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Study of hotel energy performance using data envelopment analysis

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ABSTRACT
As hotel energy consumption is affected by many technical, operational and managerial factors, it is often not possible to use the traditional benchmarking methods such as energy utilization index (EUI) in a meaningful way. This research applies data envelopment analysis (DEA) for assessing hotel energy performance in Hong Kong. A simple and basic DEA model, known as the input-oriented Charnes-Cooper-Rhodes (CCR-i) model under constant returns to scale (CRS), was developed for the evaluation of energy consumption of a sample hotel. The model was set up using a linear programming methodology to transform multiple input variables (electricity use, Towngas use, water use, outdoor temperature and relative humidity) into multiple output variables (numbers of room nights, room guests, and food & beverage covers). It is found that the DEA model can identify the relative efficiencies of different decision making units (DMU) (which are the hotel food & beverage outlets). DEA can accommodate a multiplicity of inputs and outputs; it also takes into consideration returns to scale in calculating efficiency, allowing for the concept of increasing or decreasing efficiency based on size and output levels. A drawback of this technique is that model specification and inclusion/exclusion of variables can affect the results.

KEYWORDS: Hotel energy performance, data envelopment analysis, Hong Kong**.**

1 INTRODUCTION

Hotels consume significant amounts of energy and resources for daily operations and related activities. Study of hotel energy performance is important for promoting energy efficiency and effective hotel management [1-4]. However, as the hotel energy consumption is affected by many technical, operational and managerial factors, it is often not possible to use the traditional benchmarking methods such as energy utilization index (EUI) in a meaningful way [5-7]. The current data and information for hotel energy benchmarking using EUI are usually highly simplified and related only to the total hotel gross floor area or the number of guest rooms [8]. These performance indicators that work with single measurements one at a time can give only a broad indication of building efficiency and therefore must be treated with caution and used carefully since they can mask underlying problems with individual end uses of energy [5].

This research applies data envelopment analysis (DEA) for assessing the hotel energy performance in Hong Kong. DEA is a nonparametric method in operations research and economics for the estimation of production frontiers [9-13]; it is used to empirically measure relative productive efficiency of decision making units (DMUs) and has the benefit of not assuming a particular functional form/shape for the frontier [14]. It allows people to compare various business units in terms of different inputs that are used to generate a number of outputs. The DEA technique has been used in some countries to measure and compare hotel managerial efficiency and company performance [15-22]. It is believed that when applying DEA to study hotel energy performance, it can generate useful information to support strategic decision making and planning. This balanced benchmarking technique can help companies locate best practices not visible through other management methodologies and also test their assumptions about service productivity [23]. It is hoped that by investigating the hotel energy use in a sophisticated and systematic way, environmental management and sustainable operation of hotel buildings can be improved and achieved [24].

2 DATA ENVELOPMENT ANALYSIS (DEA)

DEA, also called frontier analysis or balanced benchmarking, was first put forward by Charnes, Cooper and Rhodes in 1978 [14]. It is a performance measurement technique which can be used for evaluating the relative efficiency of DMUs in organisations [10-13]. DEA was originally developed to evaluate non-profit and governmental organisations, but it has subsequently been applied to the service operations of a variety of private companies [23]. Here a DMU is a distinct peer unit within an organisation that has flexibility with respect to some of the decisions it makes, but not necessarily complete freedom with respect to these decisions. DEA examines the resources available to each unit and monitors the conversion of these resources (inputs) into the desired outputs [25].

The definition of a DMU is generic and flexible [11]. Recent years have seen a great variety of applications of DEA for use in evaluating the performances of many different kinds of entities engaged in many different activities in many different contexts in many different countries [9, 26-31]. Various studies have investigated how DEA improves the performance of service organisations such as banks, hospitals and hotels [23]. Because it requires very few assumptions, DEA has also opened up possibilities for use in cases which have been resistant to other approaches because of the complex (often unknown) nature of the relations between the multiple inputs and multiple outputs involved in DMUs.

DEA has been used to provide unique insights about best practices and opportunities to improve productivity and profitability. For instance, studies of benchmarking practices with DEA have identified numerous sources of inefficiency in some of the most profitable firms - firms that had served as benchmarks by reference to this (profitability) criterion – and this has provided a vehicle for identifying better benchmarks in many applied studies [27, 30].

2.1 Basic Concept of DEA

Charnes, Cooper, and Rhodes [14] described DEA as a 'mathematical programming model applied to observational data [that] provides a new way of obtaining empirical estimates of relations'. DEA is the optimisation method to generalise the single-input/single-output technical efficiency measure to the multiple-input/ multiple-output case by constructing a relative efficiency score as the ratio of a single virtual output to a single virtual input. The efficiency score is defined as:

$$\text{Efficiency score} = \frac{\text{weighted sum of outputs}}{\text{weighted sum of inputs}} \tag{1}$$

DEA is a methodology directed to frontiers rather than central tendencies [12]. Instead of trying to fit a regression plane through the center of the data as in statistical regression, for example, one 'floats' a piecewise linear surface to rest on top of the observations. Because of this perspective, DEA proves particularly useful at uncovering relationships that remain hidden from other methodologies. Fig. 1 shows the basic concept of DEA with the theoretical and best practice frontiers. The theoretical frontier is the ideal situation. For a given amount of resource input, DMUs providing greater amounts of the outputs will be the efficient ones. Applying the DEA approach to this set of points of the DMUs will identify units S1, S2, S3 and S4 as efficient and they provide an envelope (best practice frontier) round the entire data set; other units are within this envelope and are inefficient. An inefficient DMU can be improved (moved to the efficient frontier) with suggested directions for improvement (to S1, S2, S3, S4 or other points along the frontier). The distance to the efficiency frontier provides a measure for the efficiency or its lack thereof.

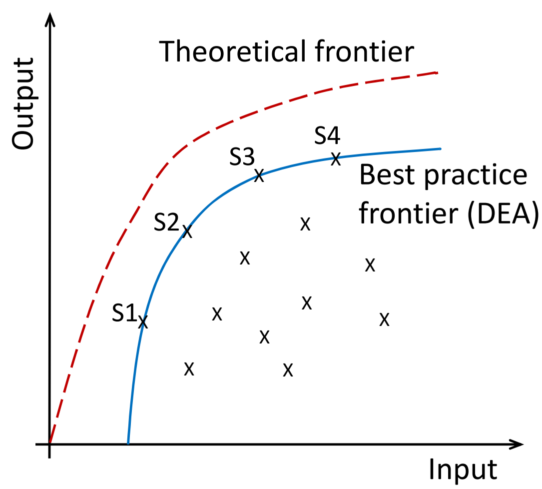

Fig. 1 Baisc concept of data envelopment analysis (DEA)

2.2 DEA Models

A basic DEA model, known as the input-oriented Charnes-Cooper-Rhodes (CCR-i) model under constant returns to scale (CRS), is described here [11, 12]. It is assumed that there are n DMUs to be evaluated. Each DMU consumes varying amounts of m different inputs to produce s different outputs. The relative efficiency score of a test DMUp is obtained by solving the following model [14]:

$$\max \frac{\sum_{k=1}^{s} v_k y_{kp}}{\sum_{j=1}^{m} u_j x_{jp}} \qquad s.t. \ \frac{\sum_{k=1}^{s} v_k y_{ki}}{\sum_{j=1}^{m} u_j x_{ji}} \le 1 \quad \forall i \quad \text{and} \quad v_k, u_j \ge 0 \quad \forall k, j \tag{2}$$

where y_{ki} = amount of output k produced by DMUi
x_{ji} = amount of input j utilised by DMUi
v_k = weight given to output k
u_j = weight given to input j

The fractional programme shown above can be converted to a linear programme as shown below (For more details on model development see [14]).

$$\max \sum_{k=1}^{s} v_k y_{kp} \qquad s.t. \quad \sum_{j=1}^{m} u_j x_{jp} = 1 \text{ and } \sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \le 0 \quad \forall i \quad \text{and} \quad v_k, u_j \ge 0 \quad \forall k, j \tag{3}$$

The above equations are run n times in identifying the relative efficiency scores of all the DMUs. Each DMU selects input and output weights that maximise its efficiency score. In general, a DMU is considered to be efficient if it obtains a score of 1 and a score of less than 1 implies that it is inefficient. For every inefficient DMU, DEA identifies a set of corresponding efficient units that can be utilised as benchmarks for improvement. The benchmarks can be obtained from the partner of this dual problem shown below. In equation (4), the first two conditions are also known respectively as input and output 'slack variables'.

$$\min \theta \qquad s.t. \quad \sum_{i=1}^{n} \lambda_i x_{ji} - \theta x_{jp} \le 0 \quad \forall j \quad \text{and} \quad \sum_{i=1}^{n} \lambda_i y_{ki} - y_{kp} \ge 0 \quad \forall k \quad \text{and} \quad \lambda_i \ge 0 \quad \forall i \tag{4}$$

An input-oriented efficient frontier is obtained when outputs are fixed at their current levels. Similarly, if the outputs are to be optimised, one can obtain an output-oriented efficient frontier when inputs are fixed at their current levels.

The constant returns to scale (CRS) is the simple and basic DEA model developed by Charnes, Cooper and Rhodes [14] and has been proven an effective tool in identifying empirical frontiers and in evaluating relative efficiency. In fact, the type of Return to Scale (RTS) refers to the shape of DEA best practice frontier (see Fig. 2); CRS would mean a straight line with a constant slope. While this is often a legitimate assumption, in situations where CRS do not prevail it is important to compare DMUs based on their scale of operations. Other types of DEA frontiers include variable RTS, non-increasing RTS and non-decreasing RTS.

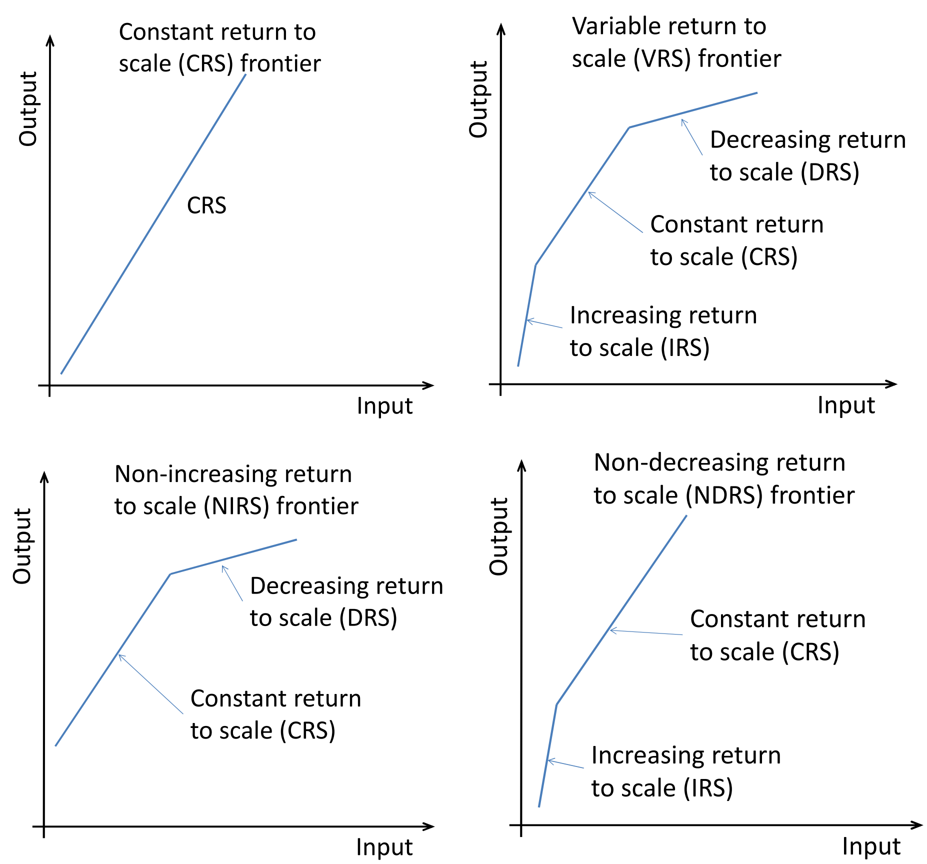

Fig. 2 Different types of Return to Scale (RTS)

To facilitate the calculations and analyses, a number of Excel spreadsheets for DEA models can be used for DEA performance evaluation and benchmarking [11, 12, 25]. With the assistant of the developed DEA Excel spreadsheets, people can easily develop new DEA models to deal with specific evaluation scenarios.

3 RESEARCH METHODS

To investigate how the DEA technique can be applied to study hotel energy performance in Hong Kong, this research has developed the input-oriented Charnes-Cooper-Rhodes (CCR-i) model under constant returns to scale (CRS) for the evaluation of hotel energy consumption of a sample hotel in Hong Kong. The sample hotel under the study is a 4-star medium size city hotel, with about 600 guest rooms, one ballroom, four function rooms, two retail floors, standard laundry workshop and outdoor swimming pool.

When selecting the input and output variables for building up the DEA model, literature review has been conducted to examine the experience of other researchers on the analysis of hotel energy performance. Table 1 shows a summary of the literature review findings. Also, discussions have been made with some hotel managers and operators. It was found that some hotels might not be willing to permit the access and use of the sensitive and confidential financial data (such as hotel occupancy, number of food & beverage covers, etc.) for the research studies. In order to obtain the data for developing the DEA model, measures are required to protect confidentiality or permission should be sought in advance.

Table 1. Summary of the literature review findings on input and output variables for hotel energy analysis

References	Input Variables	Output Variables
Beccali et al (2009) [32]	Bed, Room, Stay	Electricity/Bed, Electricity/Room Electricity/Stay
Deng and Burnett (2002) [7]	Outdoor, Air Temperature	Electricity, Diesel, Gas
Deng and Burnett (2000) [1]	Outdoor Air Temperature, Mean Occupancy, Hotel Class, Hotel GFA, Year of Construction, Guest Room Restaurant	Electricity
Hui and Wong (2010) [5]	Floor Area, Guest Room, Guest Night, Service Level Hotel Star Rating, Room, Meeting Facilities, Restaurants, Swimming Pool, Laundry, Retails, Occupancy, Health Club Casino	Electricity, Gas, Water, Waste, Water, GHG, Finance, Chemicals, Packing Materials, Solid Waste, Detergents, Food Waste

Based on the findings in Table 1 and working experiences from the hotel operators, the DEA model for this research was set up using a linear programming methodology to transform multiple input variables (electricity use, Towngas use, water use, outdoor temperature and relative humidity (RH)) into multiple output variables (numbers of room nights, numbers of room guests, and numbers of food & beverage covers). Fig. 3 shows the input and output variables selected for the DEA model of the sample hotel. The electricity, water and Towngas consumptions were classified as controllable inputs whereas the outdoor temperature and relative humidity are classified as uncontrollable inputs. The database is established for the entire hotel on a monthly basis with a total of 12 months (January to December 2010). The target is to assign each month as the DMU and assess the energy performance of the sample hotel in this 12-month period.

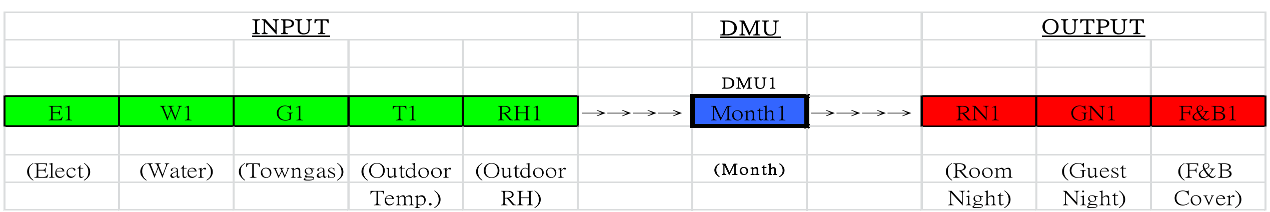

Fig. 3 DEA model for the sample hotel

Another DEA model has been established for assessing the six food & beverage (F&B) outlets in the sample hotel during a one-year period. These F&B outlets have different functions (coffee shop, restaurant and banquet), styles (western and Chinese) and floor areas (ranging from 250 to 710 m^2). Fig. 4 shows the input and output variables selected for this DEA model. The input variables are the same as the previous model (that is, electricity use, Towngas use, water use, outdoor temperature and relative humidity (RH)); the output variable is the F&B cover for each specific outlet. The aim is to evaluate the performance of these F&B outlets from the energy and resource points of view.

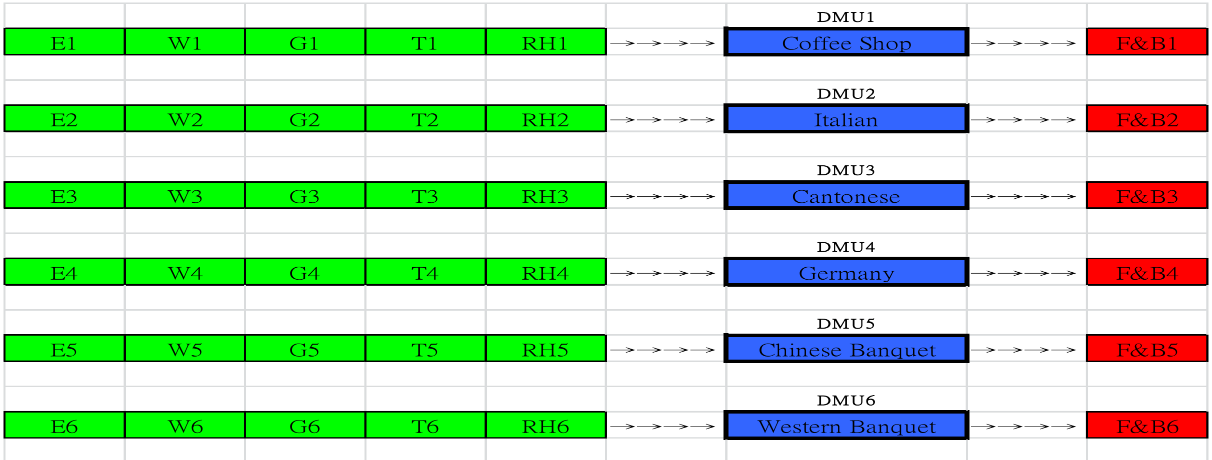

Fig. 4 DEA model for the F&B outlets of the sample hotel

4 ANALYSIS RESULTS

Before assessing the DMUs of the two DEA models for the sample hotel, the correlations of all the parameters involved (inputs and outputs) have been studied to evaluate the relative importance and examine any hidden factors among them. Table 2 shows the correlations of these parameters. The data indicate the correlation coefficient or coefficient of determination (R^2) (0 to 1) between two parameters.

Table 2. Correlations of the parameters for the sample hotel

	Elect	Water	Towngas	Temp	RH	Room Night	Guest Night	F&B Cover
Elect	1	0.3842	-0.4948	0.9396	0.0038	0.0774	0.2012	-0.163
Water	0.3842	1	-0.006	0.4435	0.2129	-0.2302	0.0755	0.0606
Towngas	-0.4948	-0.006	1	-0.6919	-0.6381	0.4354	-0.0438	0.78
Temp	0.9396	0.4435	-0.6919	1	0.22	-0.1451	0.1802	-0.3158
RH	0.0038	0.2129	-0.6381	0.22	1	-0.7677	-0.4079	-0.8504
Room Night	0.0774	-0.2302	0.4354	-0.1451	-0.7677	1	0.1334	0.7719
Guest Night	0.2012	0.0755	-0.0438	0.1802	-0.4079	0.1334	1	0.2706
F&B Cover	-0.163	0.0606	0.71	-0.3158	-0.8504	0.7719	0.2706	1

In this study, a correlation coefficient greater than 0.8 will be considered as strongly statistically correlated while a correlation greater than 0.6 will be considered as statistically correlated. If the correlation coefficient is smaller than 0.6, the two parameters are treated as not correlated. This assumption is made in line with other similar research studies on hotel performance [33-36].

The major results of the correlation analysis are given below.

a) The electricity consumption is very positively correlated (+0.94) with the monthly mean outdoor temperature. Deng & Burnett [7] also concluded by using regression analysis the strong correlation between the total electricity use and monthly mean outdoor temperature (+0.90). It is because the cooling energy for the air-conditioning systems dominates in hotels and will increase with higher outdoor temperature.
b) The towngas consumption is highly positively correlated (+0.71) with the F&B cover. Deng & Burnett [7] concluded that the coefficient of determination (R^2) for the regression is only 0.33; Deng [34] found the highest R^2 value is 0.42; Rajagopalan, Wu & Lee [2] found an R^2 of 0.55; Bohdanowicz & Martinac [33] suggested that the correlation was 0.66 for hotels and 0.51 for upscale hotels. The possible explanation for the variations might be due to different usage of towngas for the Chinese dishes and their cooking methods.
c) The towngas consumption is negatively correlated (-0.69) with the monthly mean outdoor temperature. It is because more towngas is required for producing hot water and cooking during the cooler seasons.
d) The relative humidity is negatively correlated (-0.85) with F&B cover, (-0.77) Room Night and (-0.64) Towngas, respectively.

For the assessment of monthly data of the sample hotel (see Fig. 3), using the DEA Excel spreadsheets with the CCR-i model, the analysis report was generated for the evaluation and comparison of the DMUs for the 12 months. Fig. 5 shows the relative efficiency scores of the hotel in different months. The average of the scores of all DMUs is 0.968 which is on the high side. 6 out of the 12 DMUs are efficient (score = 1) and the other 6 DMUs are inefficient (with score ranging from 0.879 to 0.972). In a broad sense, an efficiency score represents a DMU's ability to transform a set of inputs (given resources) into a set of outputs [20, 21]. In this example, hotel operations in those inefficient DMUs or months require more attentions. It should be noted that as the selected output variables include electricity, Towngas and water consumptions, not only the hotel energy performance is being assessed but also water usage. Based on the results of the slack variables (see equation (4)), the distance from the efficiency frontier can be determined for each inefficient DMU and it can be used as benchmarks for improvement.

In addition, sensitivity tests have been carried out with different scenarios by removing some of the DMUs from the DEA computation. It is found that the efficiency chart remains almost the same; the most and least efficient DMUs remain in their ranks with no changes for all the efficient DMUs. The results verified the DEA approach is still valid for limited data.

Fig. 5 Relative effciency scores of the hotel in different months

Similarly, for the assessment of F&B outlets in the sample hotel (see Fig. 4), the analysis report was generated for comparing the performance of these F&B outlets. Fig. 6 shows the relative efficiency scores of the six F&B outlets in the sample hotel. The average of the scores of all DMUs is 0.793. 3 out of the 6 DMUs are efficient (score = 1) including Chinese Banquet, Germany and Coffee Shop; the other 3 DMUs are inefficient (with score ranging from 0.361 to 0.735) including Western Banquet, Cantonese and Italian. This shows that some of the F&B outlets was considered to be operating at a relatively low to very low efficient mode in this period as far as their energy performance and water usage are concerned. Study on the results of the slack variables will provide some hints for improving the inefficient DMUs. For example, for the most inefficient DMU (Western Banquet), the outlet can look at the identified key controllable inputs including of electricity and water consumptions. By referring to the best practices in other efficient DMUs, this Western Banquet can improve and might become an efficient unit in the coming future.

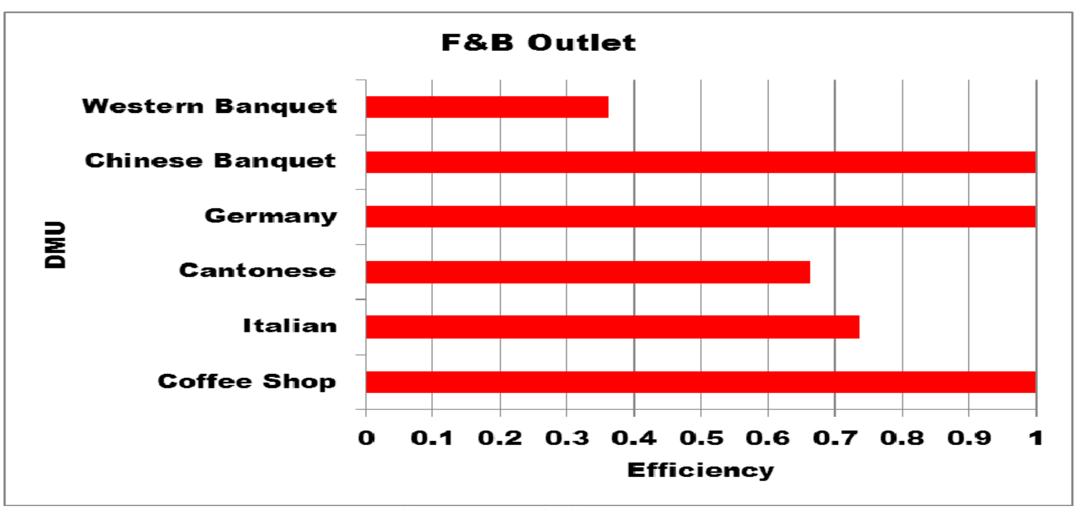

Fig. 6 Relative efficiency scores of different F&B outlets in the sample hotel

In summary, it is found that the DEA model can identify the relative efficiencies of different DMUs (which are the hotel food & beverage outlets). The potential areas of energy and cost savings are shown for further improvement action by the hotel management and strategic planning teams. By studying the DEA results, balanced benchmarking information can be obtained for improving the operations of poor-performing DMUs. Peer groups and slacks were identified among the efficient operations for the inefficient DMUs to adjust themselves in order to reach the efficient frontier.

5 DISCUSSIONS

DEA is a powerful quantitative, analytical instrument and a practical decision support tool. It can accommodate a multiplicity of inputs and outputs; it also takes into consideration returns to scale in calculating efficiency, allowing for the concept of increasing or decreasing efficiency based on size and output levels. It is believed that DEA scores can provide hotel management with a useful tool to identify inefficiency and manage the opportunity for improving the overall building energy management and hotel operation.

A drawback of this technique is that DEA model specification and inclusion/exclusion of variables can affect the results. In general, the DEA analysis results and efficiency scores are potentially sensitive to the selection of inputs and outputs, so their relative importance needs to be analysed prior to the calculation. However, there is no way to test their appropriateness. The number of efficient DMUs on the frontier tends to increase with the number of inputs and output variables. When there is no relationship between explanatory factors (within inputs and/or within outputs), DEA views each DMU as unique and fully efficient and efficient scores are very close to 1, which results in a loss of discriminatory power of the method.

The size of the data set is also an important factor when using some of the traditional DEA models. As a general rule, with five inputs and five outputs, at least 25 or so units will appear efficient and so the set needs to be much greater than 25 for any discrimination. However, some of these sample size problems can be overcome by using cross efficiency models. It is suggested by Chiang [18] that the number of DMUs should be at least twice the total number of input and output amounts; three times would be more reliable. In the present study, the two DEA models were established based on limited available data. Although the analysis results still can indicate the general properties of the DEA approach, it would be better if the size of the data set can be increased.

Sometimes, human factor is crucial to DEA investigation and evaluation. When determining the inputs and outputs to be used in any analysis, companies can ensure “buy-in” by involving the managers of the business units in the process of identifying and incorporating all the relevant resources used and services provided by a business unit [23]. This will help minimise any “push back” should the analysis yield some unflattering results. Very often, the results of DEA could lead to a major rethinking of past assumptions, conventional wisdom, personal experience and relationships to and within the organisation. This could help overcome the institutional barriers to energy efficiency improvement for the hotel industry.

DEA provided more insights for performance management than the traditional ratio analysis (EUI) commonly used in the hotel industry both in Hong Kong and overseas. The DEA approach may serve as the first stage analysis to find out the non-efficient units compared with the peer group for strategic management decision making, and the EUI approach may be used as the second stage analysis to identify the non-efficient equipment/practice of the non-efficient unit which compared with the respective equipment/practice of the efficient unit. Other technical indicators such as coefficient of performance (COP) and energy efficiency ratio (EER) can also be used to analyse the system and equipment as the micro view at the operation level.

6 CONCLUSIONS

DEA can be an important component for truly understanding efficiency within an organisation that uses a variety of resources to provide a complex set of services in multiple locations. Hotel management and operation is a good example of such a service-oriented organisation. To improve hotel energy performance, people can use DEA or balanced benchmarking to identify both best practices and inefficiencies. The technique can also allow hotel managers to test their assumptions about productivity before actual implementation of the improvement actions.

It is believed that better managing and controlling energy will reduce energy costs and help increase competitiveness and profitability of the hotel [5]. Also, using energy more efficiently can reduce greenhouse gases and pollution from electricity generation and heat production, hence contribute to environmental management and sustainable operation of hotels [24, 37]. It is hoped that by investigating the hotel energy use in a sophisticated and systematic way using the DEA approach, environmental management and sustainable energy future of hotel buildings can be improved and achieved.

In Hong Kong, at present, with the growing importance of tourism, the number of hotels is expected to grow in the coming years. It is important to promote better energy efficiency in the hotel sector and foster the concepts of sustainable tourism in new and existing hotels. The experience and knowledge on hotel energy management are not only essential to Hong Kong, but also useful to other cities in mainland China and the world. The DEA technique can be applied to evaluate other factors in hotel management such as financial, guest experience, staff deployment.

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