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Benchmarking the energy efficiency of commercial buildings

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Abstract

Benchmarking energy-efficiency is an important tool to promote the efficient use of energy in commercial buildings. Benchmarking models are mostly constructed in a simple benchmark table (percentile table) of energy use, which is normalized with floor area and temperature. This paper describes a benchmarking process for energy efficiency by means of multiple regression analysis, where the relationship between energy-use intensities (EUIs) and the explanatory factors (e.g., operating hours) is developed. Using the resulting regression model, these EUIs are then normalized by removing the effect of deviance in the significant explanatory factors. The empirical cumulative distribution of the normalized EUI gives a benchmark table (or percentile table of EUI) for benchmarking an observed EUI. The advantage of this approach is that the benchmark table represents a normalized distribution of EUI, taking into account all the significant explanatory factors that affect energy consumption. An application to supermarkets is presented to illustrate the development and the use of the benchmarking method.

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1. Introduction and literature review

As energy efficiency refers to using less energy to produce the same amount of services or useful output, energy-efficiency indicators are used to indicate the energy-consumption performance level of energy-consuming systems. The concept, definition and importance of energy-efficiency indicators are discussed in Patterson [1] and Haas [2].

Energy-efficiency benchmarking can be used to monitor changes in energy efficiency. Benchmarking models developed from energy-efficiency indicators are valuable tools for both government and the private sector in managing energy consumption. Some governments have used these tools to formulate policies for the efficient use of energy in buildings (see Federspiel et al. [3] and the references therein).

We first develop the energy-efficiency indicators before conducting the benchmarking exercise. Typically, energy-efficiency indicators for commercial buildings can be obtained by normalizing the energy use with floor area and/or operational hours. Climate adjustment of energy use data is performed when the degree–days information is available. For instance, Filippín [4] used a sample of energy consumption data and the floor area to calculate the Energy Use Intensity (EUI), i.e., kWh/ft^2 or MJ/m^2, for school buildings in central Argentina. The calculated EUIs were then ranked as a benchmark table. This simple floor-area-normalized EUI is often used for judging the energy-use performance of a commercial building. Singapore e-Energy Benchmark System [5] and Birtles and Grigg [6] used a similar method. However, Monts and Blissett [7] discussed the limitations of using the simple normalized EUI for commercial buildings. It is plausible that other factors (such as an HVAC system) may cause the energy use in specific buildings to be higher (or lower) than that in their peers.

Sharp [8] also made the same argument that such a simple normalized EUI was not good enough for a credible energy-consumption performance rating. To account for the effect of other factors that affect energy consumption, benchmarks were developed using a multivariate linear-regression approach to correlate other factors representing some important characteristics of buildings with EUI. Moreover, Sharp argued that the mean EUI can be a poor benchmark as distributions of indicators are generally skewed. Hence, Sharp used the standard errors of the resulting regression model to establish the distributional benchmark table, which was considered more reliable as it masked the effect of outliners. The benchmarking process of a specific building makes use of the ‘‘best-fitted’’ regression model to calculate the predicted EUI. With this predicted EUI, a distributional benchmark table (percentile table) is calculated by means of the distribution of standard errors. The actual EUI can be compared with the benchmark table for the benchmark score. Sharp’s method has been used in the Asia-Pacific Economic Cooperation Energy Benchmark System [9] and slightly modified as the basis of the Energy Star® benchmark [10].

Another common benchmarking method is based on the distribution of residuals of the regression model, in contrast to the approach based on the standard error-distribution in Sharp’s method. The residual is the difference between the actual

EUI and the predicted EUI. Hence, the residuals are treated as measures of inefficiency. For a given building to be benchmarked, if the actual EUI is less than the predicted EUI (negative residual), it means that the building uses less energy than other similar buildings. Moreover, the distribution of sample residuals from the regression model can be used to construct the corresponding benchmark table. Lovell-Smith and Baldwin [11] used a similar approach in which the residuals were not obtained from the regression model. However, they used the mean EUI from the sample as the predicted EUI without considering the normalization of other significant factors. Obviously, this kind of benchmark table does not provide a physical measure. Sharp's method uses the actual EUI distribution instead.

In this paper, we develop an EUI benchmarking method for commercial buildings which was initiated by the Hong Kong Special Administrative Region (SAR) Government [12]. The resulting benchmark table consists of EUI measures and the benchmarking process does not involve the re-calculation of the EUI distribution like that obtained with Sharp's method.

2. The benchmarking method

After the data-collection exercise, the benchmarking process consists of three steps: (1) climate adjustment of EUI (MJ/m^2) by degree–day normalization; (2) regression model building for discovering the relationship between the climate-adjusted EUI and the significant factors corresponding to building characteristics; and (3) normalization of the climate-adjusted EUIs for the significant factors to form a benchmark table. In step 3, the bootstrapping technique is applied to provide an efficient percentile-estimation for small samples. Details of steps (2) and (3) are given in the following sections.

2.1. Regression model

To build a regression model for energy consumption with a data set of size n, let the EUI be a climate-adjusted energy-use intensity and $x_1, \ldots, x_p$ be a set of examined factors such as building age, energy system and floor area. These factors may be transformed from the basic set (measurements) if necessary. The base level (normal or mean standard) of each factor is determined either from the population or the observed sample. Base levels are used as references that reflect the ''normal'' operating conditions (for example, the mean temperature-setting for air-conditioning) and mean characteristics of study units. These factors are then standardized according to the base levels.

A ''best-fitted'' multiple regression model is then constructed from the standardized data. For simplicity, we assume the final model is of the form:

$$\mathrm{EUI} = a + b_1 x_1^* + \cdots + b_k x_k^* + \varepsilon, \tag{1}$$

where a is the intercept; $b_i, \ldots, b_k$ are the regression coefficients; $x_1^*, \ldots, x_k^*,\ k \leqslant p$ are the significant standardized factors; and ε is the random error.

2.2. Normalization of EUI for significant factors

Normalization of the EUI for the significant factors is derived from regression model (1). Let $\mathrm{EUI_o}$ be the observed EUI and $x_1^*, \ldots, x_k^*$ be the observed standardized factors of a given record. The normalized energy utilization index $\mathrm{EUI_{norm}}$ is given by

$$\mathrm{EUI_{norm}} = \mathrm{EUI_o} - b_1 x_1^* - \ldots - b_k x_k^*. \tag{2}$$

Note that $\mathrm{EUI_{norm}} = a$ in (1) when $\{x_1^*, \ldots, x_k^*\}$ are set at the mean (base) level of $x_1, \ldots, x_k$. Hence, $\mathrm{EUI_{norm}}$ can be regarded as a normalized energy-efficiency indicator by removing the effect of deviance in the secondary factors (building characteristics). The effect of the significant factor i is measured by the regression coefficient b_i in (1) and the deviation from its base level. $\{\mathrm{EUI_{norm(1)}}, \ldots, \mathrm{EUI_{norm(\mathit{n})}}\}$ can be considered as a random sample of $\mathrm{EUI_{norm}}$ from the population. This set of $\mathrm{EUI_{norm}}$ measurements constitutes the benchmark basis for the formation of a benchmarking percentile table.

2.3. Benchmark table and benchmarking process

We construct the benchmark table, which is a set of estimated percentiles of the indicator distribution. Obviously, $\{\mathrm{EUI_{norm(1)}}, \ldots, \mathrm{EUI_{norm(\mathit{n})}}\}$ provides an empirical cumulative distribution function of the $\mathrm{EUI_{norm}}$. Bootstrapping [13] is a re-sampling method that can be used in estimating the percentiles from a random sample. The bootstrapping technique provides an efficient percentile estimation for small samples. We calculate the bootstrapped percentiles $\mathrm{EUI_{norm\ .10}}$ (10 percentile), $\mathrm{EUI_{norm,\ .20}}$ (20 percentile), …, $\mathrm{EUI_{norm\ .90}}$ (90 percentile), which form the benchmark table for the $\mathrm{EUI_{norm}}$. For a given premise to be benchmarked regarding EUI, we can compute the EUI_{norm} from Eq. (2). The computed EUI_{norm} is then compared to the benchmark table for obtaining the corresponding rank.

3. Benchmarking the EUI of supermarkets

The Energy Efficiency Office of Electrical and Mechanical Services Department in Hong Kong has conducted a study to develop energy-efficiency indicators and benchmarks for energy end-use groups. The objective of the study is to provide the Government a quantitative tool for policy formulation. The proposed benchmarking method has been adopted to establish the benchmark table for benchmarking energy efficiency. In this paper, we only discuss the development of benchmark table for the supermarket subgroup with central air-conditioning (a subgroup of stand-alone shops in a building with floor area greater than 75 m^2). See [14] for the benchmarking system and other energy end-use groups.

3.1. Selection of EUI and explanatory variables

The climate-adjusted energy-use intensity EUI (in $\mathrm{MJ/m^2}$) is chosen as the dependent variable in the multiple regression model. According to [7], the adjusted energy-efficiency indicator with the degree–day is too simple for practical use in commercial premises. There are other factors which may also affect the EUI, such as occupants' operation, behaviour and maintenance factors, that cannot be normalized only by degree–days. Piper [15] discussed some factors that influence energy use and performance in buildings. These are people factors, building-type factors, occupancy factors, climate factors, age factors, construction factors, and energy end-use system factors. Since this study concentrates on the plausible energy-efficiency improvement targets for supermarkets, the building-type factors and the construction factors are not considered. Here, nine potential explanatory variables (factors) are selected in constructing a multiple regression model. These factors are presented in Table 1.

Building age (x_1) is defined as the period between the present time and the year the building was commissioned for occupancy (as required by the Building Ordinance of Hong Kong). This factor also reflects the overall equipment condition, efficiency class, etc. The data were obtained from the Hong Kong Building Department. Internal floor area (x_2) is defined as the entire area of the enclosed space of the unit measured. Records on the surveyed objects are available from the Hong Kong Rating and Valuation Department. Operation schedule (x_3) is defined as the hours of operation per annum. The occupants' behaviour and maintenance factor (x_5) is a subjective rating score. A score would be assigned to the supermarket for the following 'good occupants operations or maintenance practices':

- turn-off lighting when not in use;
- turn-off air-conditioning when not in use;
- turn-off other equipment, not mentioned above, when not in use;
- have an effective energy-monitoring and targeting system in order to save energy;
- have a decent energy-audit [16] of the building or premises carried out, and implement energy-conservation measures for the purpose of saving energy; plan a regular maintenance program, and supply an easy-to-follow inspection manual for maintaining the efficiency of the lighting system;
- plan a regular maintenance program, and supply an easy-to-follow inspection manual for maintaining the efficiency of the HVAC system;

Table 1
Explanatory variables of energy consumptions in supermarkets

Factor	Exogenous variable	Exogenous variable name
Age	X_1	Building age
Occupancy	X_2	Internal floor area
	X_3	Operational schedule
	X_4	Number of customers/year
People	X_5	Occupants' behaviour and maintenance factor
	X_6	Indoor temperature set-point (summer)
Energy system	X_7	Chiller type of equipment
	X_8	Lighting equipment
	X_9	Lighting control

- plan a regular maintenance program, and supply an easy-to-follow inspection manual for maintaining the efficiency of other building-services systems not mentioned above; and
- have an easy-to-follow manual detailing operation methods, instructions and standard control settings for the HVAC system.

Indoor temperature set point (x_6) refers to the indoor temperature set-point of the air conditioners in summer. Chiller type of equipment (x_7) and lighting equipment (x_8) are weighted system efficiencies of the corresponding equipment. Lighting control (x_9) refers to the penetration of lighting control.

A randomly selected sample of 30 supermarkets was surveyed to develop a database for energy-efficiency benchmarking. A sample size of 30 is regarded as sufficient to provide an effective normal approximation as a general rule-of-thumb, regardless of the shape of the population distribution [17,18]. Summary statistics of the survey result (data range, average and SD) are presented in Table 2.

3.2. Climate adjustment of EUIs

The degree–day value is defined as the difference between the daily mean temperature and the defined base temperature. When the difference is positive, it represents the cooling degree–day used to correlate with the cooling energy consumption for air-conditioned premises. The overall daily mean-temperature (18.3 °C) recorded by the Hong Kong Observatory is adopted as the base temperature. In this application, the supermarket energy-consumption is adjusted according to the weather. The adjustment is made based on the degree–days that occurred within the 12-month energy-consumption record period. The corresponding degree–days that occurred during this period are adjusted, based on the average of the past 20 years annual cooling degree–days in Hong Kong. The adjustment factor is $CDD_{20\ years}/CDD_{supermarket}$, where $CDD_{20\ years}$ is 20 years' average-value (1982–2001) for the annual cooling degree–day, and $CDD_{supermarkett}$ is the corresponding 12 months' degree–days in the recorded period.

Table 2
Summary statistics of survey result

Xi	Min	Max	Mean ($\bar{X}_i$)	SD (S_i)
X_1	3	42	21.133	11.292
X_2	76	640	219.37	175.76
X_3	4380	8760	7071.9	1777.9
X_4	36500	912500	441.350	229.057
X_5	0	6	1.9667	1.7317
X_6	20	26	22.938	1.5713
X_7	2.3	2.5	2.42	0.0714
X_8	49.279	100	72.101	8.057
X_9	0	0.2	0.034	0.0627

3.3. Building the regression model

Assume that the typical distribution of energy consumption among supermarkets is affected by the selected set of explanatory variables including building age, occupancy, climate, people and energy system. A multiple regression model for the supermarket EUI (MJ/m^2/year) is given by

$$\mathrm{EUI} = a + b_1 x_1^* + \ldots + b_9 x_9^* + \varepsilon = a + \sum_{i=1}^{9} b_i \left(\frac{x_i - \bar{x}_i}{S_i} \right) + \varepsilon, \tag{3}$$

where base levels (normal standards) are used as references that reflect the "normal/mean" operating conditions.

Backward elimination [19] is applied to select the regression model where insignificant explanatory variables are eliminated. From the backward elimination procedure, a final regression model is determined for benchmarking. There is a trade-off which relates to whether we would like to have the "best" predictive model (many significant factors with large variance) for sophisticated users such as building engineers, or a simple interpretable model (a few significant factors with small variance) for other users. Responding to these arguments, the significant factors are divided into two groups for developing the benchmarking system in Section 4. Here, the coefficients of determination (R^2) are compared at each elimination step. The coefficient of determination gives the percentage of variation in *EUI* that can be explained by the variability in the explanatory variables. It also reflects the goodness-of-fit of the proposed model. The model is chosen so that: (i) it gives a "good" R^2 and (ii) the R^2 drops substantially if any variable in the chosen model is eliminated.

The following transformations of primary indicators are considered in the modelling process to accommodate the distribution characteristics and data trends.

(i) logarithm, i.e., $\mathrm{EUI} \rightarrow \log(\mathrm{EUI})$
(ii) square root, i.e., $\mathrm{EUI} \rightarrow \sqrt{\mathrm{EUI}}$
(iii) inverse, i.e., $\mathrm{EUI} \rightarrow \frac{1}{\mathrm{EUI}}$, and
(iv) Box-Cox [20], i.e., $\mathrm{EUI} = (\mathrm{EUI}^{\lambda} - 1)/\lambda$.

4. Results

The minimum, maximum, average and the SD of the supermarket EUIs (MJ/m^2/year) are 1802, 12,442, 5852.6 and 2591.2, respectively, for 30 observed supermarkets with degree–days normalization. Comparing with other survey results, the average value is much greater than that of the UK Energy Benchmark [21] with 3960 MJ/m^2/year (based on 207 supermarkets with degree–days normalization only), and Energy Star [22] with 3526 MJ/m^2/year (based on 88 supermarkets based on Sharp's method [8]). The big differences should be due to the compact size of Hong Kong supermarkets and different operating conditions in Hong Kong.

With the above selection criteria and the consideration of the transformation of EUI, we obtain the following regression model with $R^2 = 0.7082$ (t statistics in small parentheses) for the supermarket subgroup:

$$
\begin{aligned}
Y = \underset{(20.83)}{5852.6} + \underset{(3.31)}{972.7} \times \left(\frac{\text{building age} - 21.13}{11.29}\right) \\
- \underset{(-3.91)}{1519.2} \times \left(\frac{\text{floor area} - 219.37}{175.76}\right) \\
+ \underset{(1.55)}{588.4} \times \left(\frac{\text{operation schedule} - 7071.9}{1777.9}\right) \\
+ \underset{(1.41)}{470.3} \times \left(\frac{\text{number of customers} - 441350}{229057}\right) \\
- \underset{(-1.40)}{411.5} \times \left(\frac{\text{occupants' behaviour} - 1.97}{1.73}\right).
\end{aligned} \tag{4}
$$

Table 3 shows a summary of the backward-elimination procedure.

The impact of significant factors on the EUI is in line with expectation. As the building age increases, the EUI of the stand-alone supermarket (occupying a whole building unit) increases as indicated by the positive regression-coefficient. This is expected because supermarkets operate in a relatively inefficient environment. Newer buildings are better insulated due to the evolved building codes. New improved equipment, such as for HVAC, is more efficient. Moreover, the windows, roofs, walls and equipment deteriorate with age. Note that negative regression coefficients are observed in some subgroups, such as 'whole building'. This may be due to the different subgroups' operational characteristics.

The effects on the relationships between the floor area and the operational schedule on the energy efficiency indicator are due to the scale of the business. The last significant factor, good occupants' behaviour, makes the energy efficiency indicator decrease as the occupants conduct a quality maintenance-program for their equipment. Fig. 1 gives the residual plot of the regression, which indicates a fairly good fit for the data. Figs. 2–6 show the scatter plots of EUI vs the significant factors. In Fig. 4, the scattering of operation schedule is due to the fact that some of the observed supermarkets are open 24 h a day. It is one of the operational characteristics of Hong Kong supermarkets.

Table 3
Summary of backward elimination results

Step number/factors removed	R^2	Adjusted R^2
0/temperature set point	0.7316	0.6108
1/chiller type of equipment	0.7308	0.6282
2/lighting control	0.7290	0.6428
3/lighting equipment	0.7082	0.6474
4/occupants' behaviour	0.6845	0.6340
5/number of customers	0.6691	0.6309

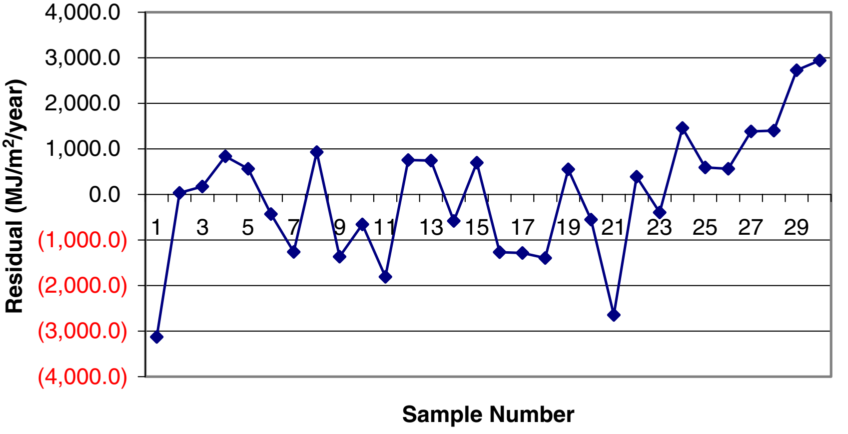

Fig. 1. The prediction error of the regression model.

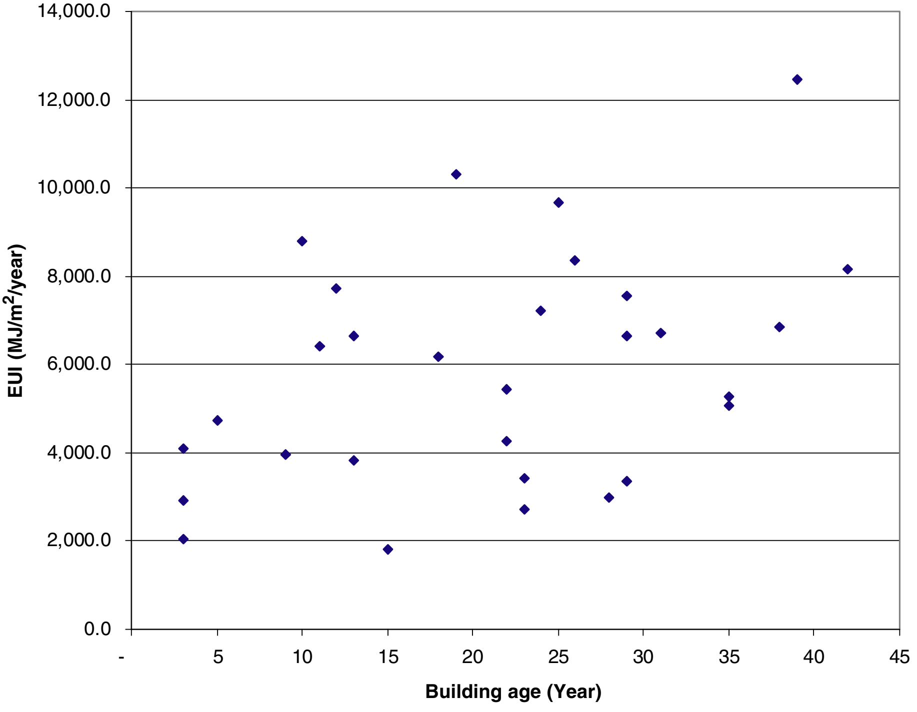

Fig. 2. EUI and building age.

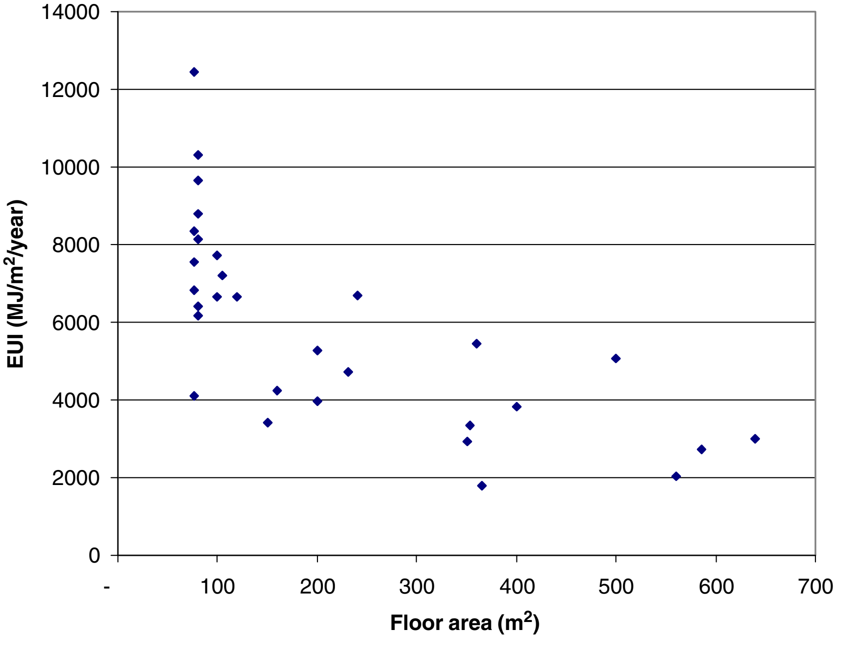

Fig. 3. EUI and floor area.

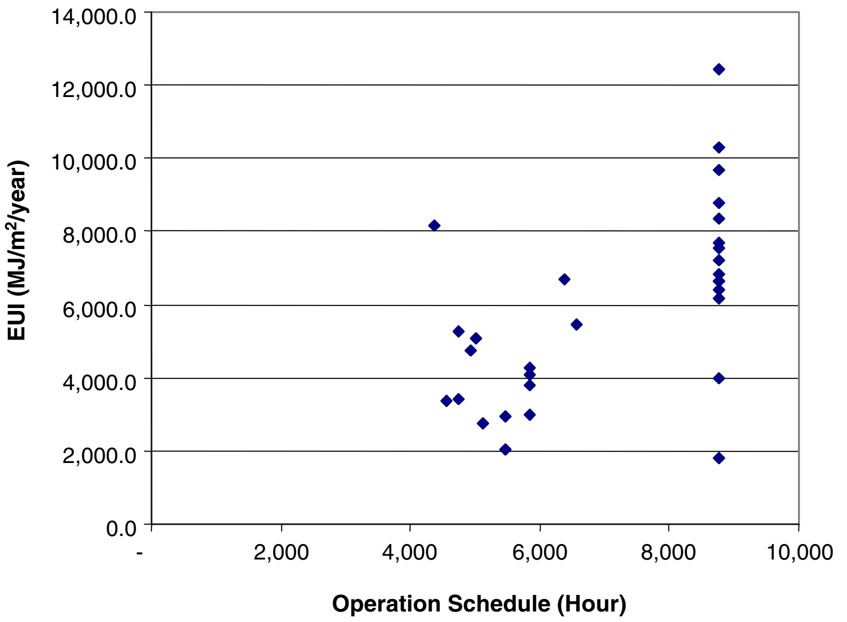

Fig. 4. EUI and operation schedule.

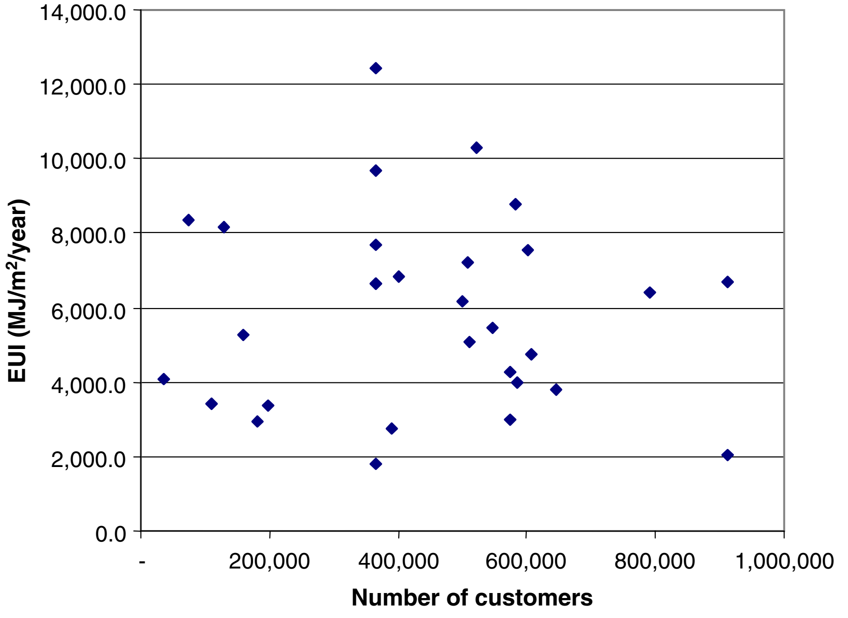

Fig. 5. EUI and number of customers.

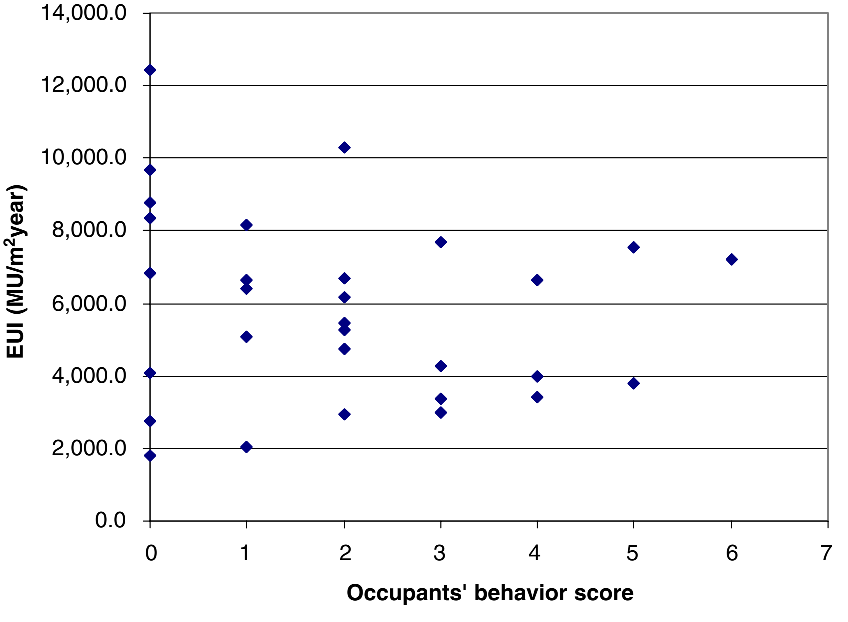

Fig. 6. EUI and occupants' behaviour score.

The EUI regression model is adopted for normalization, taking into account all the significant factors. From Eq. (4) and the proposed procedure in Section 2, we compute 30 values of $\mathrm{EUI}_{\mathrm{norm}}$ (i.e., $\mathrm{EUI}_{\mathrm{norm}(1)}, \ldots, EUI_{\mathrm{norm}(30)}$) from the sample. These 30 $\mathrm{EUI}_{\mathrm{norm}}$ can be considered to be the "observed" EUIs from the 30 supermarkets with typical (average) factor-levels: building age = 21.13, floor area = 219.37, operation schedule = 7071.9, number of customers = 44,1350, and occupants' behaviour = 1.97. That is, if a supermarket operates at the average levels, its EUI equals to 5852.6 MJ/m^2/year. Hence, these 30 EUIs provide an empirical sample of the $\mathrm{EUI}_{\mathrm{norm}}$. We obtain the percentile estimates using a bootstrapping function in the statistical software S-plus [23]. The results are shown in Table 4.

The bootstrapped values of $\mathrm{EUI}_{\mathrm{norm}}$ are used in establishing the energy performance benchmarks. Once we have the benchmark table, end-users can calculate the $\mathrm{EUI}_{\mathrm{norm}}$ based on their observed data $\mathrm{EUI}_{\mathrm{o}}$ and x_i^*s using Eq. (2)

$$\begin{aligned}\mathrm{EUI}_{\mathrm{norm}} = \mathrm{EUI}_{\mathrm{o}} - 972.7 \times \left(\frac{\text{building age} - 21.13}{11.29}\right) + 1519.2 \\ \times \left(\frac{\text{floor area} - 219.37}{175.76}\right) - 588.4 \\ \times \left(\frac{\text{operation schedule} - 7071.9}{1777.9}\right) - 470.3 \\ \times \left(\frac{\text{number of customers} - 441350}{229057}\right) + 411.5 \\ \times \left(\frac{\text{occupants behaviour} - 1.97}{1.73}\right). \end{aligned} \quad (5)$$

By matching the calculated $\mathrm{EUI}_{\mathrm{norm}}$ to the bootstrapped $\mathrm{EUI}_{\mathrm{norm}}$ percentiles in Table 4, a percentile rank can then be assigned as the benchmark score.

Table 4
Benchmark table of EUI for stand-alone supermarkets

Percentile	$\mathrm{EUI}_{\mathrm{norm}}$ (from bootstrapping results)[a]	$\mathrm{EUI}_{\mathrm{norm}}$ (from sample data)[b]
10	3949	4045
20	4584	4571
30	5035	5193
40	5474	5421
50	5943	6026
60	6313	6415
70	6526	6548
80	6771	6687
90	7305	7253

[a] $\mathrm{EUI}_{\mathrm{norm}}$ (from bootstrapping results) is calculated from the observed $\mathrm{EUI}_{\mathrm{norm}}$ using the bootstrapping function in S-plus.
[b] $\mathrm{EUI}_{\mathrm{norm}}$ (from sample data) is obtained by ranking the observed $\mathrm{EUI}_{\mathrm{norm}}$.

5. Use of the regression model for end-users

The significant factors can be classified into manageable and unmanageable. Manageable factors such as occupant behaviour can be improved through better energy-management practices or increased efficiency in energy systems. On the other hand, unmanageable factors are physical indicators that are not readily amenable to energy-management practices or the system's efficiency-improvements.

Based on the manageable factors, e.g., occupants' behaviour, in the regression, recommendations for the improvement of energy-use behaviour and the EUI can be made to the end-users. For example, suppose the average score of the occupants' behaviour is 1.97 in the regression model. If the end-user's input score is 1.5, the regression model can be used to calculate how much in percentage terms the end-user can improve due to achieving the average score of 1.97. A target score can also be converted back to the operating parameter levels for implementation.

We may consider a regression model including only the unmanageable variables in order to benchmark the subgroup's energy-consumption accordingly if we set all the manageable variables to be equal to their average value. For example, the subgroup benchmarking score can be obtained by setting the occupants' behaviour value at 1.97. Hence, by making use of the regression model, with only the unmanageable variables, the Government can set improvement targets for significant explanatory factors in each energy-consuming group. The discussed approach has been adopted to develop the on-line benchmarking system [14].

6. Conclusion

In this paper, we have developed a benchmarking process using multiple regression. A benchmarking table is derived from removing the effect of significant factors using the multiple-regression model. This can be regarded as a renormalization of the significant factors for an energy-use intensity. The resulting regression model and the benchmarking system can be used in policy analyses.

A shortcoming of this approach arises from using a complicated multiple regression. If the resulting multiple-regression model includes many significant manageable factors, the layman end-users will be asked to input too many technical details. Consequently, the end-users may be discouraged from using the benchmarking model.

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References

[1] Patterson MG. What is energy efficiency? Concepts, indicators and methodological issues. Energy Policy 1996;24(5):377–90.
[2] Haas R. Energy efficiency indicators in the residential sector. What do we know and what has to be ensured?. Energy Policy 1997;25(7–9):789–802.
[3] Federspiel C, Zhang Q, Arens E. Model-based benchmarking with application to laboratory buildings. Energy Build 2002;34:203–14.
[4] Filippín C. Benchmarking the energy efficiency and greenhouse-gases emissions of school buildings in central Argentina. Build Environ 2000;35:407–14.
[5] e-Energy Benchmark System. National University of Singapore and the Building and Construction Authority of Singapore, Singapore; 2003. Available from: http://www.bdg.nus.edu.sg/buildenergy/e-energy/commerical.html.
[6] Birtles AB, Grigg P. Energy efficiency of buildings: simple appraisal method. Build Serv Eng Res Technol 1997;18(2):109–14.
[7] Monts JK, Blissett M. Assessing energy efficiency and energy-conservation potential among commercial buildings: a statistical approach. Energy 1982;7(10):861–9.
[8] Sharp T. Energy benchmarking in commercial-office buildings. In: ACEEE 1996 summer study on energy efficiency in buildings, vol. 4; 1996. p. 321–9.
[9] Asia-Pacific Economic Cooperation Energy Benchmark System. Singapore: APEC; 2001. Available from: http://eber.ed.ornl.gov/apec/index.html.
[10] Kinney S, Piette MA. Development of California commercial-building energy benchmarking database. In: ACEEE 2002 summer study on energy efficiency in buildings, vol. 7; 2002. p. 109–20.
[11] Lovell-Smith JER, Baldwin JA. Energy use trends in the New Zealand dairy industry. N Z J Dairy Sci Technol 1988;23:237–55.
[12] EMSD, Consultancy study on the development of energy consumption indicators and benchmarks for selected energy-consuming groups in Hong Kong (Agreement No. CE14/2000) – Brief. Electrical and Mechanical Service Department, The Hong Kong SAR Government; 2000.
[13] Efron B, Tibshirani R. An introduction to bootstrap. New York: Chapman & Hall; 1993.
[14] Energy consumption indicators and benchmarks system. Hong Kong; 2002. Available from: http://www.emsd.gov.hk/emsd/eng/pee/benchmarktool.shtml.
[15] Piper JE. Operations and maintenance manual for energy management. USA: M.E. Sharpe Inc; 1999.
[16] EMSD, Guidelines on energy audit. Electrical and Mechanical Service Department, the Hong Kong SAR Government; 2002. Available from: http://www.emsd.gov.hk/emsd/eng_source/pee/em_pub_codes.htm.
[17] Mendenhall W, Reinmuth JE, Beaver R. Statistics for management and economics. 7th ed. California: Duxbury Press; 1993.
[18] Leed PD. Practical research: planning and design. 6th ed. New Jersey: Merril; 1997.
[19] Draper NR, Smith H. Applied regression analysis. 3rd ed. New York: Wiley; 1998.
[20] Neter J, Kutner MH, Nachtsheim CJ, Wasserman W. Applied linear statistical-models. 4th ed. Illinois: Irwin; 1996.
[21] UK building research establishment. Energy benchmarking in the retail sector 1999. Building maintenance information special report, report no. SR 281. London, UK: Building Cost Information Service Ltd.; 1999.
[22] Energy Star. Technical description for the grocery store/supermarket model. Available from: http://208.254.22.6/ia/business/evaluate_performance/tech_desc_supermarkets.pdf.
[23] S-Plus. Insightful Corporation. Seattle, Washington, USA. Available from: http://www.insightful.com/products/splus/default.asp.