Applied Thermal Engineering xxx (2008) xxx–xxx

Contents lists available at ScienceDirect

Applied Thermal Engineering

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

Benchmarking the performance of building energy management using data envelopment analysis

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ARTICLE INFO

Article history:
Received 11 January 2008
Accepted 23 February 2008
Available online xxxx

Keywords:
Energy efficiency
Energy management
Data envelopment analysis
Building energy

ABSTRACT

In traditional methods, benchmarking of building energy performance usually takes into consideration of a wide range of different factors, including floor area, number of occupants, climate condition, energy efficiency of the equipment used, setting of indoor temperature and so on. These different factors are then given different weights to calculate one general indicator. The indicator is "general" as it measures only the overall energy performance of a building. For obtaining more specific information, such as the energy management effectiveness of a building, this paper proposes an adjustment to the traditional approach by using data envelopment analysis. Factors related to the evaluation of building energy performance are divided into scale factors and management factors; the effect of scale factors is then removed to focus on the performance of management factors that may provide an optional indicator to refine the traditional focus on energy consumption per unit floor area. Samples under evaluation incorporate 47 government office buildings in Taiwan, and floor area and the number of occupants are used as the scale factors for climate-adjusted building energy consumption after regression analysis. According to the evaluation focusing on management performance, five evaluated buildings report minimum energy consumption in different scales and they are rated as 100% for the best management performance. Six buildings receive the rating of 80–99%, 23 buildings fall under 60% and the poorest reads 31%. The average indicator of energy performance of all evaluated buildings reads 65%.

1. Introduction

Constructing an indicator to reveal the performance of building energy management is important for energy agencies and authorities. To evaluate the performance of energy consumption in a building, there are two major methods: simulation method and statistical analysis method.

The simulation method sets up a mathematical model to calculate theoretical energy consumption and makes a comparison between theoretical energy consumption and observed energy consumption in order to evaluate the performance of energy consumption. Federspiel et al. [1] used numerical software to construct the minimum Energy Usage Intensity (EUI) for laboratories and compared this with observed EUI of the evaluated building. Carriere et al. [2] implemented DOE-2 simulation software to study the energy-saving potential of large buildings. The simulation method used factors including the properties of building construction material, the energy efficiency of related energy-consuming equipment (such as air conditioners and lights, etc.), and the usage period to calculate the theoretical energy consumption of the building.

The statistical analysis consists of collecting the survey data and comparing one unit with the others. Chung et al. [3] used multiple regression analysis to build a benchmark table by investigating the relationship between EUIs and the explanatory factors. Furthermore, Filippin [4] analyzed the energy efficiency and emissions of greenhouse gases for 15 public school buildings in the central area of Argentina.

The simulation analysis cannot be commonly used for existing buildings, due to the difficulty of collecting building data such as the heat conductivity of walls. Therefore, the statistical method is generally used for benchmarking the energy consumption of buildings. However, it is important to note that the statistical methods give only one single indicator by assigning different weights of different factors. These methods usually use the value of adjusted energy consumption per unit area as the indicator by taking into account of a legion of relative factors, such as scale factors (like floor area, number of occupants, and climate conditions) and management factors (like energy policy, and energy efficiency of the equipment used and setting of indoor temperature). The indicator obtained by above methods is too general to reveal the influence of management factors on building energy

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1359-4311/$ - see front matter © 2008 Published by Elsevier Ltd.
doi:10.1016/j.applthermaleng.2008.02.034

performance. Therefore, to separate the influence of scale factors from overall energy efficiency can be helpful for the users to focus on examining the performance of management. In other words, factors beyond the control of the management are regarded as scale factors, such as climate condition and floor area. The energy consumption of a building is then compared to that of other buildings with the same or similar scale factors; results of such a comparison therefore serve as director indicators of management efficiency in terms of energy consumption. For example, comparing energy consumption of different buildings with same floor area, number of occupants, and climate conditions is usually a greater reference value to users for improving energy management efficiency than knowing the energy consumption of different buildings with different floor area and number of occupants.

On the other hand, data envelopment analysis (DEA) has been generally used in the performance evaluation for resource usage. DEA could be applied to measure the overall energy efficiency in details by examining scale factors and management factors. Overall efficiency compared on the basis of same scale factors is called pure technical efficiency while scale efficiency refers to the difference in efficiency caused by comparisons based on different scale factors. Chauhan et al. [5] used DEA approach to determine the efficiencies of farmers with regard to energy use in rice production activities. The study has helped to segregate efficient farmers from inefficient ones, identify wasteful uses of energy from different sources by inefficient farmers and to suggest reasonable savings in energy uses from different sources. The results showed that, on an average, about 11.6% of the total input energy could be saved if the farmers follow the input package recommended by the study. Hu and Kao [6] used DEA to find the energy-saving target for APEC economies without reducing their maximum potential gross domestic productions in each year. The major finding is that China has the largest energy-saving target up to almost half of its current usage. Önüt and Soner [7] used DEA to evaluate the energy efficiency in 32 five-star hotels, and the results showed that eight hotels are efficient and 24 hotels are inefficient.

Using data envelopment analysis as the research tool and government office buildings in Taiwan as a case study, the paper first calculates the climate-adjusted building energy consumption and then the effect of scale factors is examined and removed to concentrate on the performance of management.

2. Methods

After the collection of relevant data of the evaluated units, the benchmarking process takes place and is composed of three steps: first, a regression analysis is used to calculate the regression factors of climate factors and the climate-adjusted building energy consumption. Then, the DEA utilizes the floor area and the number of occupants as the scale factors, and the climate-adjusted energy consumption is used as the input to calculate overall energy efficiency. Finally, DEA is further applied to measure the overall energy efficiency in details by examining scale factors and management factors.

2.1. Regression model

We first use the regression analysis to calculate the regression coefficients of significant factors that affect the energy usage of buildings. The investigated independent variables include buildings' usage information, such as floor area and number of occupants, and climate conditions, such as dry bulb temperature, hours of rain, and irradiation amount. The typical regression model is as follows [3]:

$$E_{\text{usage}} = a + b_1x_1 + b_2x_2 + \cdots + b_kx_k, \quad (1)$$

where E_{usage} is the energy consumption of building; a is the intercept; $b_1, b_2, \ldots, b_k$ are the regression coefficients; $x_1, x_2, \ldots, x_k$ are the significant independent variables.

After establishing the regression coefficients of climate factors, the climate-adjusted building energy consumption is calculated by adjusting the climate condition to the average values of the evaluated buildings.

2.2. Data envelopment analysis

DEA is known as a mathematical procedure that uses a linear programming technique to assess the efficiencies of decision-making units (DMU). A non-parametric piecewise frontier, which owns the optimal efficiency over the datasets, is composed of DMUs and is constructed by DEA for a comparative efficiency measurement. Those DMUs that are located at the efficiency frontier are efficient DMUs. These DMUs own the best efficiency among all DMUs and have their maximum outputs generated among all DMUs by taking the minimum level of inputs.

The concepts used in the parametric and DEA approaches are demonstrated in Fig. 1 where the case of seven DMUs with single inputs and single outputs is considered [5]. The input and output are shown on the x and y axes, respectively. The filled rhombuses represent different DMUs in the data set. In Fig. 1, P1, P2, P3 and P4 are the boundary points. The solid line joining these points forms the envelope for the data set. The DMUs lying on the boundary and represented by points P1, P2, P3 and P4 are considered as efficient DMUs, and the efficiency of other DMUS, P5, P6 and P7 are calculated by comparing with these efficient DMUs.

A unit can be made efficient either by reducing the input levels and getting the same output (input orientation) or by increasing the output level with the same input level (output orientation). The input oriented analysis is becoming more common in DEA applications because profitability depends on the efficiency of the operations. In this paper, we adopt an input oriented DEA approach for efficiency estimation.

DEA has two models: constant returns to scale (CRS) DEA model (Charnes et al. [8]) and variable returns to scale (VRS) DEA model (Banker et al. [9]). The CRS model finds each DMU's overall efficiency. The VRS model decomposes overall efficiency into pure technical efficiency and scale efficiency. Overall efficiency is basically a measure by which DMUs are evaluated for their performance relative to other DMUs. However, its value is influenced by scale efficiency, which quantifies the effect of the presence of variable returns to scale in the DMUs. Thus, pure technical efficiency is overall efficiency that has the effect of scale efficiency removed [5].

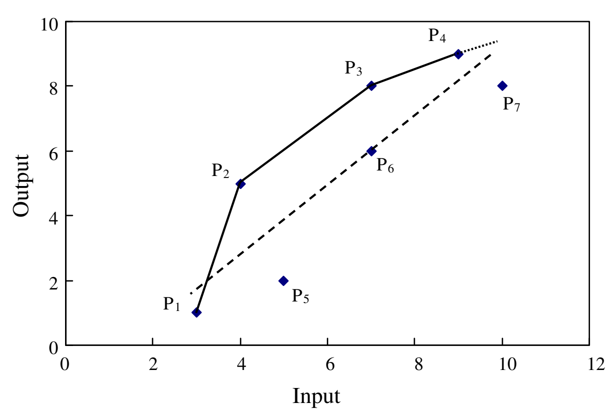

Fig. 1. Comparison of data envelopment analysis and regression analysis [5].

The concepts of DEA are illustrated in detail by Chauhan et al. [5] while those concepts adopted by the paper are outlined as follows. As shown in Fig. 2, the line MN represents the envelope of the data set with constant returns to scale. It is a straight line that passes through the origin and the extreme data points. The segment formed by P1, P2, P3 and P4 represent the envelope of the data set with variable returns to scale. The DMU lining on the line MN is consider as efficient and has an overall efficiency equaling to one; the DMU lining on the segment formed by P1, P2, P3 and P4 has a pure technical efficient equaling to one. Let us consider DMU P6 in Fig. 2. Its input and output are given by AD and MA, respectively. B and C are the points of intersection of the line AD with the line MN and the line segment of the envelope of the data set. One can interpret that AB is the ideal input required to produce the output B on MN, if constant returns to scale were to prevail. However, considering variable returns to scale to be a realistic phenomenon, one can relax the input requirement to be equal to AC to be able to produce the output B on MN. One can now define the various efficiencies as follows [5]:

Overall efficiency = AB/AD
Scale efficiency = AB/AC
Pure technical efficiency = AC/AD.

The relationship among these forms of efficiency is given as [5]

$$\text{Overall efficiency} = [\text{Pure technical efficiency}] \times [\text{scale efficiency}].$$

It is easy to graph and visualize the case of DMUs having single inputs and single outputs. The measurement of pure technical efficiency, where there are multiple and incommensurate inputs and outputs, was first addressed by Farrell [10] and developed by Farrell and Fieldhouse [11]. It focuses on the concept of a hypothetically efficient DMU, defined as a weighted average of efficient DMUs, to act as a comparator for an inefficient DMU. This hypothetically efficient DMU is known as a virtual DMU and acts as a benchmark for an inefficient DMU. A common measure of efficiency is Efficiency=Weighted sum of outputs/Weighted sum of inputs.

Using standard notations, the efficiency can be written as Efficiency:

$$\text{Efficiency} = \frac{u_1 y_1^{j^*} + u_2 y_2^{j^*} + \cdots + u_N y_N^{j^*}}{v_1 x_1^{j^*} + v_2 x_2^{j^*} + \cdots + v_M x_M^{j^*}}, \tag{2}$$

where $u_1, u_2, \ldots$ are the weight given to output $n(n = 1, 2, \ldots, N)$; $y_1^{j^*}; y_2^{j^*}; \ldots; y_N^{j^*}$ are the amount of output $n(n = 1, 2, \ldots, N)$ of DMU j^*; $v_1, v_2, \ldots$ are the weight given to input $m(m = 1, 2, \ldots, M)$; $x_1^{j^*}; x_2^{j^*}; \ldots; x_M^{j^*}$ are the amount of input $m(m = 1, 2, \ldots, M)$ to DMU j^*; and j^* is the DMU under consideration. The efficiency is usually constrained to be between zero and one. Here, the measure of efficiency requires a common set of weights to be applied across all DMUs. This immediately raises the problem of how an agreed common set of weights can be obtained.

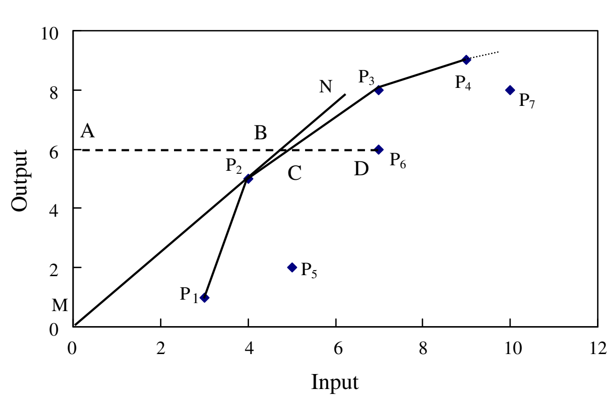

Fig. 2. Relation of input and output from DEA [5].

In 1978, Charnes et al. [8] proposed that each DMU should be allowed to select a set of weights that shows it in the most favorable situation during comparison with other DMUs. Under these circumstances, the optimal weights assigned to the different inputs and outputs by a target DMU j^* and the efficiency of the unit can be calculated as a solution to the following problem:

Maximize efficiency of DMU j^*,
subject to efficiency of all other DMU $\leqslant 1$.
The algebraic model of the formulation is as follows [5]:

$$\begin{aligned} &\max \quad f^{j^*} = \sum_{n=1}^{N} u_n y_n^{j^*} \Big/ \sum_{m=1}^{M} v_m x_m^{j^*} \\ &\text{s.t.} \quad \text{(i)} \sum_{n=1}^{N} u_n y_n^{j} \Big/ \sum_{m=1}^{M} v_m x_m^{j} \leqslant 1 \quad \text{for all } j = 1, \ldots, J, \\ &\qquad\ \ \text{(ii)}\ u_n \geqslant 0, v_m \geqslant 0 \quad \text{for all } n = 1, \ldots, N \text{ and } m = 1, \ldots, M, \end{aligned} \tag{3}$$

where f^{j^*} is the overall efficiency of the DMU under consideration; N the total number of outputs; M the total number of inputs; u_n the coefficient of the nth output $(n = 1, \ldots, N)$; and v_m the coefficient of the mth input $(m = 1, \ldots, M)$. These u_n and v_m are the variables of the problem and are constrained to be greater than zero in order to avoid any input or output being totally ignored during the process of determining efficiencies. If the solution of the above model (f^{j^*}) gives a value equal to one, the DMU j^* is said to be efficient.

The above model (3) is a fractional linear programming problem. A method to solve this model is to convert it into a linear form so that the procedure to solve a linear programming problem can be applied. In 1978, Charnes et al. [8] converted the above problem (3) to a set of linear programming problems. During the process of maximizing the ratio, the relative magnitudes of the numerator and denominator are of interest and not their individual values. The conversion into a linear programming problem can be achieved by setting the denominator equal to a constant and maximizing the numerator.

The resultant linear programming formulation is as follows [5]:
Find the maximum efficiency for DMU j^* subject to

(i) Max efficiency $\leqslant 1$,
(ii) sum of weighted inputs is unity for each DMU, $j = 1, 2, \ldots, J$.

Using mathematical notations, the above can be written as

$$\begin{aligned} &\max \quad f^{j^*} = \sum_{n=1}^{N} u_n y_n^{j^*} \\ &\text{s.t.} \quad \text{(i)} \sum_{n=1}^{N} u_n y_n^{j} - \sum_{m=1}^{M} v_m x_m^{j} \leqslant 0 \\ &\qquad\ \ \text{(ii)} \sum_{m=1}^{M} v_m x_m^{j^*} = 1 \quad \text{for all } j = 1, 2, \ldots, J, \\ &\qquad\ \ \text{(iii)}\ u_n \geqslant 0,\ v_m \geqslant 0 \quad \text{for all } n = 1, 2, \ldots, N \\ &\qquad\qquad \text{and } m = 1, 2, \ldots, M, \end{aligned} \tag{4}$$

The model (4) is popularly known as the CCR model (after the names of its developers, Charnes, Cooper and Rhodes). This is a linear programming model. The above model depicts the optimization under constant returns to scale (CRS) conditions. This condition usually does not exist in most real life problems. To tackle the problem of variable returns to scale (VRS), Banker et al. [9] developed the model (commonly known as the BCC model after the names of its developers, Banker, Charnes and Cooper). In mathematical terms, the input oriented BCC model can be described as follows [5]:

$$\begin{aligned} \min \quad & \theta \\ \text{s.t.} \quad & y^{j^*} - Y\lambda \leqslant 0, \\ & \theta x^{j^*} - X\lambda \geqslant 0, \\ & e\lambda = 1, \quad \lambda_j \in [0,1], \end{aligned} \tag{5}$$

where λ_j is the intensity vector corresponding to the jth DMU, e the row vector with all elements equal to one, and θ^{j^*} the solution of the formulation. These models estimate the efficiency in converting the inputs to outputs by constructing an empirically based production frontier and evaluating each unit against all other units included in the analysis. The unit j^* is overall efficient if the value of the objective function (θ) is one. This means that it is not possible to reduce its inputs further at the present level of yield (output).

3. Case study

In this paper, we analyze 47 government office buildings on August and September in Taiwan. Taiwan is an island located between 120° and 122° of east longitude, 22–25° of north latitude. The floor area and the occupants of the evaluated units are provided by their energy manager. Because the electricity is the only energy used in these government office buildings, the electricity usage is the only energy measurement factor and the data is provided from the power utility. The weather conditions, such as outdoor temperature and hours of rain, are provided from 10 climate measurement stations of the Central Weather Bureau. The main data information is shown in Table 1.

4. Results and discussion

4.1. The climate-adjusted energy consumption

After statistical analysis and using energy usage per floor area as the dependent variable, we find that floor area, number of occupants, outdoor temperature and hours of rain as independent variables could build a regression model in which R^2 is bigger than 0.8 (t statistics in small parentheses). The regression model is

$$\begin{aligned} y = & -\underset{(-2.5)}{1407160.8} + \underset{(6.1)}{8.2} \times A + \underset{(5.1)}{628.2} \times P \\ & + \underset{(2.5)}{44334.5} \times T + \underset{(2.9)}{3147.8} \times R, \end{aligned} \tag{6}$$

where $R^2 = 0.84$. Here, y is the total energy consumption in August and September (kW h/2 month), P is the number of occupants, T is the average outdoor temperature (degrees centigrade) during office hours, and R represents the average hours of rain per month (hours/month) during office hours.

The energy consumption of building is composed of energy consumption of air-conditioning, lighting, and office equipment. When it rains, the outdoor air will have a high enthalpy because the relative humidity is about 100%. Because indoor air quality must be maintained at a constant condition, air-conditioning systems have to consume more energy when processing outside air with high enthalpy. This will increase the energy consumption. Therefore, the hours of rain are used as an independent parameter of above regression equation.

After establishing the regression coefficients of climate factors, the climate-adjusted building energy consumption is calculated by adjusting the climate condition to the average values of the evaluated buildings.

4.2. Evaluate the energy performance of office buildings

For influencing the energy consumption of office buildings, the floor area, number of occupants and climate conditions are three major factors that energy managers cannot control, as show in Eq. (6). When climate-adjusted energy consumption is adopted as the input and the floor area and number of occupant are considered as scale factors for DEA analysis, the pure technical efficiency of buildings can represent the efficiency obtained after comparing the energy consumption of buildings with the same floor area, number of occupants, and climate conditions. In other words, the pure technical efficiency represents the management efficiency excluding the factors that the manager cannot control.

The data envelopment analysis performed in the case study includes two scale factors (floor area and number of occupants) and one input item (climate-adjusted energy consumption) as illustrated in Fig. 3. C and K represent two evaluated units same in scale conditions (floor area and number of occupants) but different in input item (energy consumption, indicated respectively as R and S). Under the same scale conditions, C reports the lowest energy consumption, and its pure technical efficiency is rated as 100%. The line RS or KC presents the potential of energy conservation, redundant energy consumption, of evaluated unit K. The pure technical efficiency of K, on the other hand, is the ratio of line OR to line OS. The higher value of pure technical efficiency means the evaluated unit has smaller ratio of energy conservation. Thus, the pure technical efficiency could represent the performance of energy management in the same output scales.

The overall energy efficiency of a building is influenced by scale factors and management factors, and the overall energy efficiency can be divided into scale efficiency and pure technical efficiency. Therefore, the pure technical efficiency calculated by comparing

Table 1
The main data information of 47 government office buildings at office time in August and September in Taiwan

	Energy consumption (kW h/2 month)	Floor area (m^2)	Number of occupants	Average outdoor temperature (°C)	Average hours of rain (h/month)[a]
Average value	95113.6	5215.9	107.4	29.8	22.4
Standard deviation	80649.0	4828.3	58.2	0.5	8.0
Maximum value	398880.0	25998.0	309.0	30.3	35.5
Minimum value	19742.0	778.5	37.0	28.7	11.0

[a] Accumulated precipitation more than 0.1 mm/h.

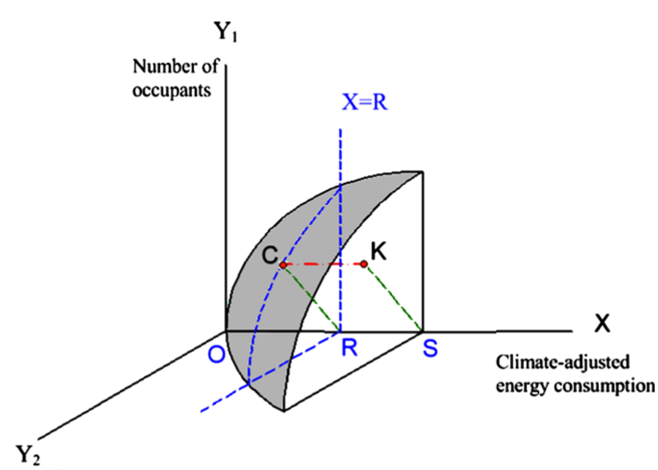

Fig. 3. Illustration of data envelopment analysis with one input item and two scale factors.

climate-adjusted energy consumption under the same scale can be expected to represent the effect of management performance.

The pure technical efficiency emerging from data envelopment analysis serves as the indicator of management performance of evaluated buildings. As indicated in Figs. 4, 5 of the evaluated buildings are rated as 100% for best energy performance. Six buildings receive a rating falling in the range of 80–99%, 21 buildings in the range of 40–60%, and two buildings under 40%. The average indicator of energy performance of all evaluated buildings reads 65%.

As indicated by Figs. 5 and 6 that outline the relationships among overall efficiency, pure technical efficiency and scale efficiency, most of the evaluated buildings with an overall efficiency lower than 60% betray a pure technical efficiency below 80%. Moreover, the pure technical efficiency shows a trend of declining with the overall efficiency. The scale efficiency of these evaluated buildings falls mostly in the range of 70–100%. It can therefore be inferred that the reason of poor energy efficiency lies mainly in ineffective energy management. The pure technical efficiency is improved as scale efficiency declines, as shown in Fig. 7. This may mean that buildings with a poorer scale usually have better energy management.

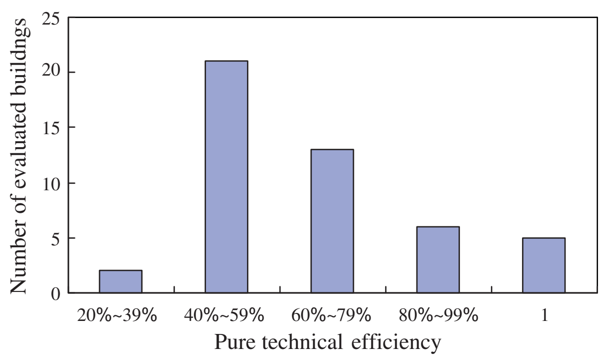

Fig. 4. The number of evaluated buildings between different pure technology efficiency.

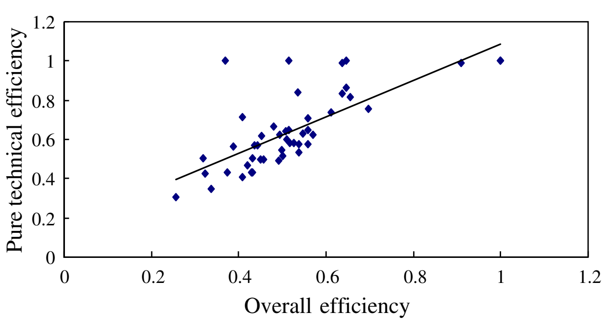

Fig. 5. Relation between pure technology efficiency and overall efficiency.

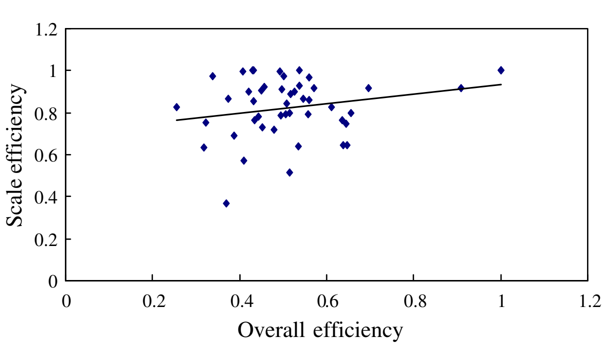

Fig. 6. Relation between scale efficiency and overall efficiency.

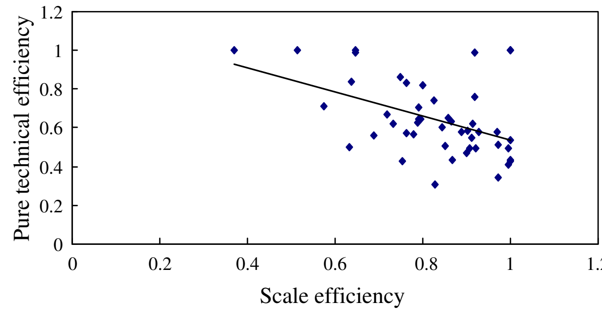

Fig. 7. Relation between pure technology efficiency and scale efficiency.

5. Conclusion

This paper using data envelopment analysis divides the overall energy efficiency into scale factors and management factors and then has the effect of scale factors removed to focus on the performance of management factors that may provide an optional indicator to refine the traditional focus on energy consumption per unit floor area. Samples under evaluation incorporate 47 government office buildings in Taiwan, and floor area and the number of occupants are used as scale factors for climate-adjusted building energy consumption after regression analysis. According to the evaluation focusing on management performance, five evaluated buildings report minimum energy consumption in different scales and they are rated as 100% for the best management performance. Six buildings receive the rating of 80–99%, 23 buildings fall under 60% and the poorest reads 31%. The average indicator of energy performance of all evaluated buildings reads 65%.

Acknowledgements

Thanks to the Bureau of Energy, the Ministry of Economic Affairs, and the Taiwan Green Productivity Foundation for data support and budget providing.

References

[1] Clifford Federspiel, G. ZhanQiang, S. ArenEdward, Model-based benchmarking with application to laboratory buildings, Energy and Buildings 34 (2002) 203–214.
[2] M. Carriere, G.J. Schoenau, R.W. Besant, Investigation of some large building energy conservation opportunities using the DOE-2 model, Energy Conversion and Management 40 (1999) 861–872.
[3] William Chung, Y.V. Hui, Lam Y. Miu, Benchmarking the energy efficiency of commercial buildings, Applied Energy 83 (2006) 1–14.
[4] C. Filippin, Benchmarking the energy efficiency and greenhouse gases emissions of school buildings in central Argentina, Building and Environment 35 (2000) 407–414.
[5] Narvendra Singh Chauhan, K.J. Mohapatra Pratap, Pandey Keshaw Prasad, Improving energy productivity in paddy production through benchmarking – an application of data envelopment analysis, Energy Conversion and Management 47 (2006) 1063–1085.
[6] Jin-Li Hu, Chih-Hung Kao, Efficient energy-saving targets for APEC economies, Energy Policy 35 (2007) 373–382.
[7] Semih Önüt, Selin Soner, Energy efficiency assessment for the Antalya Region hotels in Turkey, Energy and Buildings 38 (2006) 964–971.
[8] A. Charnes, W.W. Cooper, E. Rhodes, Measuring the efficiency of decision making units, European Journal of Operational Research 2 (1978) 429–444.
[9] R.D. Banker, A. Charnes, W.W. Cooper, Some models for estimating technical and scale inefficiencies in data envelopment analysis, Management Science 30 (1984) 1078–1092.
[10] M.J. Farrell, The measurement of productive efficiency, Journal of Royal Statical Society, Series A: General 120 (III) (1957) 253–281.
[11] M.J. Farrell, M. Fieldhouse, Estimating efficient production under increasing return to scale, Journal of Royal Statical Society, Series A: General 25 (2) (1962) 252–267.