type (BT) (e.g. partial), building style (BS) (e.g. 1.5 story), types of air conditioning system (AC) (e.g. Central air), number of bathrooms (BA) (e.g. 1), floor space (FS) (e.g. 88.3 m^2), ratio of the number of bathroom to the number of bedrooms (RR) (e.g. 0.5), total number of rooms (TR) (e.g. 2) with differing information recording approaches (i.e. qualitative or quantitative), are used to describe features of building samples. Compared to other peers, accurate building condition related information seems more difficult to obtain. Though subjective, visual building condition assessment is still the mainstream technique for showing overall profile of building condition [29]. Six-point scale condition assessment is taken (Criteria shown in Table 1) due to its theoretical advantage over others in enough information discriminating capacity [29]. The number of occupants living in respective building is indicated by the number of bedrooms (BE). The typical temperature term degree day (°C-day or °F-day) is applied to characterizing local temperature, including cooling degree day (CDD), heating degree day (HDD), total degree day (TDD), and ratio of CDD over HDD (RCH). Apparently, TDD and RCH are redundant but