Applying DEA and PLS path modeling for efficiency evaluation

WEI-WEN WU
Department of International Trade,
Ta Hwa Institute of Technology,
1. Ta Hwa Road, Chiung-Lin, Hsin-Chu 307, Taiwan
itmike@thit.edu.tw

Abstract:-Organizations need to work on productivity improvement in order to enhance their operational performances. A number of works have taken efforts in efficiency evaluation and ranking using analytic methods such as the data envelopment analysis (DEA). However, few works have highlighted the relationship among significant factors that affect productivity. Performing efficiency evaluation and ranking is essential for productivity improvement. Apart from that, it is also a requirement to create a clear picture in terms of the relationship among critical productivity factors. PLS path modeling is a popular causal analysis technique, by which a causal map can be created. Therefore, this paper suggests a solution combining DEA with PLS path modeling for conducting a more profound efficiency evaluation. In addition, an empirical study of the hotel industry in Taiwan is presented to illustrate the application of the proposed solution.

Key-words: - efficiency evaluation, DEA, productivity factor, PLS path modeling

1 Introduction

The excellence of operational performance is the sustainable source of an organization's competitiveness, which results from increasing revenue, lowering operational costs, maximizing the use of resources, and gaining a greater share of the market. More importantly, the fruitful operational performance is based on the robust productivity of business activities. Here therefore arises an imperative issue that all organizations need to fight for productivity improvements in order to enhance their operational performance. The operational performance can be viewed as process performance [6]; it also can be regarded as the outcomes of an organization's processes such as reliability, production cycle time, and inventory turns [29][41][24]. As for productivity, [37] remark that productivity has been approached as an umbrella concept including efficiency, effectiveness, quality, predictability and other performance dimensions, as well as a narrower concept reflecting only production efficiency.

In business practices, organisations are everlastingly forced to put effort in efficiency evaluation and ranking as well as productivity improvement. [34] comments the productivity is the relationship between inputs and outputs within a productive system. According to [25], the productivity is a measure of the efficiency and effectiveness to which resources (inputs) are utilized for the creation of products/services (outputs); and productivity assessments and evaluations should be continued to include a more holistic focus of the organization. Moreover, [33] remark that productivity improvement requires maximizing desirable operational outcomes while minimizing operational expenses. Furthermore, numerous works have deemed that the efficiency evaluation is a kind of the productivity analysis and is helpful to improve operational performance. For example, [12] remark that the efficiency measurement has become a hot topic because all organizations need to struggle for productivity improvement. In addition, [16] note that efficiency and productivity analyses are vital managerial control tools for assessing the degree to which inputs are utilized in the process of obtaining desired outputs.

For dealing with the issue of performance measurement, data envelopment analysis (DEA) has an impressive growth both in theoretical developments and applications [12]. The DEA evaluates the performance of Decision Making Units (DMUs) through a transformation process of multiple inputs and outputs, which employs a technique based on Linear Programming and without a need to introduce any subjective or economic parameters [3]. Numerous works apply the DEA as a productivity analysis tool for conducting efficiency evaluation and ranking in the hotel industry, such as: analyzing the efficiency of 54 hotels in the United States [26[26], examining the efficiency of 53 international tourist hotels in Taiwan [40], applying the four-stage DEA procedure to calculate the pure managerial efficiency of 54 international tourist hotels [42], measuring hotel managerial efficiency [8], analyzing the impact of ecommerce on hotel performance [36], and so on. However, few works highlight the relationship among significant factors that affect productivity. Performing efficiency evaluation and ranking is essential for productivity improvement. On top of that, it is also required to make an understandable portrait in terms of the relationship among critical productivity factors.

Productivity factors can be divided into input factors and output factors. For the purpose of having the relationship among significant productivity factors, PLS path modeling is helpful. PLS path modeling is a popular causal analysis technique, by which a causal map can be created. Causal maps represent the causal knowledge of subjects in a specific domain, and they have been applied widely in the areas of policy analysis and management sciences to demonstrate the relationships between relevant factors, knowledge, and conditions [27]. Therefore, this paper suggests a solution combining DEA with PLS path modeling for conducting a more profound efficiency evaluation. Additionally, an empirical study of Taiwanese hotel industry is presented to illustrate the application of the proposed solution. The remainder of this paper is organized as follows. In section 2, the literature review is conducted. In section 3, the proposed solution is discussed. In section 4, an empirical study is illustrated. Finally, based on the findings of this research, conclusions and implications for management are presented.

2 Literature review

2.1 Productivity measurement as a MCDM problem

Productivity involves a set of interactive factors that are usually divided into inputs and outputs. Basically, the productivity can be represented as a ratio at which the inputs are used to form the outputs. Hence, productivity measurement involves measuring the performance as a ratio of outputs to inputs. Dealing with the productivity measurement as well as the efficiency evaluation and ranking is a sort of mu1tiple criteria decision-making (MCDM) problem that requires considering a large number of inputs and outputs as multiple evaluation criteria or attributes. Referring to [20], when measuring productivity or efficiency for hotel industry, we need to consider the relationship between multiple inputs (material, staff, capital and equipment) and multiple outputs (tangible and intangible products/services).

As for the feature of MCDM, it is a decision-making process that consists of defining the decision goal, gathering relevant information, generating the broadest possible range of alternatives, evaluating the alternatives for advantages and disadvantages, selecting the optimal alternative, and monitoring the results to ensure that the decision goal is achieved [17]. Furthermore, [11] note that: (1) MCDM models are characterized by the need to evaluate a finite set of alternatives with respect to multiple criteria; (2) the main purpose of MCDM problems is to compute and rank the overall values of the alternatives; and (3) alternatives are generally evaluated with respect to each of the criteria to obtain priority scores which are then aggregated into overall values. More importantly, in order to effectively handle the MCDM problem, it is indispensable to employ MCDM methods [30].

2.2 DEA as a productivity analysis tool

The DEA has been proposed as a tool for selecting a finite set of alternatives considering multiple criteria [35]. Referring to [3], when we utilize the DEA as a productivity analysis tool, DMUs are viewed as alternatives while inputs/outputs are regarded as criteria. In using the DEA, the productivity score of any unit is computed as the maximum of a ratio of weighted outputs to weighted inputs, subject to the condition that for all other units of the dataset [37].

The primary activities of organizational operations are required to effectively convert restricted inputs into fruitful outputs. The DEA is a nonparametric approach to compare the relative efficiencies of a set of DMUs (decision-making units), which can identify efficient or inefficient DMUs through the use of linear programming models [13][18]. Referring to [2], (1) service industry such as the hospitality industry has its own characteristics and is difficult to draw any conclusions about the relative productivity without considering the mix and nature of services provided; and (2) the DEA is popular for usage because it can handle multiple inputs and outputs without requiring an assumption on functional type. Hence, the DEA is a favorable method to be used for measuring the productivity.

2.3 Issues of productivity measurement

Although the DEA is a suitable approach to measure the productivity, there is a lacking of a standard to choose the appropriate inputs and outputs as well as to decide what size is the best for a set of inputs and outputs. Indeed, such issues are also affected by both research intention and data limitation. For example, [2] employ the DEA to analyze hotel efficiency with five inputs (full-time equivalent employees, number of rooms, total gaming related expenses, total food and beverage expenses, and other expenses) and one output (total revenue). Moreover, [40] utilizes the DEA to examine hotel efficiency with multi-inputs (total operating expenses, the number of employees, the number of guest rooms, the total floor space of the catering division, the number of employees in the room division, the number of employees in the catering division, and catering cost) and multi-outputs (total operating revenues, the number of rooms occupied, average daily rate, the average production value per employee in the catering division, total operating revenues of the room division, and total operating revenues of the catering division). In addition, [20] measure the hotel efficiency using the DEA with dataset from the Taiwan Tourism Bureau including four inputs (number of full-time employees, guest rooms, total area of meal department, operating expenses) and three outputs (room revenue, food and beverages revenue, other revenues).

According to [14], there are three difficulties in measuring productivity, including: identification of the appropriate inputs and outputs; measures of those inputs and outputs; and the ways of measuring the relationship between inputs and outputs. Moreover, [37] note that the productivity of hotel industry can be significantly impacted by such factors: hotel size, location, service orientation, ownership and management arrangement, hotel age, design, type and number of facilities, demand patterns and variability, staff flexibility, and marketing practices' effectiveness. Furthermore, the complicated relationship between inputs and outputs is affected by both the number of inputs/outputs as well as their measurement units; and different combinations between the number of inputs/outputs and types of units can result in many productivity metrics that disclose diverse information or implications [37]. This means that choosing the appropriate inputs/outputs or deciding the number of inputs/outputs is the generic issue of productivity measurement, it is no fault of the DEA. To solve such an issue, the author suggests that to successfully implement the DEA, it is required to conducting the causal analysis with the PLS path modeling.

3 The proposed solution

In order to better deal with the MCDM problem of productivity measurement, in reference to the literature [17][3][11][30][35], the procedure of proposed solution is divided into four main phases. As shown in Fig. 1, the first step is to define the decision goal in terms of productivity measurement. The next is to select the DMUs for the productivity measurement.

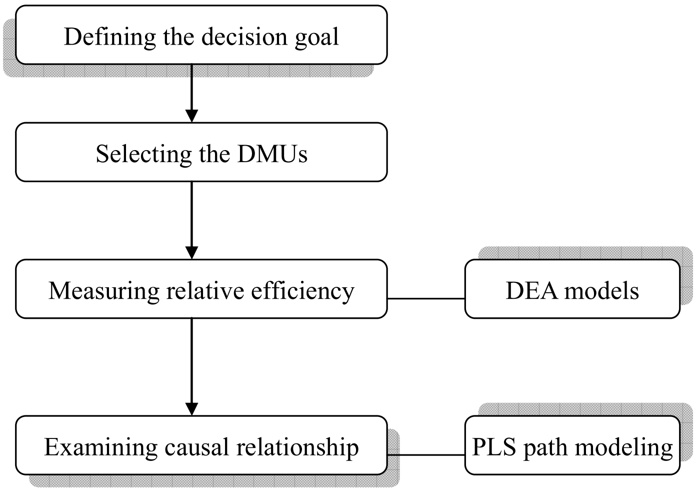


Fig. 1. The proposed solution.

In phase 3, it is the task of measuring the relative efficiency of DMUs using DEA models. There are several DEA models that have been developed such as the CCR model [7], the BCC model [4], and the super-efficiency models [2]. Among these DEA models, the super-efficiency DEA model allows an efficiency score above one for ranking the efficient units, and assigns an efficiency score less than one to inefficient units. That is, the efficiency scores of the efficient units can be greater than or equal to one, when using the super-efficiency model [28][5]. Obviously, the super-efficiency model is a better method to handle the efficiency measurement in practice.

The DEA is a mathematical method that measures the relative efficiency of decision-making units (DMUs) with multiple inputs and outputs without the needs of predefined production functions or assumptions. Moreover, the relative efficiency can be defined as the ratio of total weighted output to total weighted input. By comparing n units with s outputs y_{rk} $(r = 1,...,s)$ and m inputs $x_{ik}(i = 1,...,m)$, the efficiency h_k of DMU k can be expressed as follows:

$$h_k = \text{Max} \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}}$$

subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 \quad \text{for } j = 1,...,n.$$

$$u_r \ge \varepsilon \text{ for } r = 1,...,s; \; v_i \ge \varepsilon \text{ for } i = 1,...,m.$$

where the weights u_r and v_i are non-negative, the ε is a non-archimedian value as a device to enforce strict positivity on the variables.

The CCR or BCC model produces an efficiency score (between zero and 1) for each unit, and they do not allow for a ranking of the efficient units themselves [16]. For this issue of ranking efficient units, Andersen and Petersen (1993) first developed the super-efficiency model which can rank efficient units. Referring to [1], the super-efficiency model can be expressed as below:

$$h_k = \text{Max} \sum_{r=1}^{s} u_r y_{rk}$$

subject to:

$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \ge 0 \quad \text{for } j = 1,...,n, j \ne k,$$

$$\sum_{i=1}^{m} v_i x_{ik} = 1, \tag{1}$$

$$u_r \ge \varepsilon \text{ for } r = 1,...,s; \; v_i \ge \varepsilon \text{ for } i = 1,...,m.$$

In Phase 4, PLS path modeling is employed for examining the causal relationship among productivity factors consisting of input factors and output factors. PLS path modeling and LISREL (LInear Structural RELations) are two main SEM (Structural equation modeling) approaches to modeling relationships between latent variables [39][38]. By comparing the PLS path modeling with the LISREL, we may better understand several characteristics about them, such as: (1) LISREL focuses on maximizing the explained covariation among the various constructs, while PLS path modeling maximizes the explained variation among the various constructs [22]; (2) LISREL with its assumption of homogeneity in the observed population, while PLS path modeling is particularly more advantageous to employ when models are complex [15][19]; and (3) although both LISREL and PLS path modeling are SEM, the former highlights theory confirmation while the latter stresses causal explanation [22]. More importantly, PLS path modeling is more suited for analyzing exploratory models with no rigorous theory grounding, it requires minimal assumptions about the statistical distributions of data sets, and it can work with smaller sample sizes [43][32].

According to [21], the PLS path modeling algorithm can be divided into three main steps. Step 1 is the quantification step where initial latent variables are calculated as below:

$$\mathrm{y}_j^t = \sum_{i=1}^{p_j} w_{ji}^t x_{ji}, \tag{2}$$

where y_j^t is the outer estimate of the latent variable ξ_j at step t, x_{ji} is the manifest variable i associated with the latent variables ξ_j and p_j is the number of manifest variables in block j.

Step 2 is to perform the iterative algorithm where latent variables are estimated iteratively with respect to the inner model and the outer model. This process is repeated until convergence is obtained.

•Inner estimation focuses on the centroid scheme for inner estimate z_j^t of the latent variable ξ_j :

$$z_j^t = \sum_{\xi_{j'} \in J} \text{sign}(\text{cor}(\mathrm{y}_j^t, \mathrm{y}_{j'}^t))\mathrm{y}_{j'}^t, \tag{3}$$

where J is the set of all latent variables connected to ξ_j.

•Prior to performing the outer estimation y_j^t of latent variable ξ_j, outer weights are updated using mode A (reflective indicators) estimation:

$$w_{jh}^t = \text{cov}(x_{jh}, z_j^t). \tag{4}$$

Once the outer weights have been updated, the outer estimation is performed using Eq. (2).

Step 3 is to use the ordinary least squares regressions for the estimation of structural relations between latent variables.

4 Empirical study

In this section, an empirical study is presented to illustrate the application of proposed solution. Phase 1 is required to define the decision goals. This study aims to conduct efficiency evaluation as well as to examine the causal relationship among productivity factors for the international tourist hotels in Taiwan. The data of this study were obtained from the "Annual Report of International Tourist Hotels" published by the Taiwan Tourism Bureau in December 2008. Tourist hotels in Taiwan can be divided into international tourist hotels and ordinary tourist hotels. In phase 2, excluding 12 hotels due to incomplete data, the statistics of 48 international tourist hotels (as the DMUs) are used for this study.

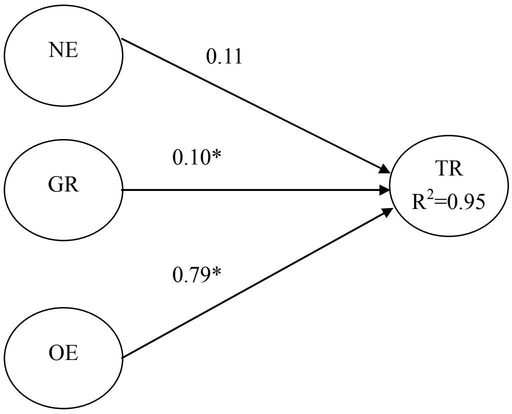
In phase 3, the Super-efficiency DEA model is adopted because it allows the efficiency values of efficient DMUs to be greater than one in order to rank efficient DMUs [23]. Referring to the literature [40][20][10][44][9], this study uses six productivity factors which including: Number of Employees (NE), Guest Rooms (GR), Operating Expenses (OE), Room Revenue (RR), Food and Beverages Revenue (FBR), and Total Revenue (TR). The statistics of these productivity factors can be attained from the "Annual Report of International Tourist Hotels". For profoundly measuring the relative efficiency of DMUs, the study conducts comparisons with three treatments: Treatment A includes three inputs (NE, GR, OE) and one output (TR); Treatment B consists of three inputs (NE, GR, OE) and two outputs (FBR, RR); and Treatment C comprises five (NE, GR, OE, FBR, RR) and one output (TR). Moreover, Score A and Score B as well as Score C are respectively represented for Treatment A and Treatment B as well as Treatment C.

To calculate the relative efficiency based the super-efficiency DEA model, the data analysis is performed with the help of software called EMS (Efficiency Measurement System). As shown in Table1, we can know that (1) the results of Score B and Score C are similar; (2) Score B has the least number of efficient DMUs; (3) there are only three efficient DMUs (U2, U4, and U14) across three treatments.

Table 1 Data and efficiency values

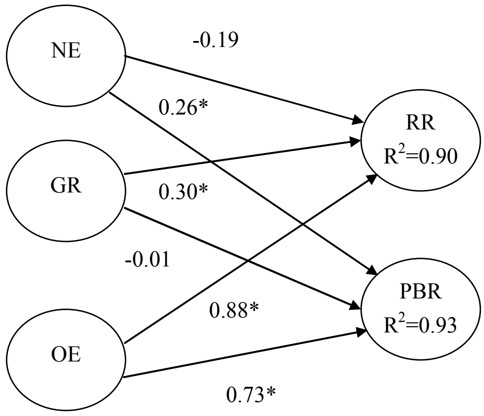
DMU	Number of Employees	Guest Rooms	Operating Expenses (NT$)	Food and Beverages Revenue (NT$)	Room Revenue (NT$)	Total Revenue (NT$)	Score A	Score B	Score C
U1	912	873	2,348,922,190	1,110,840,080	1,366,496,222	2,927,114,868	97.17%	114.11%	116.68%
U2	739	569	1,426,452,817	1,083,059,791	785,872,962	2,440,856,676	134.53%	118.77%	136.99%
U3	858	686	2,223,260,561	1,127,782,429	899,473,278	2,297,435,227	81.07%	92.34%	92.34%
U4	707	420	1,776,731,410	842,101,565	836,015,735	1,810,092,995	100.47%	114.23%	114.23%
U5	812	606	1,278,642,519	634,618,811	628,621,840	1,562,307,577	70.90%	78.42%	78.42%
U6	447	288	1,165,714,972	569,454,520	501,853,326	1,174,755,925	94.80%	100.35%	100.35%
U7	503	432	914,242,889	683,246,354	395,742,933	1,161,059,775	73.71%	98.39%	98.39%
U8	614	402	1,071,494,471	519,551,121	424,533,147	1,103,704,831	63.98%	72.31%	72.31%
U9	464	343	668,227,370	314,254,103	460,734,607	922,194,978	79.79%	101.23%	101.95%
U10	495	250	659,793,356	455,233,827	194,238,884	709,575,909	66.14%	95.28%	95.28%
U11	219	220	622,923,644	142,764,598	162,288,765	695,480,739	96.15%	51.85%	96.15%
U12	360	268	640,526,659	385,273,752	244,489,582	682,002,331	62.11%	79.20%	79.20%
U13	227	388	348,208,497	205,494,711	359,427,308	636,044,026	106.75%	137.85%	138.28%
U14	271	202	376,368,616	200,553,759	241,820,630	507,820,622	77.84%	94.27%	94.27%
U15	293	209	434,371,883	224,153,678	217,943,587	488,790,031	65.26%	79.86%	79.86%
U16	273	336	434,817,326	183,638,268	200,351,917	418,262,873	54.30%	61.31%	61.31%
U17	226	287	262,064,795	89,626,117	177,081,298	293,101,544	61.33%	66.06%	66.06%
U18	170	215	215,928,586	113,531,120	125,830,771	247,917,295	63.52%	76.67%	76.67%
U19	152	243	159,754,819	34,300,410	155,753,640	210,026,329	71.97%	94.45%	94.45%
U20	97	201	133,033,373	71,538,483	93,402,946	169,791,653	69.87%	82.33%	82.33%
U21	64	97	44,345,770	8,871,749	34,912,642	44,130,793	54.48%	76.27%	76.27%
U22	734	436	1,409,612,089	815,125,688	422,216,019	1,551,160,100	82.77%	96.06%	96.06%
U23	539	592	1,047,419,681	469,341,269	359,657,824	955,287,442	53.66%	60.66%	60.66%
U24	362	457	642,435,003	397,497,759	237,374,314	670,983,415	59.67%	81.45%	81.45%
U25	234	283	398,210,661	194,316,442	194,060,809	456,922,533	65.14%	69.18%	69.18%
U26	167	302	193,153,258	73,953,366	132,541,726	214,184,739	60.71%	66.48%	66.48%
U27	117	274	140,352,282	39,952,065	97,813,056	145,482,093	56.75%	67.52%	67.52%
U28	271	354	485,153,688	264,581,089	237,024,156	589,596,010	69.60%	75.25%	75.25%
U29	436	222	663,649,325	162,019,454	122,986,751	491,302,101	51.52%	37.78%	51.52%
U30	277	404	346,964,325	206,992,079	116,843,565	355,040,621	56.02%	78.48%	78.48%
U31	184	155	261,470,984	158,841,734	125,205,121	314,166,203	68.96%	81.41%	81.41%
U32	192	226	221,779,607	129,781,300	94,778,457	240,323,028	59.83%	77.17%	77.17%
U33	403	381	484,633,650	165,129,749	335,733,563	564,478,198	65.67%	79.87%	80.40%
U34	288	343	341,703,814	109,761,347	208,003,258	351,447,495	56.86%	62.23%	62.23%
U35	115	221	194,820,640	96,163,726	81,545,860	181,830,600	52.63%	67.24%	67.24%
U36	148	270	176,597,303	92,335,670	75,973,325	173,618,774	53.82%	70.74%	70.74%
U37	305	405	423,762,132	137,524,516	298,192,827	478,807,791	62.74%	73.71%	73.71%
U38	268	250	352,029,059	128,420,290	293,785,405	443,386,044	71.51%	104.09%	104.09%
U39	158	224	216,742,910	61,917,632	110,082,827	190,428,547	48.45%	51.30%	51.30%
U40	132	107	202,521,551	112,836,564	32,843,681	161,134,541	45.94%	73.27%	73.27%
U41	133	201	140,061,802	42,518,759	56,415,615	108,204,161	42.29%	46.71%	46.71%
U42	53	50	87,445,403	29,637,477	39,799,449	99,676,634	65.55%	64.25%	67.37%
U43	374	257	721,658,028	371,100,193	260,551,728	855,817,068	77.56%	75.16%	77.56%
U44	233	208	295,404,891	135,000,706	171,552,657	336,936,950	64.79%	74.98%	74.98%
U45	185	390	181,498,657	76,294,380	143,096,277	221,819,994	66.91%	76.38%	76.38%
U46	372	315	590,989,486	326,114,209	248,411,595	642,044,176	62.70%	73.41%	73.41%
U47	214	276	272,055,349	104,188,199	137,463,863	267,871,689	54.38%	58.82%	58.82%
U48	192	152	235,100,506	179,084,238	48,330,372	253,442,319	61.56%	100.32%	100.32%
Mean	333	319	581,938,596	293,339,982	274,774,378	662,872,089	68.42%	79.78%	81.57%
Min	53	50	44,345,770	8,871,749	32,843,681	44,130,793	42.29%	37.78%	46.71%
Max	912	873	2,348,922,190	1,127,782,429	1,366,496,222	2,927,114,868	134.53%	137.85%	138.28%

In phase 4, PLS path modeling is employed for examining the relationship among productivity factors, and it is executed by the software SmartPLS which excels at graphic path modeling with latent variables. Through the implementation of PLS path modeling for this study, we can obtain standardized regression coefficients for the paths, and R^2 values for endogenous variables. Specifically, Fig. 2 shows that OE (0.79) has higher positive influence on TR than GR (0.10) does; and the combination of GR and OE has 95% predictive ability for the TR. Moreover, Fig. 3 demonstrates that GR and OE have positive influence on RR, while NE and OE have positive influence on PBR; that is, only OE positively affect both RR and PBR. Further, the combination of "GR → RR" and "OE → RR" has 90% predictive ability for the RR, while the combination of "NE → PBR" and "OE → PBR" has 90% predictive ability for the PBR. Additionally, Fig. 4 illustrates the most part of analysis results as the same as those in Fig. 3; but it provides advanced information such as: PBR (0.57) has higher positive influence on TR than RR (0.45) does; and the combination of significant productivity factors has 98% predictive ability for the TR.



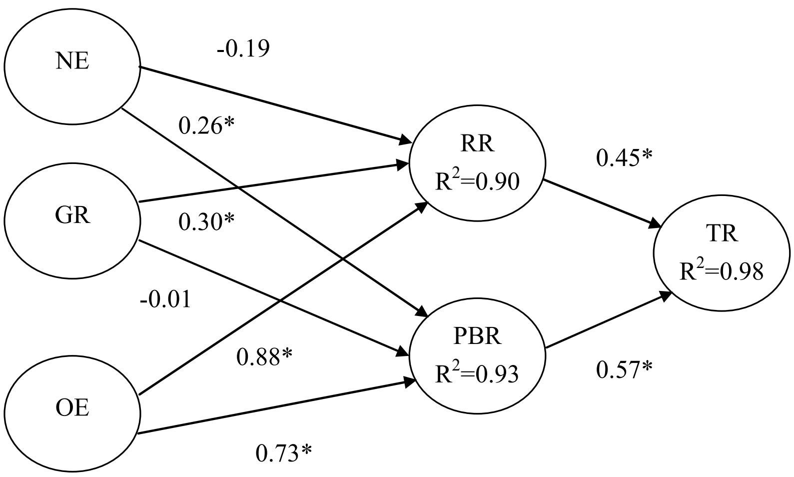
*p < 0.05

Fig. 2. Treatment A



*p < 0.05

Fig. 3. Treatment B



*p < 0.05

Fig. 4. Treatment C

5 Conclusions

Efficiency measurement has been a subject of tremendous interest as organizations have struggled to improve productivity [12](Cook & Seiford, 2009). It has been well recognized that one single performance measure cannot suffice for performance evaluation and benchmarking, multiple measures are therefore always necessary [9](Chen and Zhu, 2003). The DEA can handle multiple inputs and outputs without rigid requirements of assumptions or functional types. The DEA has become a popular analysis tool used for efficiency evaluation and ranking as well as productivity improvement through measuring the relative efficiency of a set of comparable DMUs [16](Golany & Roll, 1989). Moreover, a DMU is deemed to be efficient if the ratio of weighted sum of outputs to the weighted sum of inputs is relatively high [31](Ramanathan, 2007).

However, even though the DEA is helpful and powerful to deal with the tasks of efficiency evaluation and ranking, we need to consider some issues such as: how to select the proper inputs and outputs; how to decide the number of inputs and outputs; and how to measure the relationship between inputs and outputs [14](Fitzimmons & Fitzimmons, 1998). To solve these issues, it is also required to think about the research intention and the data limitation in practice. Taking the above issues into account, this paper suggests a solution combining DEA with PLS path modeling for conducting a more profound efficiency evaluation. That is, apart from implementing the DEA, it is required to conduct the causal analysis with the PLS path modeling. In this sense, the empirical study conducts comparisons with three treatments.

From this empirical study, we can derive some management implications. Firstly, it is obvious that a solution combining DEA with PLS path modeling is better than using just the DEA for efficiency evaluation. This is because the analysis results of using PLS path modeling can provide valuable information in terms of the relationship among significant productivity factors. Such that information can help an organization bring out the directions of possible strategies for productivity improvement, not limited to merely think of increasing outputs or decreasing inputs. Secondly, it is ideal to apply the Treatment C because it identifies more efficient DMUs than that of the Treatment A does. A lager list of efficient DMUs is better than a smaller list of that. This is because the former can be used to conduct further analyses.

Thirdly, the Treatment C offers a holistic view in terms of the relationship among productivity factors. For the Treatment C, PLS path modeling creates a causal map by which we may derive meaningful management implications. For example, to increase Room Revenue, it is required to raise investment in Guest Rooms and Operating Expenses, whereas to increase Food and Beverages Revenue it is required to raise investment in the Number of Employees and Operating Expenses; that is, to enhance either Room Revenue or Food and Beverages Revenue, it is indispensable to amplify Operating Expenses. Hence, how to effectively use and control the Operating Expenses is an imperative management task for productivity improvement. Moreover, the most of Total Revenue is affected by Room Revenue as well as Food and Beverages Revenue. Interestingly, Food and Beverages Revenue is more important than Room Revenue. This reveals that offering excellent Food and Beverages is the key role as a magnet to attract costumers and finally contributing to Total Revenue.

This paper is successful in proposing a solution combining DEA with PLS path modeling for conducting a more profound efficiency evaluation. The proposed solution has contributed to extend practical applications of combining the DEA model and the PLS path modeling in efficiency evaluation and ranking as well as productivity improvement. Also, an empirical study of the hotel industry in Taiwan is presented to illustrate the application of the proposed solution. From the findings of this empirical study, we gain some management implications. However, this study has some limitations. For instance, different input and output factors could produce dissimilar analysis results. As for future research, it is worthwhile to employ data mining techniques for exploring complex interactions among factors affecting productivity.

References

[1] N. Adler, L. Friedman, Z. Sinuany-Stern. Review of ranking methods in the data envelopment analysis context. *European Journal of Operational Research*, Vol.140, No.2, 2002, pp.249-265.

[2] P. Andersen & N.C. Petersen. A procedure for ranking efficient units in data envelopment analysis. *Management Science*, Vol.39, No.10, 1993, pp.1261-1264.

[3] D. Bouyssou. Using DEA as a tool for MCDM: some remarks. *Journal of the Operational Research Society*, Vol.50, No.9, 1999, pp.974-978.

[4] R.D. Banker, A. Charnes & W.W. Cooper. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, Vol.30, No.9, 1984, pp.1078–1092.

[5] R.D. Banker & H. Chang. The super-efficiency procedure for outlier identification, not for ranking efficient units. *European Journal of Operational Research*, Vol.175, No.2, 2006, pp.1311-1320.

[6] C. Caplice & Y. Sheffi. A review and evaluation of logistics performance measurement systems. *The International Journal of Logistics Management*, Vol. 6, No.1, 1995, pp. 61-73.

[7] A. Charnes, W.W. Cooper & E. Rhodes. Measuring the efficiency of decision-making units, *European Journal of Operational Research*, Vol.2, No.6, 1978, pp.429-444.

[8] C.F. Chen. Applying the stochastic frontier approach to measure hotel managerial efficiency in Taiwan. *Tourism Management*, Vol.28, No.3, 2007, pp.696-702.

[9] Y. Chen & J. Zhu. DEA Models for Identifying Critical Performance Measures. *Annals of Operations Research*, Vol. 124, No.1, 2003, pp.225-244.

[10] W. Chiang, M. Tsai & L.S. Wang. A DEA evaluation of Taipei hotels. *Annals of Tourism Research*, Vol.31, No.3, 2004, pp.712-715.

[11] E.U. Choo, B. Schoner & W.C. Wedley. Interpretation of criteria weights in multicriteria decision making. *Computers & Industrial Engineering*, Vol.37, No.3, 1999, pp.527-541.

[12] W.D. Cook & L.M. Seiford. Data envelopment analysis (DEA) – Thirty years on. *European Journal of Operational Research*, Vol.192, No.1, 2009, pp.1-17.

[13] J. De Mello, E. Gomes, L. Meza & L. Neto. Cross Evaluation using Weight Restrictions in Unitary Input DEA Models: Theoretical Aspects and Application to Olympic Games Ranking. *WSEAS TRANSACTIONS on SYSTEMS*, Vol.7, No.1, 2008, pp.31-39.

[14] J.A. Fitzimmons & F.M. Fitzimons. *Service Management: Operations, Strategy and Information Technology*, Irwin: McGraw-Hill, 1998.

[15] C. Fornell & F. Bookstein. Two structural equations models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research*, Vol.19, No.4, 1982, pp.440-452.

[16] B. Golany & Y. Roll. An Application Procedure for DEA. *OMEGA*, Vol.17, No.3, 1989. 237-250.

[17] P. Hess & J. Siciliano. *Management: Responsibility for Performance*. New York: McGraw-Hill, 1996.

[18] C.H. Huang, Y.H. Lin, & M.L. Tseng. Application of Cost- Benefit Analysis and Data Envelopment Analysis to Evaluate the Municipal Solid Waste Management Projects in Metro Manila. *WSEAS TRANSACTIONS on BUSINESS and ECONOMICS*, Vol.5, No.12, 2008, pp.524-540.

[19] J. Hulland. Use of partial least squares (PLS) in strategic management research: a review of four recent studies. *Strategic Management Journal*, Vol.20, No.2, 1999, pp.195-204.

[20] S.N. Hwang & T.Y. Chang. Using data envelopment analysis to measure hotel managerial efficiency change in Taiwan. *Tourism Management*, Vol.24, No.4, 2003, 357-369.

[21] E. Jakobowicz, & C. Derquennea, A modified PLS path modeling algorithm handling reflective categorical variables and a new model building strategy. *Computational Statistics & Data Analysis*, Vol.51, No.8, 2007, pp.3666-3678.

[22] E.J.M. Lauria & P.J. Duchessi. A methodology for developing Bayesian networks: An application to information technology (IT) implementation. *European Journal of Operational Research*, Vol.179, No.1, 2007, pp.234-252.

[23] L.C. Lin. & C.H. Hong. Operational performance evaluation of international major airports: An application of data envelopment analysis. *Journal of Air Transport Management*, Vol.12, No.6, 2006, pp.342-351.

[24] I. Manikas & L.A. Terry, A case study assessment of the operational performance of a multiple fresh produce distribution centre in the UK. *British Food Journal*, Vol.111 No.5, 2009. pp.421-435.

[25] B. Marsh, A Consolidated Approach to Productivity Assessment. *Journal of Industrial Technology*, Vol.18, No. 2, 2002, pp.1-8.

[26] R. Morey & D. Dittman. Evaluating a hotel GM's performance: A case study in benchmarking. *Cornel Hotel Restaurant and Administration Quarterly*, Vol.36, No.5, 1995, pp.30-35.

[27] S. Nadkarni & P.P. Shenoy. A causal mapping approach to constructing Bayesian networks. *Decision Support Systems*, Vol.38, No.2, 2004, pp.259-281.

[28] T.A. Nahra, D. Mendez & J.A. Alexander. Employing super-efficiency analysis as an alternative to DEA: An application in outpatient substance abuse treatment. *European Journal of Operational Research*, Vol.196, No.3, 2009, pp.1097-1106.

[29] A. Neely, M. Gregory & K. Platts.

Performance measurement system design; a literature review and research agenda. *International Journal of Operations & Production Management*, Vol. 15, No.4, 1995, pp.80-116.

[30] S. Opricovic & G.H. Tzeng. Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European Journal of Operational Research*, Vol.156, No.2, 2004, pp.445-455.

[31] R. Ramanathan. Supplier selection problem: integrating DEA with the approaches of total cost of ownership and AHP. *Supply Chain Management: An International Journal*, Vol.12, No.4, 2007, pp.258-261.

[32] C. Ranganathan & V. Sethi. Rationality in Strategic Information Technology Decisions: The Impact of Shared Domain Knowledge and IT Unit Structure. *Decision Sciences*, Vol.33, No.1, 2002, pp.59-86.

[33] D. Reynolds & D. Biel, Incorporating satisfaction measures into a restaurant productivity index. Hospitality Management, Vol.26, No.2, 2007, pp.352-361.

[34] R.G. Schroeder. *Operations Management; Decision Making in the Organizations Function*. New York: McGraw-Hill, 1985.

[35] J. Seydel. Data envelopment analysis for decision support. *Industrial Management & Data Systems*, Vol.106, No.1, 2006, pp.81-95.

[36] J.K. Shang, W.T. Hung, C.F. Lo & F.C. Wang, Ecommerce and hotel performance: three-stage DEA analysis. *The Service Industries Journal*, Vol. 28, No. 4, 2008, pp.529-540.

[37] M. Sigala. Integrating customer relationship management in hotel operations: managerial and operational implications. *Hospitality Management*, Vol.24, No.3, 2005, pp.391-413.

[38] D. Temme, H. Kreis & L. Hildebrandt. *PLS Path Modeling-A Software Review*, SFB 649 Discussion Papers SFB649DP2006-084, Humboldt University, Berlin, Germany, 2006.

[39] M. Tenenhaus, V.E. Vinzi, Y.M. Chatelin, & C. Lauro. PLS path modeling. *Computational Statistics and Data Analysis*, Vol.48, No.1, 2005, pp.159-205.

[40] S.H. Tsaur. The operating efficiency of international tourist hotels in Taiwan. *Asia Pacific Journal of Tourism Research*, Vol.6, No.1, 2000, pp.73-81.

[41] C.A. Voss, P. Åhlström & K. Blackmon. Benchmarking and operational performance: some empirical results. *International Journal of Operations & Production Management,* Vol.17, No. 10, 1997, pp.1046-1058.

[42] F.C. Wang, W.T. Hung & J.K. Shang, Measuring Pure Managerial Efficiency of International Tourist Hotels in Taiwan. *The Service Industries Journal*, Vol.26, No.1, 2006, pp.59-71.

[43] B.H. Wixom & H.J. Watson. An empirical investigation of the factors affecting data warehousing success. *MIS Quarterly*, Vol.25, No.1, 2001, pp.17-41.

[44] C. Yang & W.M. Lu. Performance benchmarking for Taiwan's international tourist hotels. *INFOR*, Vol.44, No.3, 2006, pp.229-245.