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BENCHMARKING THE ENERGY PERFORMANCE OF OFFICE BUILDINGS: A DATA ENVELOPMENT ANALYSIS APPROACH

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RESUMEN: Lograr la eficiencia energética en edificios es un importante reto al que enfrentan tanto los países desarrollados como en vías de desarrollo. Sin embargo, muy pocos trabajos previamente han evaluado la eficiencia energética de edificios de oficinas utilizando datos reales. Para superar esta limitación, este artículo propone un índice de eficiencia energética para edificios con un gran porcentaje de ventanas y utiliza este índice para identificar los principales factores arquitectónicos que afectan al desempeño energético. En este trabajo se evalúa, por primera vez, la eficiencia energética de 34 edificios de oficinas en Santiago de Chile, mediante el uso del método análisis envolvente de datos. La eficiencia energética se descompone en dos índices: el índice de eficiencia energética arquitectónica y el índice de eficiencia de gestión energética. Esta descomposición es un paso esencial en la identificación de las principales causas de ineficiencia energética y diseñar medidas para su mejora. Los resultados muestran que los edificios de oficinas evaluados tienen un margen significativo para mejorar su eficiencia energética, ahorrar costos operativos y reducir el efecto invernadero.

Palabras claves: Eficiencia energética; Análisis envolvente de datos; Edificio de oficinas; Chile

ABSTRACT: The achievement of energy efficiency in buildings is an important challenge facing both developed and developing countries. Very few papers have assessed the energy efficiency of office buildings using real data. To overcome this limitation, this paper proposes an energy efficiency index for buildings having a large window-to-wall ratio, and uses this index to identify the main architectural factors affecting energy performance. This paper assesses, for the first time, the energy performances of 34 office buildings in Santiago, Chile, by using data envelopment analysis. Overall energy efficiency is decomposed into two indices: the architectural energy efficiency index, and the management energy efficiency index. This decomposition is an essential step in identifying the main drivers of energy inefficiency and designing measures for improvement. Office buildings examined here have significant room for improving their energy efficiencies, saving operational costs and reducing greenhouse gas emissions. The methodology and results of this study will be of great interest to building managers and policymakers seeking to increase the sustainability of cities.

Keywords: Energy efficiency; Data envelopment analysis; Office building; Chile

1. Introduction

Maximizing the energy efficiency of buildings is one of the main challenges facing both developed and developing nations (Anastaselos et al., 2016). Global energy consumption has shown sustained growth since the 1970s. Although this growth trend has decelerated in developed countries since 2010, growth has continued at a high rate in developing countries. Indeed, energy consumption by emerging economies is projected to surpass that of developed economies by 2020 (Perez-Lombard et al., 2008). The building sector is a major energy consumer, responsible for 20% to 40% of global energy consumption (Abu Bakar et al., 2015), with office buildings being an important component of this consumption. In the USA, Spain and the UK, energy use by office buildings has been estimated to represent 3.2%, 2.7% and 2.0%, respectively, of the country's global energy balance (Perez-Lombard et al., 2008).

To reduce negative environmental impacts of buildings, it is essential to increase their energy efficiency, defined as the ability to perform the same or greater amounts of work by expending the same or lower amounts of energy (Abu Bakar et al., 2015). Benchmarking procedures are very useful tools for improving the energy performance of buildings. Through comparative analysis, buildings with the best performance can be identified and used as a reference for inefficient buildings (Sangi and Müller, 2016), which, in turn, can adopt benchmarks for best practices to increase their efficiency (Lee and Lee, 2009). Therefore, assessments of the energy efficiency of office buildings can be considered as the starting point for identifying potential savings (Wang et al., 2013).

Benchmarking is a statistical analysis process comprising three stages: (i) collecting information on the performance of a representative number of units (e.g. office buildings); (ii) comparing performances by using an index; and (iii) proposing improvements based on technical, managerial or economic perspectives (Li, 2016). The index applied to evaluate and compare the energy performances of units is a key issue in this process. Researchers have developed and proposed various indices. The most common index for measuring energy efficiency is the energy efficiency index (EEI; also known as the building energy index), defined as the ratio of energy input (kWh) to a factor related to energy used (typically, building floor area, in m^2) (Kavousian et al., 2015). Alternative indices, each with its own strengths and weaknesses, have been proposed and include: the energy usage intensity (Chung et al., 2006); climate energy index, which is based on climate as a predictor of efficiency (Emmanuel et al., 2013); EEI for building, which uses a reference model to establish the performance of a real building (González et al., 2011); energy efficiency ontology, which is a conceptual and qualitative method that aims to establish the role of components, systems and devices in the overall energy efficiency of a building (Vinagre Diaz et al., 2013); and energy rating factor, which weights the relevance of six performance indicators as energy efficiency prediction parameters (Escrivá-Escrivá et al., 2011). Any reliable and robust index must be adapted to the characteristics of the analyzed buildings. Hence, no unique index exists that can be applied in all cases to assess and compare the energy performances of office buildings.

Efficiency of energy use by office buildings mainly depends on two factors: (i) architectural factors, such as compactness, shape factor, and building envelope (Korolija et al., 2011; Pacheco et al., 2012; Granadeiro et al., 2013), and (ii) energy-management factors, such as equipment efficiency and operating strategy (Lee, 2008; Ezzeldin and Rees, 2013). Because building users cannot control architectural factors, the overall EEI is not very useful for characterizing the performance of currently operational office buildings. In this context, it is preferable to use two different efficiency indices – one focused on architectural factors, and another on energy-management issues. Information provided by these indices should be doubly useful. The architectural energy efficiency index (AEEI) provides information about the main architectural factors affecting energy performance. This index is essential for building sustainable buildings that minimize energy consumption. The management energy efficiency index (MEEI) allows managers to evaluate the energy performance of already-built office buildings.

Data envelopment analysis (DEA) is a linear programming methodology used to measure the efficiencies of units by considering multiple inputs and outputs. DEA is a widely used tool for benchmarking (Cooper et al., 2006) and assessing the energy efficiencies of different types of units, including buildings. DEA has been applied, for instance, to assess the energy performances of hotels (Önët and Soner, 2006), water utilities (Guerrini et al., 2013), government buildings (Lee, 2008; Lee and Lee, 2009) and multifamily properties (Lu, 2014). One of the most attractive features of using DEA for assessing the energy efficiency of office buildings is that the overall EEI can be split into AEEI and MEEI, as partial indices (Lee, 2008; Lee and Lee, 2009).

Against this background, the objectives of this paper are threefold. The first objective is to propose an index for evaluating the energy performances of office buildings characterized by large window-to-wall ratio (WWR) values. Using this index, the main architectural factors affecting energy performance can be identified. The second objective is to assess the overall EEI of a sample of office buildings, and to decompose this overall index into AEEI and MEEI sub indices. The third objective is to estimate the potential energy-saving opportunities for each building, as analyzed from the architectural and energy-management perspectives. The empirical application focuses on 34 office buildings in Santiago, Chile. The case study is very relevant because Chile is an emerging economy. Many office buildings have been built in this country in recent years. Hence, building managers and policymakers in other countries can learn some notable lessons from the Chilean case.

This paper contributes to the current strand of literature in the field of building energy performance measurement by developing an alternative EEI for buildings with large WWR values. The paper provides insights into architectural factors that affect energy performance in office buildings. Most previous reports have computed an overall EEI, whereas, to the best of the authors' knowledge, no published study to date has estimated energy efficiency scores from the architectural and energy-management perspectives. This paper assesses energy efficiency using real data from buildings that are currently in operation. This approach differs from other papers, in which simulation methods are more commonly used.

From a policy perspective, the methodology and results of this study should be of great interest for office building managers and policymakers. Identification of inefficient office buildings would aid managers in implementing measures to reduce energy consumption and save operational costs. Furthermore, identification of the main architectural factors affecting energy performance will provide essential information for policymakers seeking to develop technical norms for building more sustainable buildings.

2. Methodology

Following the methodological approach described by Lee (2008) and Lee and Lee (2009), this paper carries out a benchmarking procedure composed of two sequential steps. First, a regression analysis is used to calculate the predicted energy use of office buildings, with the aim of identifying the main architectural factors contributing to energy performance. Second, DEA is applied to estimate the AEEI, MEEI and overall EEI of the sample.

2.1 *Regression model*

The dependent variable to be predicted by the model is the energy used. Investigated independent variables include the building area, facade area, number of floors, shape factor* and floor height. All of the variables are quantitative; thus, the following multiple regression model is used:

* Shape factor is defined as the surface area of the building divided by its volume (m^2/m^3).

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_k x_k + \varepsilon \quad (1)$$

where α_0 is the intercept; α_1, $\alpha_2, \ldots \alpha_k$ are regression coefficients that measure the influence of each independent variable over the dependent variable (y); $x_1, x_2, \ldots, x_k$ are the significant independent variables; and ε is an error term.

The regression model is implemented in SPSS† software, while ensuring no multicollinearity among independent variables. Several combinations of dependent and independent variables are obtained. To select the best model, the following criteria are considered: (i) significance value of independent variables; (ii) adjusted coefficient of determination (R^2); and (iii) standard error of the estimates. The one-tailed significance of the model should be less than 0.05, and the confidence interval should be at least 95%. The adjusted R^2 provides information about the goodness of fit of the adjustment by measuring the proportion of the total variability of the dependent variable relative to its average. The R^2 value ranges between 0 (no correlation between the actual and estimated variables) and 1 (perfect correlation) (Chatterjee and Simonoff, 2012).

2.2 Data envelopment analysis

DEA is a nonparametric method that uses linear programming techniques to evaluate the relative efficiency of units (office buildings). Based on available data from all analysed units, an efficient production frontier is constructed. Units located on or outside this frontier are characterised as efficient or inefficient units, respectively. Units that generate the maximum set of outputs given a vector of inputs (output-oriented DEA), or that use the minimum set of inputs to produce a given output (input-oriented DEA), are placed on this frontier (Cooper et al., 2006). In accordance with previous reports (Önut and Soner, 2006; Lee and Lee, 2009; Lu et al., 2014), this paper adopts an input-oriented DEA approach.

Figure 1 demonstrates the standard DEA approach with a simple example, in which each unit uses a single input to produce a single output. The same concept may be applied to other production processes with multiple inputs and/or outputs. Points A through F represent six units for which efficiency is to be evaluated. Units A through D are efficient units located on the efficient production frontier. Units E and F are inefficient because they could reduce the use of inputs to produce the same level of output (input-oriented approach).

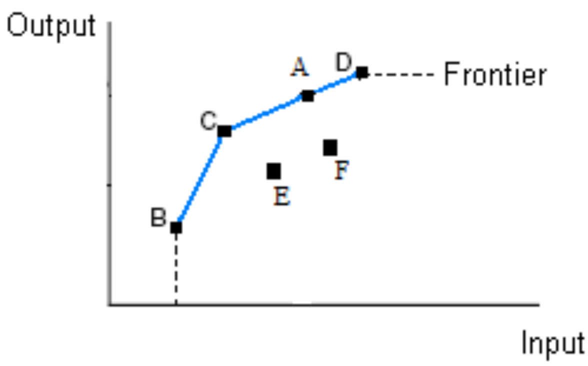

Figure 1. Data envelopment analysis approach.

Depending on how inputs are combined to produce outputs, DEA models can be characterised as achieving constant returns to scale (CRS) (Charnes et al., 1978) or variable returns to scale (VRS) (Banker et al., 1982). If outputs increase in the same proportion as inputs, then the model achieves CRS; otherwise, the model achieves VRS. The CRS approach assumes that all units operate at an optimal level.

† Details of this statistical software package can be found at: http://www-01.ibm.com/software/cl/analytics/spss/

The CRS model evaluates the overall efficiency of each unit, whereas the VRS model decomposes the overall efficiency into pure technical efficiency and scale efficiency (Pla Ferrando, 2014).

According to Lee (2008) and Lee and Lee (2009), scale factors are factors that cannot be controlled by office building managers. In this case study, the scale factors are architectural factors. Thus, scale efficiency can act as a proxy for AEEI; pure technical efficiency can be a proxy for MEEI; and the efficiency scores can be computed as follows:

$$\text{Overall efficiency} = \text{Pure technical efficiency} \times \text{Scale efficiency}. \quad (2)$$

$$\text{Overall efficiency} = \text{MEEI} \times \text{AEEI}. \quad (3)$$

According to Eqs. (2) and (3), an office building is overall efficient if and only if it is efficient from both the energy-management and architectural points of view.

Each of $k = 1, \dots, K$ office buildings uses an input matrix X with order $(N\ x\ K)$ to produce an output matrix Y with order $(M\ x\ K)$; and λ is a vector of intensity variables (weights of each input and output) $(K\ x\ 1)$. For each unit k, a measure of overall input efficiency $E_k(X, Y) = \theta$ is obtained by solving the following optimisation problem using linear programing under VRS (Banker et al., 1982):

$$\begin{aligned} E_k(X,Y) = \text{Min} \quad & \theta \\ \text{s.t.} \quad \lambda X & \leq \theta X_k, \\ \lambda Y & \geq Y_k, \\ I\lambda & = 1, \\ \lambda & \geq 0. \end{aligned} \quad (4)$$

The formulation of the VRS model (Eq. 4) coincides with the formulation of the CRS model, except for inclusion of the convexity constrain $(I\lambda = 1)$. The measure of efficiency (θ) is bounded between 0 and 1. A unit is efficient if its efficiency score equals unity; the unit is inefficient if $0 \leq \theta < 1$. The difference between the efficiency score and unity represents the potential improvements needed for a unit to be efficient. Hence, it can be quantified the relative savings that could be expected for an inefficient building if it were to behave like an efficient office building. This approach is used to estimate potential energy savings from both architectural and energy-management perspectives.

3. Case Study

The case study involves 34 office buildings in Santiago, Chile (latitude 33°26’16’’S). Santiago presents a semiarid climate. From October to May (spring to autumn), high levels of radiation and almost no rain are observed. January is the warmest month, with an average of 325.7 hours of sunshine, mean maximum temperature of 29.7 °C and mean minimum temperature of 13.0 °C.

Table 1. Disaggregated energy consumption by cluster of the office building real estate market in Santiago.

CASE	HVAC	LIGHT	POWER	TOTAL
C1	49.0%	38.2%	12.8%	100.0%
C2	42.7%	13.3%	44.0%	100.0%
C3	42.8%	24.8%	32.5%	100.0%
C4	38.7%	56.5%	4.9%	100.0%

Energy consumption by buildings is disaggregated as described in Table 1, which contains results of energy audits performed on different clusters or families of buildings during the summer of 2015. In most clusters, the main consumption is related to heating, ventilating and air conditioning (HVAC). Buildings considered in this study also have this feature.

Table 2. Main data for 34 office buildings in Santiago, Chile.

	Average	Standard deviation	Maximum value	Minimum value
Energy consumption January (kWh/month)	276,219	242,533	1,371,160	34,960
Floor area (m^2)	17,700	15,878	89,625	2,500
Façade area (m^2)	9,634	5,977	32,423	2,790
Glazed façade area (m^2)	6,473	5,256	29,975	1,333
Window-to-wall ratio (%)	64	17	99	26
Number of floors	20	9	52	5
Typical floor height (m)	3.15	0.22	3.60	2.59
Total height (m)	62.9	32.1	187.2	17.0
Shape Factor (1/m)	0.1980	0.1005	0.6157	0.0923

Digital plans with the precise dimensions of the buildings are elaborated from legal documentation available in municipalities. Buildings are visited to determine whether external solar protections are used. Architects and constructors are contacted to identify the glass types used in the facades and their solar heat gain coefficients. Building managers are contacted to obtain the electric bills for each building for January 2012 and 2013. These electricity data are used as the measurement factor in analyses. Electricity is the only source of energy in the analysed buildings. Several variables describing the building geometry are used in the analysis. The main data are shown in Table 2.

4. Results and Discussion

4.1 Variables affecting architectural energy performance

To identify architectural variables affecting energy performance, a regression analysis is carried out. The first step is to find an energy index that is statistically representative of the analysed buildings. Initially, the traditional energy index (kWh/m^2) is considered as the dependent variable. However, no statistically significant regression model is found when this dependent variable is used. This result is consistent with previous studies (Escrivá-Escrivá et al., 2011; Emmanuel et al., 2013), which have concluded that there is no unique energy index that can be applied in all case studies.

As this study focuses on office buildings characterised by large WWR values, the index of energy usage per WWR (E/WWR) can be considered as potentially representative and used as the dependent variable in the regression model. The regression model to predict energy used per WWR is as follows:

$$\frac{E}{WWR} = 85075.89 + 66.71 \times FA - 9.33 \times FL - 717580.70 \times SF, \quad (5)$$

where E is the energy use during January 2013 (kWh/month); WWR is the window-to-wall ratio (%); FA is the sum of the surface areas of all facades (m^2); FL is the total floor area of the building (m^2); and SF is the shape factor of the building, calculated as the surface area of the building divided by its volume (m^2/m^3). Eq. (5) evidences that, for office buildings in Santiago, energy use can be predicted from architectural factors alone.

To test whether independent variables present multicollinearity, the condition number test (Belsley et al., 1980) was conducted. The condition number in our empirical application was smaller than 20 meaning that the regression has not significant multicollinearity. Moreover, heteroscedasticity was tested by applying the White test (White, 1980). To evaluate goodness of the fit, actual and estimated E/WWR values are plotted (Figure 2), and the coefficient of determination (R^2) is calculated. The regression model shows an R^2 value of 0.922 and excellent goodness of fit. These findings emphasise the importance of the transparent part of the facades for the energy performance of the buildings.

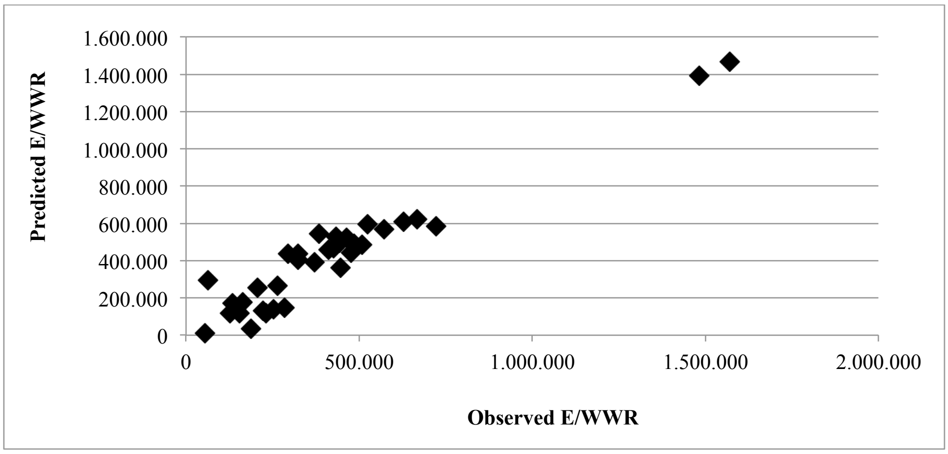

Figure 2. Observed vs. predicted E/WWR.

4.2 Architectural and management energy efficiency indices

Having identified the variables affecting E/WWR, this study next applies the DEA model (Eq. 4) to the set of office buildings using the variable E/WWR as input and FA, FL and SF as outputs. Resolution of the DEA model leads to two energy efficiency scores: the pure technical efficiency score (proxy for MEEI) and the scale efficiency score (proxy for AEEI). Results are shown in Table 3, which also provides information about potential energy savings from architectural and management perspectives.

Only one of the 34 office buildings is completely (architecturally and managerially) efficient in the use of energy. This building is used as a reference for the other buildings in the sample. This is one of the largest buildings in Santiago that has complex energy consumption control systems. The average score of energy efficiency is 0.38; thus, globally, the 34 office buildings could save 62% of their current energy consumption. Given the energy consumed by the sample in January 2013 (9,391,459 kWh), the potential for energy savings is not negligible.

Much of the energy inefficiency of the buildings is associated with architectural factors, as illustrated by the AEEI values. Improving the architectural energy performance of already-built buildings is a very difficult and costly endeavour. Although only one of the 34 office buildings is efficient in terms of its AEEI (Table 2), five buildings (15%) are almost architecturally energy efficient (with AEEI values > 0.9). The minimum value of AEEI is 0.2, corresponding to one office building having large energy inefficiency from an architectural perspective.

Four buildings (12%) in the sample are efficient in terms of their MEEI values and, thus, are efficient in their energy management (Table 3). The average MEEI score (0.64) is similar to the average AEEI score (0.61). This result suggests that office buildings in Santiago have significant room for energy savings apart from their architectural factors.

For an office building to be completely efficient, it should be efficient from both the shape and management perspectives (i.e. AEEI and MEEI should be equal to unity). Otherwise, the office building has potential to improve its energy efficiency. Figure 3 shows the relation between AEEI and MEEI for all buildings in the sample. The graph is divided into quadrants indicating whether a building scores well in terms of management (MEEI > 0.60) and/or architecture (AEEI > 0.60). The upper right quadrant contains buildings with the best energy performances (large AEEI and MEEI values). Specifically, six of the 34 buildings (18%) have good performances globally. By contrast, the lower left quadrant contains office buildings with the worst energy performances (low AEEI and MEEI values). Five buildings (15%) are located in this quadrant; efforts to improve their energy performances should focus on both management and architectural factors. The lower right quadrant contains the largest number of buildings

(14 buildings, 41%). These buildings perform well from the energy-management perspective but have architecture-related energy problems. These buildings should focus on architectural factors to improve their energy efficiency. However, making changes to a building that has already been built is not usually a cost-effective measure. Instead, it is advisable to apply architectural factors in the early design stages of future buildings. Finally, nine office buildings (26%) have large values for AEEI and low values for MEEI. These buildings should focus on energy management, where there is greater potential for cost-effective measures in existing buildings.

Table 3. Energy efficiency scores and potential energy savings for the 34 office buildings.

Office Buildings	Energy Efficiency Score			Potential Energetic Savings		
	Overall efficiency	**MEEI**	**AEEI**	**Total**	**Management**	**Architecture**
1	0.31	0.65	0.47	69%	35%	53%
2	0.27	0.40	0.66	73%	60%	34%
3	0.31	0.70	0.45	69%	30%	55%
4	0.60	0.89	0.68	40%	11%	32%
5	0.25	0.64	0.39	75%	36%	61%
6	0.30	0.49	0.62	70%	51%	38%
7	0.33	0.68	0.49	67%	32%	51%
8	0.34	0.69	0.50	66%	31%	50%
9	0.34	0.69	0.50	66%	31%	50%
10	0.56	0.62	0.89	44%	38%	11%
11	0.24	0.46	0.53	76%	54%	47%
12	0.12	0.63	0.20	88%	37%	80%
13	0.28	0.59	0.48	72%	41%	52%
14	0.34	0.66	0.51	66%	34%	49%
15	0.29	0.54	0.54	71%	46%	46%
16	0.35	0.63	0.56	65%	37%	44%
17	0.29	0.62	0.47	71%	38%	53%
18	0.35	0.63	0.55	65%	37%	45%
19	0.40	0.73	0.55	60%	27%	45%
20	0.33	0.72	0.46	67%	28%	54%
21	0.80	1.00	0.80	20%	0%	20%
22	0.52	0.73	0.71	48%	27%	29%
23	0.53	1.00	0.53	47%	0%	47%
24	0.22	0.52	0.42	78%	48%	58%
25	0.22	0.53	0.41	78%	47%	59%
26	0.36	0.39	0.92	64%	61%	8%
27	1.00	1.00	1.00	0%	0%	0%
28	0.39	0.43	0.91	61%	57%	9%
29	0.36	0.36	0.99	64%	64%	1%
30	0.59	0.64	0.92	41%	36%	8%
31	0.40	0.42	0.97	60%	58%	3%
32	0.33	0.54	0.62	67%	46%	38%
33	0.30	1.00	0.30	70%	0%	70%
34	0.40	0.44	0.89	60%	56%	11%
Average	**0.38**	**0.64**	**0.61**	**62%**	**36%**	**39%**

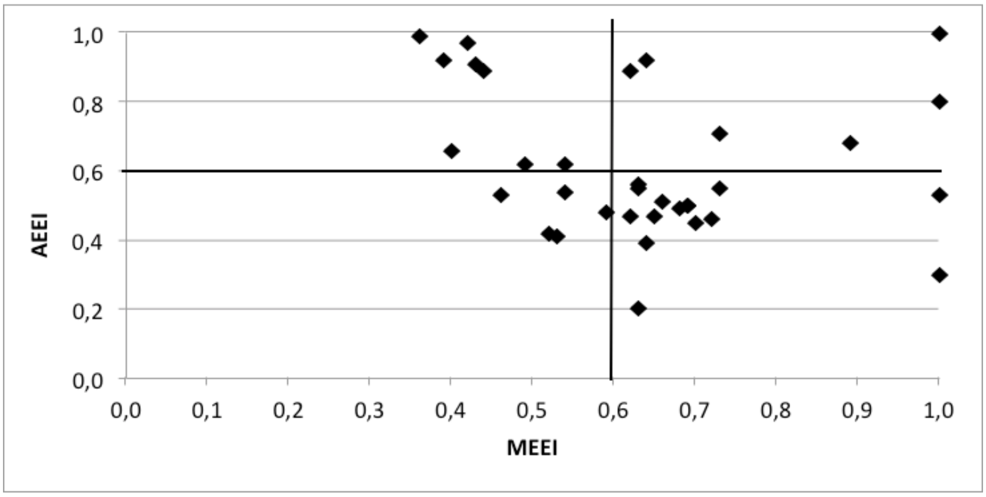

Figure 3. Relation between AEEI and MEEI for the 34 office buildings.

4.3 Explanatory factors of the management energy efficiency index

To gain a more realistic picture of building management energy efficiency, it is necessary to evaluate whether certain factors affect the MEEI of office buildings (Aste et al., 2016). Two hypotheses are formulated, as follows:

- Hypothesis A: MEEI is associated with the way that office buildings are occupied. Some buildings have several renters (each floor is rented by a different company), while others are rented by a single company.
- Hypothesis B: MEEI is associated with the classification of the office buildings. Buildings in Santiago are categorised as A- or B-Class, according to their construction standards.

To test these hypotheses, the nonparametric Mann–Whitney test is applied. Intuitively, this test is similar to the traditional one-way analysis of variance (ANOVA), but does not assume a normal distribution. The Mann–Whitney test is more suitable for this study because the Kolmogorov–Smirnov test indicates that the MEEI values are not normally distributed (Pham, 2006). Nevertheless, it was assumed that samples are independent. Hypotheses to be tested are as follows:

H_0: The K samples are derived from the same population.
H_1: Some samples are derived from other populations.

The null hypothesis is rejected when the p-value is less than or equal to 0.05 (i.e. differences in inefficiency scores among the sample are different at the 95% significance level).

To investigate whether the way that office buildings are occupied affects the MEEI, office buildings are categorised as having several renters or being rented by a single company. Table 4 shows that buildings that are rented by floor have higher mean MEEI values than single-owner buildings. An important difference between these two types of buildings is the way in which the HVAC systems are administered. Single-owner buildings tend to have integrated HVAC systems, such that all floors are permanently temperature-conditioned. These buildings spend more money on electricity. The four buildings that are energy efficient from the management perspective have several renters, whereas none of the office buildings with single renters are energy efficient. The Mann–Whitney test allows us to reject the hypothesis of equality of means for MEEI at the 95% significance level. This finding indicates that the type of renter is an explanatory factor for energy-management performance.

Regarding classification of the office buildings, sample data are categorised as A- or B-Class buildings. A-Class office buildings are significantly more efficient in energy management than B-Class buildings (Table 4). Thus, the classification of buildings is associated with the energy-management performance.

Table 4. Assessment of factors affecting MEEI values for the 34 office buildings.

Factor	Number of buildings	Mean MEEI	% efficient office buildings	p-value of the Mann-Whitney test
Type of rent				
Shared	24	0.684	16.7	0.001
Single	10	0.307	0.0	
Classification				
A-Class	25	0.651	8.0	0.022
B-Class	9	0.357	22.2	

5. Conclusions

Assessment of the energy efficiency of office buildings is essential in terms of improving the sustainability of cities and saving operational costs. Benchmarking procedures provide essential information for increasing the energy efficiency of buildings. However, to implement successful measures aimed at improving energy efficiency, it is vital that the overall energy efficiency be split into the AEEI and MEEI. This paper proposes an EEI adapted to buildings with large WWR values and identifies the main architectural factors affecting energy performance. Overall EEI is computed and decomposed into sub indices by the DEA approach, and the factors affecting MEEI values are explored.

The empirical application focuses on 34 office buildings in Santiago, Chile. The results provide the following primary findings. (i) The index E/WWR is affected by the sum of the surface areas of all facades, total floor area of the buildings and shape factor. (ii) Only one office building in the sample is completely energy efficient. Globally, the assessed buildings could save 62% of their current energy consumption. (iii) The average MEEI is similar to the average AEEI. (iv) Fourteen office buildings perform well from the energy-management perspective but present architecture-related energy problems. (v) The type of renter and market classification are factors explaining the MEEI values.

Findings from this study should be of great interest to building managers and policymakers. First, decomposition of the overall EEI into two sub indices provides essential information for developing and implementing measures to improve energy efficiency. Second, identification of the main variables explaining the index E/WWR provides vital information for developing technical norms and preventing excess energy consumption by future office buildings. Third, office buildings that have already been built in Chile have room for improving their energy management, with the potential for large economic savings. In conclusion, this study provides a scientific basis for improving the energy performances and long-term sustainability of office buildings.

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